Earth Observations for Official Statistics

Satellite Imagery and Geospatial Data Task Team report

5th December 2017

White cover publication, pre-edited text subject to official editing and subject to further consultation

United Nations

Australian Bureau of Statistics

Queensland University of Technology, Australia

Queensland Government, Australia

Commonwealth Scientific and Industrial Research Organisation, Australia

European Commission – DG Eurostat

National Institute of Statistics and Geography, Mexico

Statistics Canada

Executive summary

This handbook, written by members of the United Nations Task Team on Satellite Imagery and Geo-spatial Data, provides a guide for National Statistical Offices considering using satellite imagery (known as earth observations) data for official statistics. It was produced as an input to the United Nation Global Working Group on Big Data for Official Statistics report to the United Nations Statistical Commission for 2017.

The handbook provides a brief introduction to the use of earth observations (EO) data for official statistics, types of sources available and methodologies for producing statistics from this type of data. It also summarises the results of four pilot projects produced by Task Team members; Australian Bureau of Statistics (ABS), Australia, Instituto Nacional de Estadística Geografíca e Informática (INEGI), Mexico, Departamento Administrativo Nacional de Estadistica (DANE), Colombia and Google. Supplementary material includes a methodology literature review, and the full reports of the pilot projects.

In the final chapter, guidelines are presented for National Statistical Offices to consider and refer to when considering whether to implement earth observations data sources into their statistical production process, and issues to consider throughout the implementation and output processes. Rather than being prescriptive, the guidelines are intended to prompt National Statistical Office to critically consider their own business needs, and apply the recommendations as appropriate to their circumstances. As the international experience using these data for statistical purposes grows, National Statistical Offices can build on the guidelines provided in this handbook with their own expertise and knowledge.

Foreword

Official statisticians have been using a diversity of data sources in the production of official statistics for decades, including "designed" data sources such as censuses and surveys, and "found" data sources such as administrative and transactional data.

As a result of increasing interaction with digital technologies by citizens, and the increasing capability of these technologies to provide digital trails, new sources of data have emerged and are increasingly available to official statisticians. Such sources include data from sensor networks and tracking devices e.g. satellites and mobile phones.

Statistical agencies around the world have a strong interest in exploring the viability of using satellite imagery data, or more broadly termed as earth observations (EO) data, to improve official statistics on a wide range of topics spanning agriculture, the environment, business activity and transport.

EO data have significant potential to provide more timely statistical outputs, to reduce the frequency of surveys, to reduce respondent burden and other costs, to provide data at a more disaggregated level for informed decision making and to provide new statistics and statistical insights.

EO data may also support the monitoring of the Sustainable Development Goals (SDGs) by improving timeliness and relevance of indicators without compromising their impartiality and methodological soundness.

This handbook provides a brief introduction to the use of EO data for official statistics, types of sources available, examples of using EO data to compile the indicators for SDGs and methodologies for producing statistics from this type of data. It also summarises the results of four pilot projects produced by United Nations Satellite Imagery and Geospatial Data Task Team members to explore the feasibility of using EO data for official statistics, and additionally, other relevant and useful case studies. Supplementary material includes a methodology literature review.

In the final chapter, guidelines are presented for National Statistical Offices to consider and refer to when considering whether to use EO data in producing official statistics, and issues to consider throughout the implementation and output processes.

Producing this handbook would not have been possible without the hard work, dedication and significant contributions of the chapter authors. I would like to express my appreciation to Dr Hannes I. Reuter (Eurostat), Dr Arnold Dekker, Flora Kerblat, Dr Alex Held and Dr Robert Woodcock (Commonwealth Science and Industrial Research Organisation) Alexis McIntyre (Geoscience Australia), Professor Kerrie Mengersen and James McBroom (Queensland University of Technology), Sandra Yaneth Rodriquez (Departamento Administrativo Nacional de Estadistica), and Jacinta Holloway (Australian Bureau of Statistics). I would also like to thank the authors of the Task Team Pilot reports, Patrick Dunagan (Google), Ronaldo Ocampo and José De La Torre (Instituto Nacional de Estadística Geografíca e Informática), Jennifer Marley, Ryan Defina, Kate Traeger, Daniel Elazar, Anura Amarasinghe and Gareth Biggs (Australian Bureau of Statistics). Thank you also to Ben Fitzpatrick and Brigitte Colin (Queensland University of Technology) for their contributions to the methods case studies in Chapter 4. Thank you also to Statistics Canada for allowing us to include their work as an example of using EO data for official statistics in practice.

Receiving comments and feedback from experts in the earth science, statistical methodology, agriculture and geospatial fields has been essential to producing this handbook. I would also like to thank Sybille McKeown, Daniel Elazar, Martin Brady and Thomas Walter (Australian Bureau of Statistics), Alexis McIntyre (Geoscience Australia), Dr Andries Potgieter (University of Queensland), Dr Matthew Pringle and Dr Michael Schmidt (Queensland Department of Science, Information Technology and Innovation), Dr Giulia Conchedda and Jacques Delincé (Food and Agriculture Organization of the United Nations) and Javier Gallego (Joint Research Center - European Commission) for their comments and suggestions to improve the handbook content.

Dr Siu-Ming Tam

Chair, United Nations Satellite Imagery and Geo-spatial Data Task Team

1. Introduction

Remote sensing is a technology that aims to observe and study the Earth systems, and their dynamics. Data related to remote sensing, specifically satellite images, have a purpose to observe and study the Earth from space; its land surface, the oceans and the atmosphere (ESA, 2016)[1]. Civilisation interacts with the natural components of Earth systems, adapting them in diverse and complex ways, generating modified Earth systems suitable for measuring by Earth Observation (EO).

In this sense, what society does, and its relation with Earth, has different responses which modify geospatial variables. These can be directly or indirectly detected by EO; indeed, socio-economic activity is distributed across most of the planet. Then, if the National Statistical Offices (NSOs) are among the most important sources of basic socio-economic information for their Governments, EO data and information is a key geospatial source that complements, improves and updates official statistics. This means a change of paradigm from past and current statistical approaches measuring effects of social life on Earth (anthropogenic effects), its evolution, distribution, impacts and sustainability. Basically, the main challenges that mankind is facing in what is now called the Anthropocene.

EO data and the information derived from these data is a special case of geospatial Big Data. Big Data is defined as "any large and complex collection of data sets that becomes difficult to process using traditional data processing applications", and therefore includes data from EO satellites. In many cases, Big Data is considered to be unstructured data or data that is used for another aim than the original creator of the data intended. In the case of EO it is actually purposefully created to be highly structured and to measure specific aspects of the Earth. The complexity of EO data is to extract meaningful information about a real object, value, state or condition from its reflected or emitted electromagnetic signal coming from the earth, the atmosphere or ocean, travelling through the atmosphere and measured in space, ocean or soil.

Satellite EO as an information source in support of many sectors of government and industry has been proven, and was reconfirmed in September 2015 by world leaders, whilst adopting the 2030 Agenda for Sustainable Development. They recognised the critical importance of "transparent and accountable scaling-up of appropriate public-private cooperation to exploit the contribution to be made by a wide range of data, including EO and geospatial information, while ensuring national ownership in supporting and tracking progress". In adopting the 2030 Agenda for Sustainable Development, world leaders agreed that a global indicator framework would be an essential tool to measure, monitor and report progress on achieving the Sustainable Development Goals (SDGs). At the 47th Session of the United Nations Statistical Commission (UNSC) 8-11 March 2016, global indicators were presented and discussed to help NSOs to monitor these 17 SDGs. Effective use of the information in satellite imagery can have a transformational impact on many of humanity's most significant challenges, such as helping global scientists, resource and planning managers and politicians better monitor and protect fragile ecosystems, ensure resilient infrastructure, manage climate risks, enhance food security, build more resilient cities, reduce poverty, and improve governance, among others.

The Global Working Group (GWG) on Big Data for Official Statistics was created in 2014, as an outcome of the 45th meeting of the UN Statistical Commission. In accordance with its terms of reference, the UN GWG provides strategic vision, direction and coordination of a global programme on Big Data for official statistics, including for indicators of the 2030 agenda for sustainable

[1] http://www.esa.int/SPECIALS/Eduspace_EN/SEMF9R3Z2OF_0.html

development. It also promotes practical use of Big Data sources, while promoting capability building, training and sharing of experiences.

Finally, UN GWG fosters communication and advocacy of use of Big Data for policy applications and offers advice in building public trust in the use of Big Data from the private sector.

In this context, this report focuses on EO data and methods as explored by the UN GWG Task Team on Satellite Imagery and Geo-Spatial Data.

In the past the uptake by NSOs of EO information has been slow. However, many NSOs are now discovering the potential of using new and consistent data sources and methodologies to integrate various "geo" variables to support and inform official statistics. These can be generated by a combination of geospatial information, EO and other Big Data sources and are able to fill data gaps, provide information where no measurements were ever made and improve the temporal and spatial resolutions of data (e.g. daily updates on crop area and yield statistics).

This shift in paradigm from traditional statistical methods (e.g. counting, measuring by humans) towards estimation from sensors (with associated aspects of validity, approximation, uncertainty), simulation and modelling will not be simple, as an established statistical system with its advantages and disadvantages currently exists. It will require convincing, statistically sound results, run in a production process for a number of years, well thought out arguments and excellent scientific methods, willingness to shift resources in the institutions, positive cost-benefit-analysis (e.g. subsidiary or replacement) and the motivation (e.g. cost/ staff reductions) to move ahead in a fast changing world to adapt to higher spatial and temporal resolutions to address policy questions.

This comes hand in hand with the incorporation of these new methods into the Generic Statistical Business Process Model (GSBPM). The official documentation of the GSBPM helps to describe and define the set of business processes needed to produce official statistics. NSOs are given a standard framework and harmonised terminology to help to modernise their statistical production processes, as well as to share methods and components. Additionally the GSBPM can also be used for integrating data and metadata standards, as a template for process documentation, for harmonising statistical computing infrastructures, and to provide a framework for process quality assessment and improvement (UNECE, 2013). Currently, according to the survey in UNECE (2015) most of the countries still need to develop a strategy for Big Data or GSBPMs to treat these kinds of data accordingly.

In contrast, production processes somehow similar to the business processes or GSBPMs are in place outside the NSOs. Examples are found in different statistical domains - e.g. for Forest the Global Forest Observations Initiative (GFOI)- and are discussed in more detail in Chapters 2 and 4. We selected the exemplary field of agriculture production where the two organisations mentioned below are e.g. contributing strongly to the Group on Earth Observations Global Agricultural Monitoring (GEOGLAM).

The US Department of Agriculture releases monthly the World Agricultural Supply and Demand Estimates (WASDE) report (USDA, 2016) with the earliest reports available from 1973. The UN-Food and Agriculture Organisation (FAO) provides the monthly FAO Cereal Supply and Demand Brief (FAO, 2016), with additional detailed information in a quarterly Crop Prospects and Food Situation prepared by economists. These reports provide at the national or even subnational level estimates and forecasts of agriculture production, acreage and prices based on a mixture of data. The USDA reports clearly link their results to analytical data based on weather information and satellite data (e.g. down to 250 m spatial resolution from MODIS imagery).

A slightly different example is the European Commission, where the Monitoring Agricultural Resources (MARS) bulletins (EC, 2016) report the latest predictions on crop vegetation growth (cereal, oil seed crops, protein crops, sugar beet, potatoes, pastures, rice) including the short-term effects of meteorological events. These reports are supported since 1992 by near real-time crop growth monitoring and yield forecasting information called the MARS Crop Yield Forecasting System (MCYFS). Several more of these systems exist around the world. The latest with the cooperation of Statistics Philippines is the Philippine Rice Information System (PRISM, 2016) which aims to combine a variety of data sources to determine much more than a traditional statistical GSBPM product would be able to cover. PRISM aims to obtain parameters like rice crop seasonality; area; yield; damage (e.g. flood, wind, drought); and yield-reducing factors (e.g. diseases, animal pests, and weeds) that will certainly not be reported from a statistical perspective, but are needed for an evidence based policy support. The statistical community needs to reflect for what purpose and with which tools intend to provide information for current and near-future evidence based policy relevant questions.

One major opportunity to address within this context is the use of EO data. Currently we observe rapid changes in the EO world in terms of capabilities and availability. In 1997-1998 from the 23 available/programmed Landsat-TM scenes for a specific spot for one given year only 2, respective 4 scenes were useable due to cloud cover in North-eastern Germany (Grenzdörffer, G., 2001). This contrasts completely the availability for arid or semi-arid areas where maybe one or two scenes were not available. Over the past decades data consumers have seen an increased global coverage in imagery and sensors (e.g. MODIS, Sentinels, WorldView, Bella Vista – see Chapter 2) up to daily global mosaics (planet labs, 2016)). However, weather (e.g. clouds – Wilson & Jetz, 2016) and location (e.g. Norway and its sun lit times) will still play a role in decreasing the amount of suitable data captures. This enormous amount of data brings a shift in the traditional way EO data are handled. The EU Copernicus Sentinels satellite will create 3PB data per year, globally the estimations reach 1 EB. The community will move away from local processing of a single scene for one given day into a workflow which combines a) multiple sensors (e.g. SAR, thermal, optics – see Chapter 2) with b) various other input data streams at c) various dates and d) different resolutions. Thereby the processing will move into high performance computing data centres (e.g. Google Earth Engine, planet-API, National Computing Infrastructure in Australia, Digital Globe DGBX platform) using Big Data processing tools (e.g. MapReduce, Hipi) along the lines of moving the algorithms to the data not the data to the algorithms. Many gains in information coupled with more complex uncertainties are to be expected, especially in the combination of different data sources. Risks and challenges (e.g. Ma et al, 2015, Li et al., 2016) need to be mitigated; however, the gain in temporal and spatial resolution to address police relevant questions justifies these risks.

Related to the capabilities and availabilities is the recent development of the concept of providing Analysis Ready Data (ARD). Here, satellite data have been processed to a minimum set of requirements and organised into a form that allows immediate value-adding and analysis without additional user effort. Advantages are reproducibility, consistency and faster methodological developments. An example is the usage of an ARD dataset for the detection of water surfaces over a time span of 27 years - which would be usable for the Land Surface Area Calculations in the statistical domain (Lewis et al, 2016).

Last but not least a word of friendly guidance on EO data and methods to the uninitiated. EO can cover large areas (even inaccessible) repetitively with various spectral bands and spatial resolutions which can be analysed on a computer for many applications (e.g. base map, vegetation cover, crop estimation, erosion, water quality, coral reefs, flooding, and failure of a dam). Some disadvantages are that humans – the operators, select the sensors, calibrate the data, and perform the analysis, e.g. specialist knowledge

is needed to be successful. NSOs also need to be aware EO data has various limitations. EO will not provide any statistical indicators by default; it provides some spatial, spectral, and temporal information which can be related to indicators. Therefore, it is recommended to start small to gain experience - even on large Analysis Ready Datasets - and scale up afterwards.

Finally, this paper attempts to provide a relevant overview of EO data (Chapter 2) and methods (Chapter 3), showcasing several pilot projects from around the world (Chapter 4) and provide guidance to statisticians in the UN system and NSOs on how to use EO in their domains (Chapter 5).

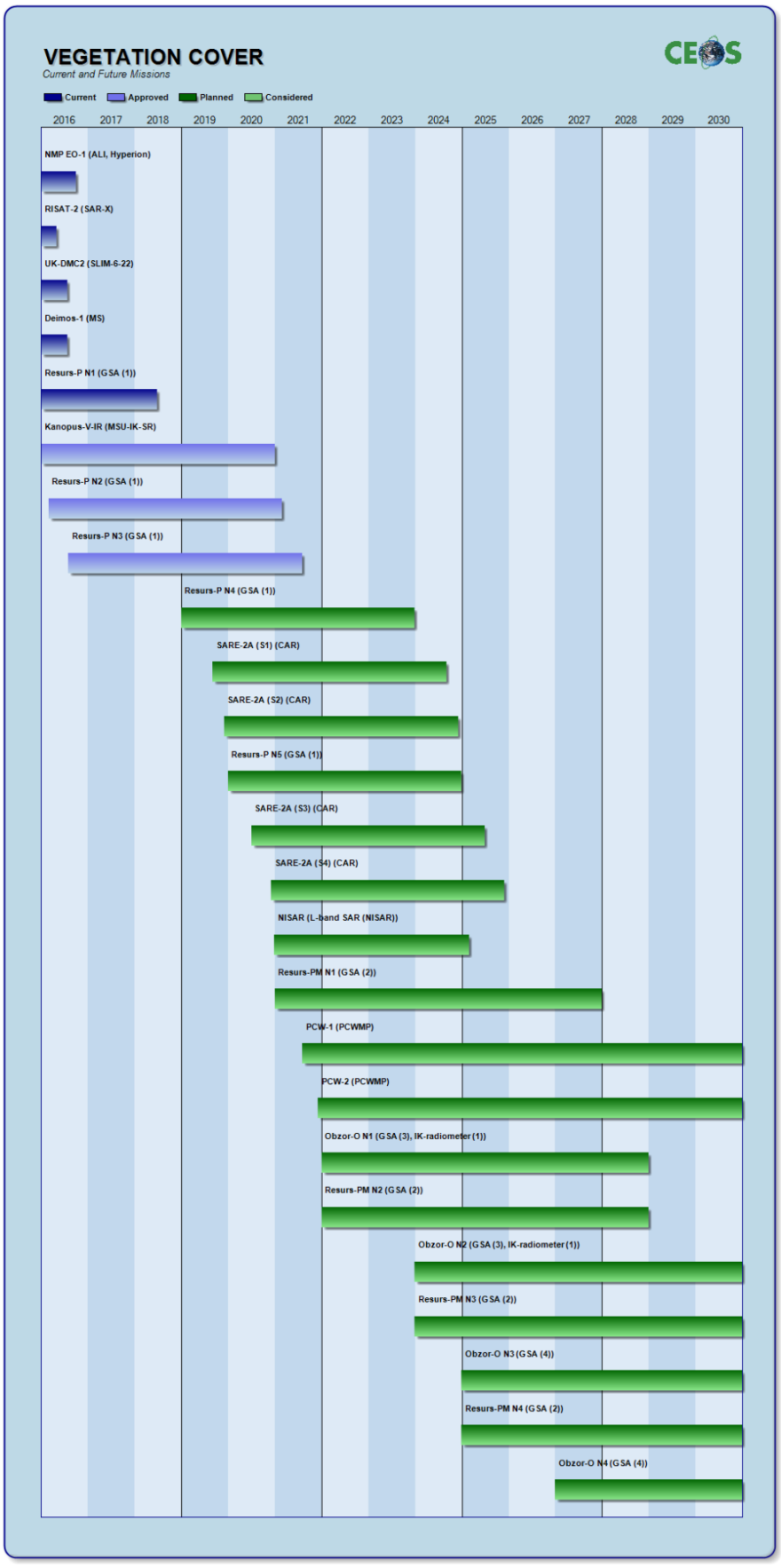
2. Data Sources

2.1 Big Data and Earth Observations

This chapter aims at providing guiding information to NSOs for consideration whether they could and should use EO satellite data derived information as a form of Big Data to relate to e.g. the UN SDGs indicators, or other NSO relevant information and if yes, which sources would be most relevant. This chapter also aims to shed light on some strengths and limitations of using EO data for official statistics, which is essential when specialists are required to provide fast and reliable information to decision makers.

There is a proliferation of earth observing systems (archival, current and planned- over 100s of sensors) so it is useful to categorise these sensors by their sensing characteristics. This is meant as a guide to be able to interpret publicly available lists of EO sensors such as on the CEOS (Committee on Earth Observation Satellites) website (www.ceos.org), and more specifically on the database page: http://database.eohandbook.com/ as well as the OSCAR (Observing Systems Capability Analysis and Review Tool) database of the WMO (World Meteorological Organisation) https://www.wmo-sat.info/oscar/satellites.

Each of these databases has merit for selecting the most suitable sensors (See 2.1.2 Earth Observation Data Information Sources). In Figure 1, for example, a selection is shown for vegetation cover measurement. It indicates guaranteed data continuity until 2030 at a minimum, coupled with the challenge of selecting the most fit-for-purpose EO sensor(s).


VEGETATION COVER
Current and Future Missions
CEOS
Current
Approved
Planned
Considered
2016
2017
2018
2019
2020
2021
2022
2023
2024
2025
2026
2027
2028
2029
2030
NMP EO-1 (ALI, Hyperion)
RISAT-2 (SAR-X)
UK-DMC2 (SLIM-6-22)
Deimos-1 (MS)
Resurs-P N1 (GSA (1))
Kanopus-V-IR (MSU-IK-SR)
Resurs-P N2 (GSA (1))
Resurs-P N3 (GSA (1))
Resurs-P N4 (GSA (1))
SARE-2A (S1) (CAR)
SARE-2A (S2) (CAR)
Resurs-P N5 (GSA (1))
SARE-2A (S3) (CAR)
SARE-2A (S4) (CAR)
NISAR (L-band SAR (NISAR))
Resurs-PM N1 (GSA (2))
PCW-1 (PCWMP)
PCW-2 (PCWMP)
Obzor-O N1 (GSA (3), IK-radiometer (1))
Resurs-PM N2 (GSA (2))
Obzor-O N2 (GSA (3), IK-radiometer (1))
Resurs-PM N3 (GSA (2))
Obzor-O N3 (GSA (4))
Resurs-PM N4 (GSA (2))
Obzor-O N4 (GSA (4))

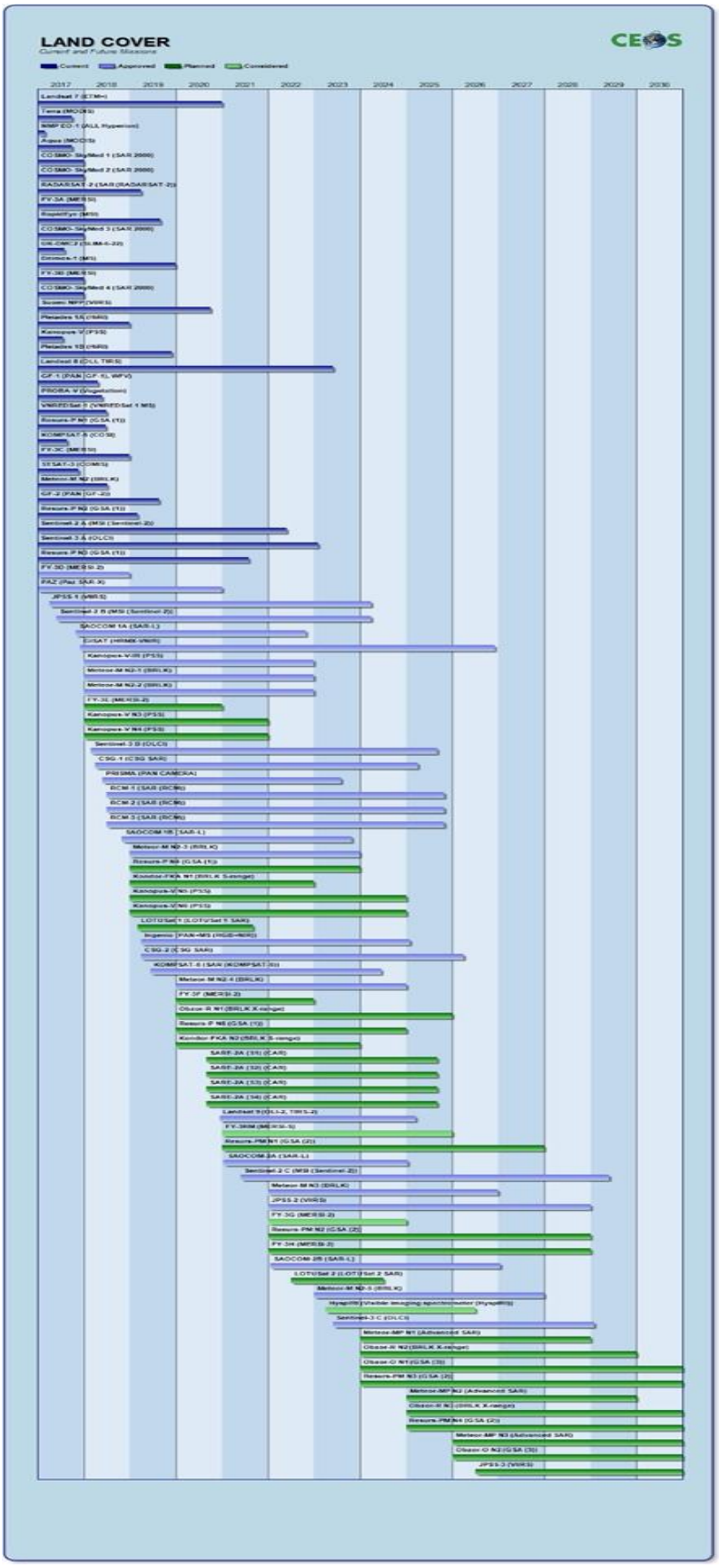


Figure 1: Extract from the CEOS database for Vegetation Cover and Land Cover measurements

Source: http://database.eohandbook.com/timeline/

2.2 Two main EO systems: LEO, GEO

Three main types of EO systems exist, based on their orbit around the earth, which has consequences for the spatial resolution and the temporal resolution; the LEO (Low Earth polar Orbiting), the MEO (Medium Earth Orbit) and the GEO (geostationary) satellites.

LEO satellites typically fly between 400 and 800 km altitude in an orbit that goes across both poles (with a slight deviation called the inclination). Effectively they scan the earth in fixed orbit at approximately 28,000 km/hr whilst the earth rotates beneath them, thus building up a global picture over some period of time (between daily to monthly depending on the swath width they record or the amount of satellites simultaneously in orbit). Each earth rotation takes about 90 minutes. These satellites have increased coverage towards the poles and decreased coverage around the equator (see Figure 3). As they are relatively close to the earth their spatial resolution can be as high as 30 cm pixels in black & white (panchromatic) and about 1 m in colour or multispectral bands for commercially available imagery.

The most well-known of the publicly available LEO sensors are the MODIS (MODerate-resolution Imaging Spectroradiometer since 1999) and Landsat sensors (since 1984) with spatial resolutions of 250/500/1000 m for MODIS and 30 m for Landsat. 80 m Landsat data is available since 1973. (Note: spatial resolution of e.g. 30 m indicates a pixel with dimension of 30 by 30 m = 900 m2.) The recently launched Sentinel-2A satellite (with many more following Sentinel-2B, 2C, 2 D etc.) has 10 m spatial resolution (as well as some bands at 20 m and at 60 m resolutions).

The Landsat 30 m resolution and Sentinel-2 10 m data are examples of a public good; providing freely available data with a significant track record of documentation and peer reviewed literature covering all aspects of the sensor to applications relevant to society.

Landsat 4, 5, and 7 images consist of seven spectral bands with a spatial resolution of 30 by 30 m for Bands 1 to 5 and 7. The spatial resolution for Band 6 (thermal infrared) is 120 m, but is subsequently resampled to 30m pixels to align with the other 5 bands. Figure 2 shows the operational time windows of the various Landsat satellite generations.

Landsat 8 is now the preferred satellite from the Landsat series as it is significantly more sensitive, has additional spectral bands, and is very well calibrated. The previous Landsat series images should only be used for archival analysis to detect change over time or frequency of events (see the Water Observations from Space Flood frequency web mapping facility by GeoScience Australia http://www.ga.gov.au/scientific-topics/hazards/flood/wofs).

The Sentinel-2 satellites will become increasingly relevant as the data becomes increasingly globally available.

A Brief Overview of Landsat Data

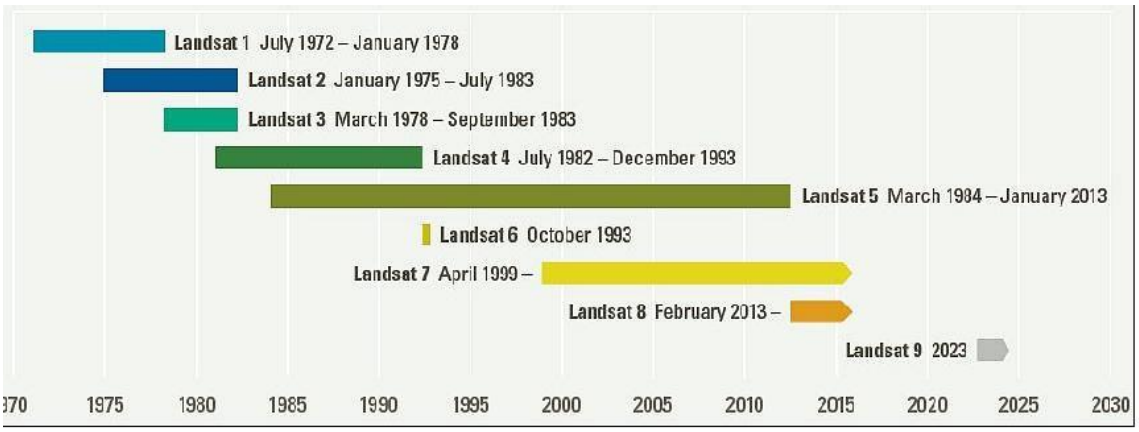


Figure 2: Landsat Satellite Generations

Source: https://directory.eoportal.org/web/eoportal/satellite-missions/l/landsat-7

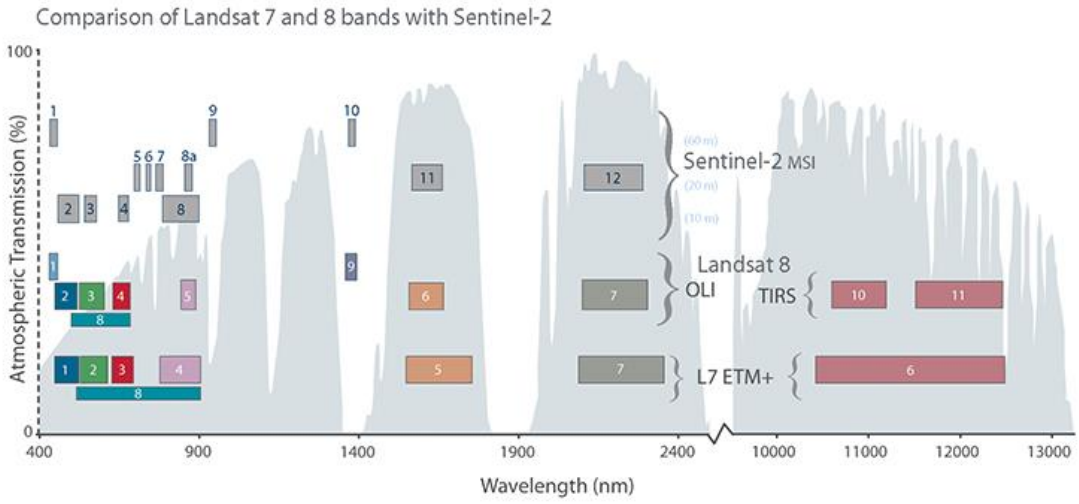


Figure 3: Spectral bands: Landsat Satellite Generations vs Sentinel-2

Source : http://landsat.gsfc.nasa.gov/sentinel-2a-launches-our-compliments-our-complements/

Landsat satellite imagery is recorded and saved in rows and paths based on a construct known as the Worldwide Reference System (WRS). Structuring and saving the imagery using the WRS in this way enables inquiry over any location of the world by specifying a nominal scene centre designated by paths and row numbers (see Figure 4).

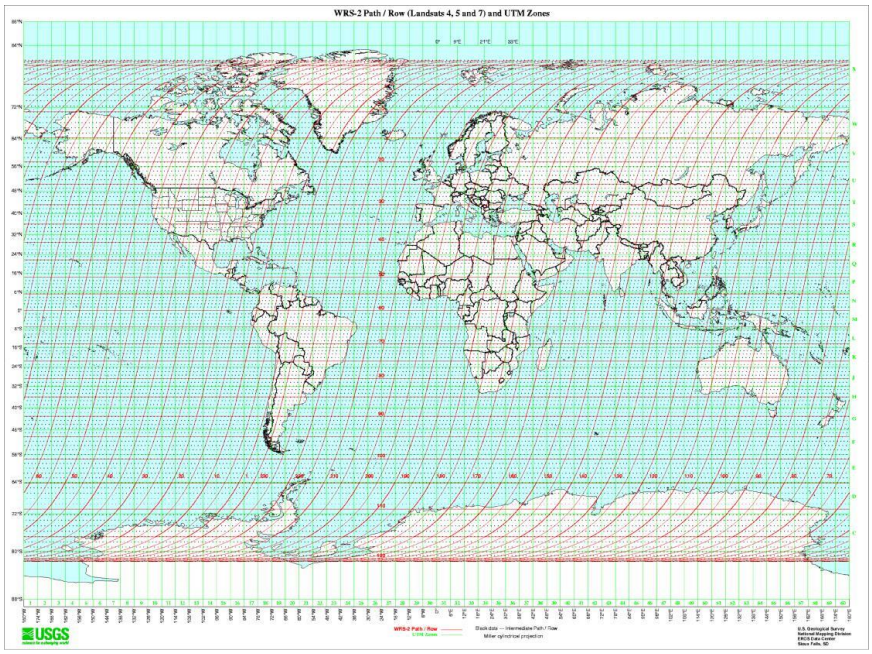


Figure 4: Worldwide Reference System

Source: http://landsat.gsfc.nasa.gov/the-worldwide-reference-system/

The Landsat 1-3 WRS-1 notation assigns sequential path numbers from east to west to 251 nominal satellite orbital tracks, starting with number 001 for the first track which crosses the equator at 65.48 degrees west longitude. A specific orbital track can vary due to drift and other factors; thus, a path line is only approximate. The orbit is periodically adjusted after a specified amount of drift has occurred in order to bring the satellite back to an orbit that is nearly coincident with the initial orbit. An example for an area of Melbourne, Australia, showing path/row grids is shown in Figure 5.

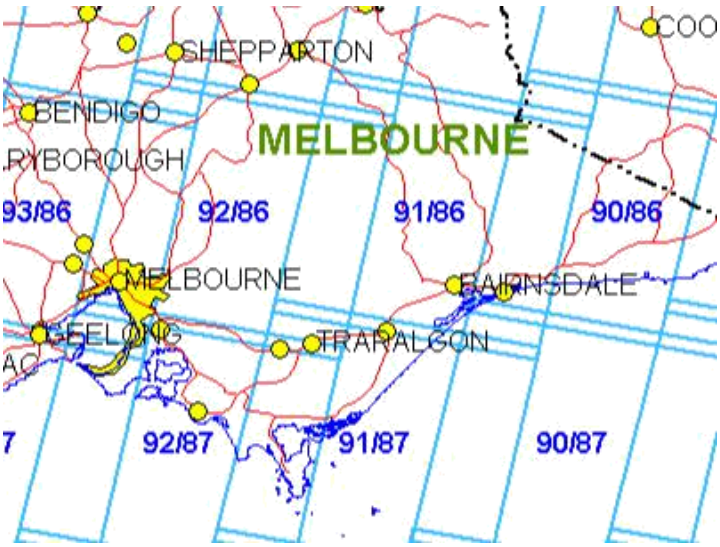


Figure 5: Path and Row Satellite Grids for a Selected Area of Melbourne, Australia.

Landsat 8 and Landsat 7 follow the WRS-2, as did Landsat 5 and Landsat 4, whereas Landsat 1, Landsat 2, and Landsat 3 followed WRS-1.

The Landsat 4, 5, and 7 Worldwide Reference System-2 (WRS-2) is an extension of the global Landsat 1 through 3 WRS-1 and utilises an orderly Path/Row system in a similar fashion. There are, however, major differences in repeat cycles, coverage, swathing patterns and Path/Row designators due to the large orbital differences of Landsats 4 and 5 compared to Landsats 1 through 3.

Once the satellite data is pre-processed into Analysis Ready Data this file system is removed and replaced by each pixel of each image being placed in a spatio-temporal database from which any slice of data through time and space can be selected.

GEO satellites are located above the equator at an altitude of about 36,000km where they can stay exactly positioned over the same spot on earth. Originally designed for meteorological use they are becoming so sophisticated that the sensors are also useful for non-meteorological purposes. The current highest spatial resolution is 500 m with images taken at 10 minute intervals from the HIMAWARI-8 Satellite, the first of a series of similar satellites (GOES-R Type) that will cover most of the world. Himawari-8 is positioned over Indonesia and covers half the globe, although at larger off nadir (=off vertical) angles the satellite creates increasingly skewed pixels.

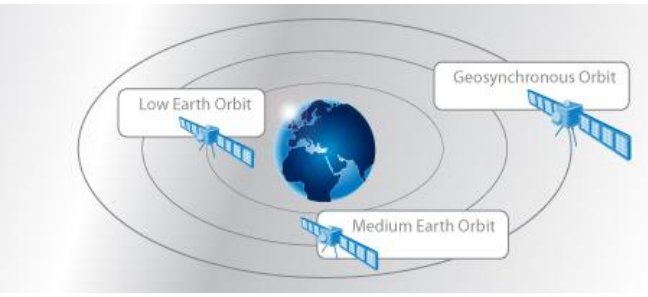


Figure 6: Visual representation of satellite orbits

Source: http://www.idirect.net/Company/Resource-Center/~/media/Files/Corporate/iDirect%20Satellite%20Basics.pdf

The MEO (Medium Earth Orbit, approximately 20,000 km) satellites are mainly focused on navigation, communication, and geodetic/space environment science, with an orbit time of 12 hours to 2 hours. For more information, please visit NASA (National Aeronautics and Space Administration) website: http://earthobservatory.nasa.gov/Features/OrbitsCatalog/

2.3 Active and passive sensors

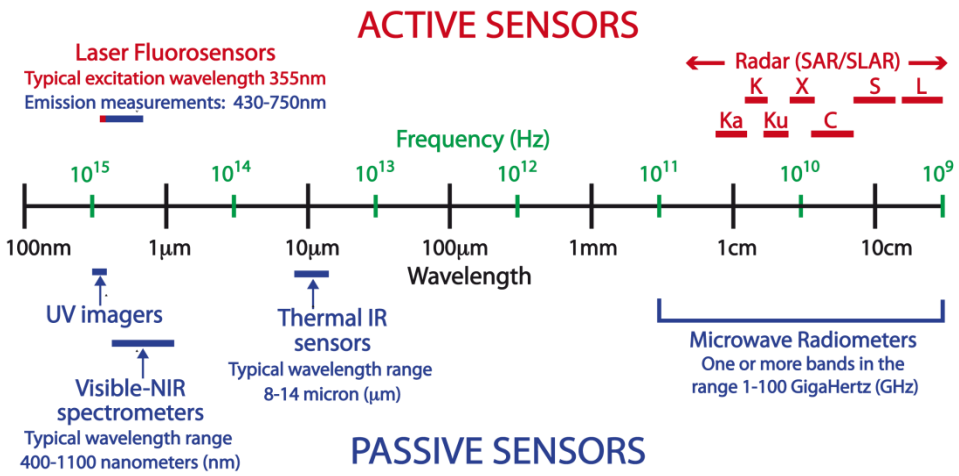


Figure 7: Active/Passive sensors characteristics

Source: http://lms.seos-project.eu/learning_modules/marinepollution/marinepollution-c01-s02-p01.html.

Wavelengths and frequencies of electromagnetic waves are on logarithmic scales. Passive instruments detect signals which are naturally available, e.g. sun irradiance reflected or thermal radiation emitted from a target. Active instruments provide their own source of radiation for target illumination and returned signal detection.

It is also important to discriminate the electromagnetic wavelength domain these sensors record and whether they measure reflected sun energy, emissions from the earth (the passive earth observing sensors) or a signal they emit and then record as it is reflected by the earth (the active sensors).

For the passive sensors wavelengths measured vary from those the human eye can see such as the blue to green to yellow to orange to red wavelengths (the visible or VIS Wavelengths); the NIR (Nearby Infrared) wavelengths, the SWIR (Shortwave Infrared Wavelengths), MIR (Mid Infrared Wavelengths in research mode currently), the TIR (Thermal Infrared Wavelengths) measuring temperature emission through to the microwave region (or radar). The VIS to NIR to SWIR to MIR sensors operate mainly during the day time (with some exceptions such as using night time lights to detect marine (shipping & energy resource platforms) or terrestrial artificial light sources. The TIR and passive microwave sensors can also detect emissions at night. Passive microwave may be used to estimate soil moisture on land or ocean salinity.

A separate, recent development is the detection of gravity anomalies using satellites. These anomalies over time can infer the depletion or recharge of large subsurface groundwater reservoirs as an example.

The active sensors either emit light by lasers in the VIS to NIR domain (LiDAR:Light Detection And Ranging) or emit microwave energy by synthetic aperture radar (SAR). These systems can work day and night as they have their own source of electromagnetic energy. LiDAR is used for accurate estimations of elevation and canopy height or in shallow waters for the bottom depth (bathymetry). Research and development on LiDAR is focusing on being able to discriminate aspects of the canopy or of the water column.

SAR is used for imaging the radar backscatter signal from which land cover, flood cover, agricultural crops, forests etc., illegal & unreported vessels can be detected and measured. SAR interferometry can

detect millimetre shifts, such as shifts in resource extraction areas (subsidence) or volcanic or earthquake regions.

2.4 Applications of algorithms to EO

EO is generally used to determine the spatial distribution of a variable (what's where?) and to determine the nature of the variable. For example, colour, depth, fluxes, vigour, concentration, density, mass, etc. By adding the temporal aspect of repeat coverage the question of state, condition and trend can then be answered. Therefore, these measured reflections or emissions need to be translated into meaningful information, such as for official statistics, through the application of algorithms. In general these algorithms are mathematical equations, statistical or biophysical, geophysical, chemo physical methods or any combination of these approaches.

The nature of these algorithms has a significant consequence for their use in producing official statistics. It is possible to discriminate five broad categories with many possible permutations; the first three are pixel-based methods and the fourth uses this information as well as spatial and contextual information. In the fifth method hybrid approaches are described.

1. **Empirical methods:** where a statistical relationship is established between the spectral bands or frequencies used and the variable measured (field-based) without there necessarily being a causal relationship. This method is the least suitable for automation across large areas and varying conditions (sun angle, season, latitude, slope and aspect of terrain, atmospheric conditions) unless accompanied by a significant, ongoing field measurement activity, preferably with each satellite overpass.

2. **Semi-empirical methods:** where a causal relationship is established between the spectral bands or frequencies used and the variable assessed. This method is less prone to providing spurious results, although results may have significantly increased error outside the field-based range. This method has medium suitability for automation across large areas and has less stringent requirements for frequent field based sampling.

3. **Physics-based inversion methods:** which are also known as semi-analytical inversion methods. All required variables are assessed in one spectral inversion simultaneously. This method provides physics-based consistency in results, and is most suitable for automation across large areas, provided the inversion model is properly parameterised for the desired variables. These are also called biophysical, biogeochemical or geophysical inversion methods.

4. **Object based image analysis method (OBIA):** This method combines spatial, pattern, texture and spectral information together (e.g. through initial image segmentation) with contextual information supervised by a human operator. This method has suitability for automation across the natural or manmade system for which it was developed and is being increasingly used.

5. **Artificial intelligence and machine learning methods:** these are intelligent, high-dimensional statistical (often non-linear) models for identifying highly complex relationships in data. Depending on how these methods are trained (using field measurements or physics-based models), they cross the realms of empirical to semi-empirical to physics-based and OBIA based inversion methods.

Methodological approaches to working with EO data are further discussed in depth in Chapter 3.

When the physical processes are well understood, we can develop physics-based inversion models. Often prefixes will be used such as bio-physical or geo-physical etc., indicating the nature of the variable being sensed. Sometimes EO data can provide useful inputs to such physical models, and this is the ideal situation. Inverting physical models is only one way of using them. For example, fractional cover or Leaf Area Index (LAI) can be used in a biophysical model in a forward manner – to predict, for example, gross primary productivity or evapotranspiration. Another example is water quality; some aspects of which can be determined from space using physics based inversion models. The advantage of these inversion models is that once properly parameterised they no longer need in situ data and thus are a prime candidate for automation of processing of large EO data volumes. Therefore, if it is possible, the physics based forward and inverse approaches are recommended as they decrease the need for in situ data and increase the opportunity to be automated.

However, often EO can't provide direct measures of the inputs, and that is when semi-empirical methods that find correlations between an EO derived variable and some real biophysical variable are required. When the physical processes aren't well understood (e.g. ecology), we can't use physical models and resort to empirical, semi-empirical or OBIA or machine learning models, which rely on statistics to define the relationships rather than physics. In this case, the empirical relationships need to be continually checked (field work or simulations) to ensure they are not changing across space and especially through time.

2.5 Combining data: data-data, data-model and model-data assimilation

Increasingly use is being made of combining the information of two or more EO sensors in order to counteract the disadvantages of some EO sources. This is called data-data fusion or blending. An example of this approach is using land reflectance in the VIS and NIR coupled with TIR imagery, or using sensors with high repeat frequency and low spatial resolution with low frequency and high spatial resolution to compensate for each other's weakness.

It is also possible to merge EO information with an underpinning model of the phenomenon under study. This approach is called data-model fusion.

When EO and/or field observation data is used to improve the performance of a model and the model output is then used to strengthen the validity or accuracy of the field data or EO products or vice versa in ways that maintain consistency amongst system variables, is cognisant of model and observation uncertainty, and enhances information value of generated outputs is called model-data assimilation.

2.6 Current examples of EO data applications

Many applications of EO derived geospatial information exist across domains, including but not limited to the following; biosecurity, biodiversity, forestry, agriculture, soil moisture, catchment water balance, land atmosphere energy exchange, digital elevation models, minerals, mine site environmental management, urbanisation, infrastructure, commodity stockpiles, environmental pollution, water quantity and quality, seagrasses and coral reefs, shallow water bathymetry, coastal and ocean water productivity, algal blooms, sea state, currents, upwelling and down welling zones, atmospheric air quality, emergency management and mitigation, disaster risk management, environmental accounting (i.e. monitoring land cover changes). Many more applications will be developed as sensors become more sophisticated, and the EO data become more accessible (see section 2.8 on Analysis Ready Data (ARD).

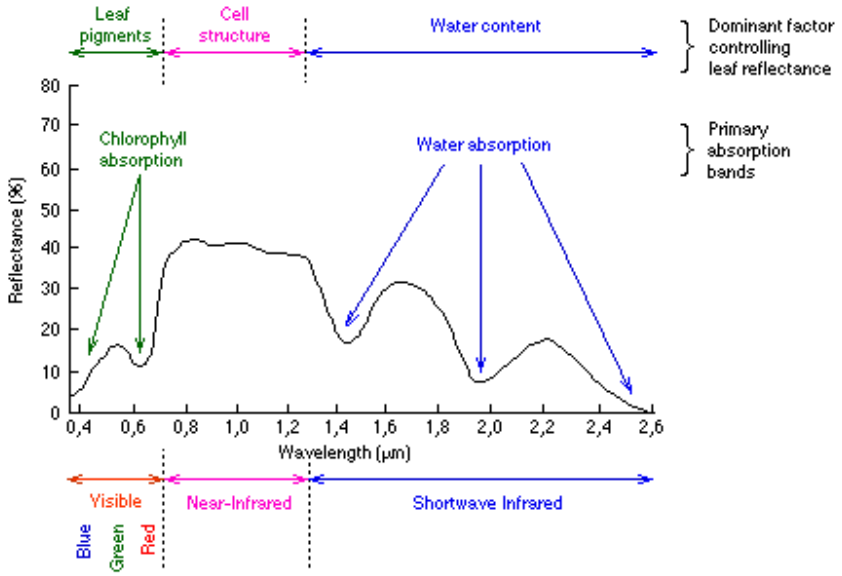


Figure 8: Remote sensing basics: wavelengths and reflectance signatures

Source: http://www.geog.ucsb.edu/~jeff/115a/remote_sensing/remotesensing.html

2.7 CEOS and GEO: international EO organisations

The GEO (Group on Earth Observations) and CEOS (Committee on Earth Observation Satellites) are two key players related to EO;these two global organisations work closely on various subjects linked to EO data, and CEOS is often called the "space" arm of GEO. The 2030 Agenda to implement and monitor the UN SDGs is a great opportunity to reflect the collaboration between the two entities, already working on a GEO initiative, called EO4SDGs, dedicated to the UN SDGs.

The EO enabling space agencies (through CEOS) and GEO acknowledge they have yet to fully address the major barriers faced by potential users of EO derived information. The translation of the signal measured in space to a meaningful variable requires this signal to pass several pre-processing steps until a signal is calculated, from which (in the case of VIS, NIR or TIR) effects of sensor noise, the atmosphere, the sun angle, terrain angle, clouds and cloud shadows, canopy shadowing or in the case of water sun and sky glint reflectance are removed.

CEOS was created in 1984, with an original function to coordinate and harmonise EO to make it easier for the user community to access and use data. CEOS initially focused on interoperability, common data formats, the inter-calibration of instruments, and common validation and inter-comparison of products. However, over time, the circumstances surrounding the collection and use of space-based EO have changed. Over the past three decades, CEOS has significantly contributed to the advancement of space-based Earth Observation community efforts. CEOS Agencies, (31 members) communicate, collaborate, and exchange information on EO activities, spurring useful partnerships such as the Integrated Global Observing Strategy (IGOS). A full list of CEOS members is available at http://ceos.org/about-ceos/agencies/.

CEOS played an influential role in the establishment and ongoing development of GEO and the GEOSS (Global Earth Observation System of System). CEOS Agencies work together to launch multi-agency collaborative missions and such cooperative efforts has highly benefited users all around the world. CEOS also provides an established means of communicating with external organisations, enabling CEOS to understand and act upon these organisations' EO needs and requirements.

Established in 2005, GEO is a voluntary partnership of governments and organisations that envisions "a future wherein decisions and actions for the benefit of humankind are informed by coordinated, comprehensive and sustained Earth observations and information."
See https://www.earthobservations.org/vision.php

GEO has created an initiative ("EO4SDGs", Earth Observations in Service of the 2030 Agenda for Sustainable Development), to organise and realise the potential of EO sources to advance the 2030 Agenda and enable societal benefits through achievement of the SDGs. EO4SDGS especially works to expand GEO's current partnerships, enhance its strong relationship with the UN, and foster consolidated engagement of the individual Member countries and Participating Organisations. CEOS is highly supporting this GEO initiative, and has also created an ad hoc team on SDGs (http://ceos.org/ourwork/ad-hoc-teams/sustainable-development-goals/) to better coordinate CEOS Agencies' activities around SDGs.

GEO is working closely with key UN entities includes the UN Statistics Division, the United Nations Committee of Experts on Global Geospatial Information Management (UN GGIM), the UN Sustainable Development Solutions Network (UN SDSN). Additional potential partners include development banks, Non-governmental organisations (NGOs), and international entities. Engagement and partnerships with these entities help build processes, mechanisms and human capacity to include EO data in national development plans and integrate them with national statistical accounts to improve the measuring, monitoring and achievement of the SDGs.

One of the actions of the EO4SDGs consists of Capacity Building and Engagement; support to countries in the implementation of all appropriate measures to properly address the 2030 Agenda. Drawing on capacity building activities within GEO, this action coordinates and fosters capacity building efforts at appropriate levels on effective ways to convey methods, enable data access, and sustain use of EO in the context of SDGs. Activities here draws on and support GEO efforts to characterise user needs. Given the basis of the SDGs in statistical data, this action includes engagement with the SDG statistical community about EO as well as capacity building within GEO and the EO community about SDG statistical principles and practices.

GEO and CEOS will therefore be fully engaged in the process of implementing the UN SDGs, especially when showing where EO can be useful to monitor some key indicators or to help achieve the goals/targets.

Some projects or initiatives are already crucial for EO monitoring and their continuity will help better connecting EO and official statistics worlds. For example, see 2.14.2 the example of GFOI (Global Forest Observations Initiative), a GEO initiative.

It is recommended for the National Statistical Offices in countries that are members of GEO to establish a working relationship with their national space/meteorological/science agencies in this area of using EO data for official statistics.

2.8 Introduction to EO based Analysis Ready Data (ARD)

Many satellite data users, particularly those in developing countries, lack the expertise, infrastructure and internet bandwidth to efficiently and effectively access, prepare, process, and utilise the growing

volume of raw space-based data for local, regional, and national decision-making[2]. Where such expertise does exist, data preparation is often limited to a small number of specialists, which limits the number of end-users of EO data and/or use a diversity of techniques making it difficult for observations and derived products to be appropriately compared. This results in often inconsistent and sometimes conflicting results. This is a major barrier to successful utilisation of space-based data, and the success of major global and regional initiatives that are supported by CEOS[3] and GEO.

Therefore, it is useful to introduce the concept of "Analysis Ready Data" (ARD). EO data needs to be corrected for many effects caused by the distance from the subject being measured and all the transmission effects as the signal passes from the earth's surface and is measured in space. Some of these effects are due to the atmosphere, the solar angle, the viewing angle from the sensor to the target etc. Pre-processing the data to correct for these effects creates EO data as if the sensor is collecting data within a few meters of the surface.

This pre-processing of EO data can be automated, thereby reducing the burden on the geospatial and information experts that are focused on extracting valuable information from this data. Moreover, if ARD is well defined and preferably peer reviewed, the user of the data can be confident they are working with data that has an acceptably high level of validity and accuracy.

CEOS has begun to consider the following interim definition:

"*Analysis Ready Data (ARD)" are satellite data that have been processed to a minimum set of requirements and organized into a form that allows immediate value-adding and analysis without additional user effort".*

Once raw data is processed to ARD it becomes more accessible and useful to properly harness the multiple technologies and initiatives behind 'Big Data', that allow real-time analysis and data mining to produce better science. Once the ARD state has been reached the algorithms and methods discussed previously can be applied and importantly are more likely to be comparable across different groups of users and sensor configurations. For NSOs to derive indicators for statistical purposes there is a requirement to bring the pre-processed EO data to a 'Product' stage where it has been classified into more meaningful variables such as a land cover classification. This still requires additional expertise which may be outside or inside an NSO. Refer to section 2.10 and Lewis et al, 2016 for more information on ARD.

2.9 Variety of EO sources (in situ, airborne)

To work with EO data, NSOs need to be aware of which sources can be used to monitor relevant variables for official statistics. Besides the most well-known MODIS and Landsat images, there are many sources of available satellite imagery data, free or commercial, from different EO satellites, collecting various measurements about the land and land cover, water and atmosphere. MODIS and Landsat are the most used satellite data sources due to their early launch (providing relatively long-term archives) and longevity, leading to a significant amount of peer reviewed publications, spatial resolution coupled with open and free data policies.

However, the two MODIS satellites, originally intended as research instruments, will not be replaced by identical systems but by an intermediate current system called SUOMI-VIRRS to be followed up

[2] NASA useful page to get information on how to use data: https://earthdata.nasa.gov/earth-observation-data/tools

[3] From CEOS Draft discussion paper on Analysis Ready Data (CEOS Systems Engineering Office 2016)

by the NPOESS sensors that combine meteorological and climate and land and ocean observations. The Landsat capacity for multispectral 30 m resolution data is no longer the highest spatial resolution freely available data and is no longer considered state-of-the-art in sensor development, although Landsat 8 is a significant improvement over the Landsat 5 and 7 satellites.

Below is a guide to selecting the best spectral bands to use for Landsat 8.

Band	**Wavelength**	**Useful for mapping**
Band 1 – coastal aerosol	0.43 - 0.45	Coastal and aerosol studies.
Band 2 – blue	0.45 - 0.51	Bathymetric mapping, distinguishing soil from vegetation and deciduous from coniferous vegetation.
Band 3 - green	0.53 - 0.59	Emphasises peak vegetation, which is useful for assessing plant vigour. Total suspended matter in water bodies.
Band 4 - red	0.64 - 0.67	Discriminates vegetation spectral slopes; also measures the primary photosynthetic pigment in plants (terrestrial and aquatic) : chlorophyll-a.
Band 5 - Near Infrared (NIR)	0.85-0.88	Emphasises biomass content and shorelines.
Band 6 - Short-wave Infrared (SWIR) 1	1.57 - 1.65	Discriminates moisture content of soil and vegetation; penetrates thin clouds
Band 7 - Short-wave Infrared (SWIR) 2	2.11 - 2.29	Improved moisture content of soil and vegetation and thin cloud penetration
Band 8 - Panchromatic	0.50 - 0.68	15 meter resolution, sharper image definition
Band 9 – Cirrus	1.36 - 1.38	Improved detection of cirrus cloud contamination
Band 10 – TIRS 1	10.60 – 11.19	100 meter resolution, thermal mapping and estimated soil moisture
Band 11 – TIRS 2	11.5 - 12.51	100 meter resolution, Improved thermal mapping and estimated soil moisture

Table 1: Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)

Source: http://landsat.usgs.gov/best_spectral_bands_to_use.php plus modifications by authors (Dekker, A., Held, A., and Kerblat, F.)

The European Commission's Copernicus Sentinel system of satellites (Sentinel types 1 through 6 now funded through to 2030, managed by the European Space Agency and EUMETSAT) are state of the art

operational systems with significantly enhanced capabilities. Take for example the Sentinel-2 satellite with 10 m pixels and (with the launch of Sentinel 2B from 2017 onwards) a repeat visit cycle of one image every five days.

We are now in the early stages of a technology revolution; a global sensing revolution, in which ground-based, aerial and space-based sensors, and new forms of data analytics, will enable entirely new approaches to the global administration of our planet. These new geospatial technologies can transform the accuracy, frequency, transparency and progress on assessing many of the indicators for the SDGs or other forms of official statistics at a significantly reduced cost per variable per square kilometre. NSOs and decision-makers will need to take into account this continuous technologic evolution, including a democratisation of EO satellite use. Going forward, it is recommended that NSOs increase training of their people in working with these data sources and permanently update these skills as technologies change.

2.10 Use of ARD or EO sources for official statistics

The advantage of EO data is its large spatial and temporal coverage, and its accessibility, reliability, and accuracy have improved dramatically. With EO satellite data, almost 100% of the earth surface is covered repeatedly, far more than could ever be achieved using field based or airborne technologies.

A disadvantage of EO is that contrary to field based, or in-situ measurements, EO estimates are derived indirectly (although one could argue that all sensor technologies do this including the human eye, which is effectively a remote sensing system with 3 wavelengths, also called spectral bands). While results of EO for potential operational use in many areas look promising, in other areas EO has not yet succeeded in extracting all the required information gaps and opportunities for further development of many operational applications still exist.

EO data, especially when used jointly with in-situ or model data, can make an essential contribution to resources management and development. However, it is not always easy to generate a clear picture of the boundaries between complementarity and substitutability of these techniques. Herein lies the risk for the common practitioner and planner; it is easy to become overwhelmed by all these advances and promises, while also feeling constrained by the institutional inability to cope with the long time periods and significant budgetary resources required for in-situ measurements. To make sound decisions, practitioners need to be aware of both the potential value and limitations of applications of EO technology and products, through informed recommendations and the development of practical, result-oriented tools. See Chapter 5 Figures 32 and 33 for more information.

Collecting, using, analysing and storing Big Data is a challenge that can be at least partially addressed by using EO satellite sources due to their highly structured nature and being designed for their specific purpose.

NSOs are currently using traditional data sources (surveys, collection of samples, etc.) which are still valid and useful, but EO data can help complete or obtain more accurate, frequent, spatially or temporally extrapolated, or temporally interpolated measurements.

In 2015, the UN Global Working Group on Big Data conducted a survey enquiring about the strategic vision of NSOs and their practical experience with Big Data. It is interesting to see that among the 93 countries which responded, the statistical offices considered “faster statistics”, “reduction of respondent burden” and “modernization of the statistical production process” to be the main benefits of using Big Data. Two other reasons to use Big Data followed; “new products and services” and "cost reduction”.

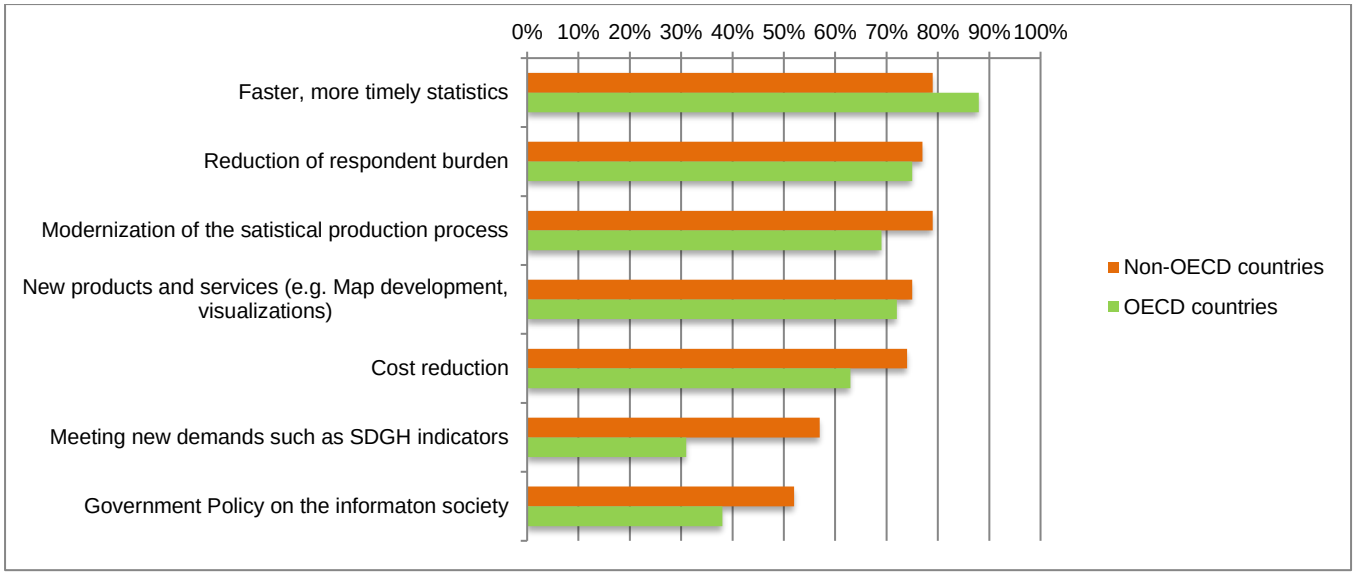


Figure 9: Main benefits of Big Data for NSOs

Source: Figure 5: Global survey analysed in the "Report of the Global Working Group on Big Data for Official Statistics"

EO derived information is a growing opportunity to complement traditional sources (ground or socio-economic data) when there is a lack of data. Using EO data products can make spatially or temporally denser data (globally), improve frequency or richness of data, and save money on traditional methods (surveys methods are highly time-consuming and expensive). EO data can be a game-changer for monitoring global initiatives (such as the current ones GFOI, GEOGLAM (GEO Global Agriculture Monitoring), etc.), and therefore would be useful methods to help monitor the UN SDGs by measuring and collecting some relevant indicators. If the stage of an automated EO processing system is achieved updates to official statistics could be done more frequently e.g. monthly.

Despite the potential benefits of EO, it is not always the most appropriate source for producing official statistics. Below are some criteria for practitioners to consider when assessing whether EO data is fit for their purposes. A further cost benefit analysis process is outlined in Chapter 5.

2.11 Validity and definitions

For empirical, semi-empirical, OBIA, AI and machine learning approaches there are three major sources of uncertainty in satellite estimations: (i) retrieval errors, (ii) sampling errors, and (iii) inadequate ground reference observations. In the case of physics-based inversion models (iv) the parameterisation of the model can introduce uncertainties; however these methods deal better with the first three sources of uncertainty. A physics-based inversion model does not necessarily need ground observations for validation once it is parameterised in a representative manner of the variability of the target variables. This is a bonus in the case of needing to estimate variables in remote areas. Moreover, physics-based inversion methods can be easily transferred from one EO sensor to another without needing an entire new set of ground measurements.

Additional sources of uncertainty originate in the need for model calibration, different spatial scales, and the need for bias correction of the estimated values prior to being used. An important challenge in the use of remote sensing based estimates is how to reconcile them with ground reference measurements, as both can be observations of a very different nature. Thus, observations from space need to be analysed, validated, and used in accordance with their limitations.

Sampling and measurement errors can result from the measurement of a variable in the wrong place (e.g. rainfall measured at the cloud base instead of at the ground surface) and from indirect estimations and biases in measurement sensors, entailing errors in the magnitude of the (e.g. precipitation) rate being measured. These errors will vary with the geographic and atmospheric setting.

However, ground reference measurements also have errors in validity, representativeness, completeness, and in the case of laboratory analysis also contain errors of sample preparation, material extraction, storage, and measurement errors. Thus, both EO data and ground reference data are variables with errors. Essentially these are measurement error models that need to account for errors in the ground reference variables, often seen as the independent variables. Note that in the case of crop classification, these cannot be obtained directly from EO data but can be from ground reference data. Although there will be measurement errors, ground reference data do not require modelling to turn them into the variables of interest to agricultural statistics, thus avoiding modelling errors.

A useful publication on validity of EO based information products (focusing on hydro meteorological variable estimation) can be found in: From Earth Observation for Water Resources Management: Current Use and Future Opportunities for the Water Sector (https://openknowledge.worldbank.org/bitstream/handle/10986/22952/9781464804755.pdf). Here a short summary is given, with some additional information as pertaining to physics-based inversion models.

Despite the uncertainties inherent to in-situ or ground reference measurements, it is believed the accuracy of an EO data product will rarely be as high as that of an equivalent field measurement at that location. Nevertheless, despite the generally lower site specific accuracy, EO products should still be considered an important alternative data source, as EO imagery can provide information with greater spatial extent, spatial density, and/or temporal frequency than can most field-based (point-based) observation networks. . Furthermore, EO derived information can be acquired much faster and are more cost effective than most traditional survey based methods. Once validated, the data can also be readily extrapolated across large regions and remote areas with high efficacy. It is for these reasons that a combination of EO and field (ground reference) data generally provides the best information outcomes. If it is possible to have a model (e.g. deterministic) that sufficiently describes the phenomenon of interest then model, EO and field data assimilation is the most powerful way to derive the required information.

2.12 When is EO considered as “valid”? The fit-for-purpose argument

The most useful definition in the case of trying to establish the validity of an EO based information product is the concept of it being fit for purpose. An EO scientist will, in general, try to achieve the highest level of precision, accuracy and validity. For statisticians, in a geospatial analysis context, fit for purpose for EO derived information will focus around the question: is there an advantage with respect to existing non-EO based methods? Aspects which may be considered are timeliness, spatial and temporal coverage, assessing multiple variables from the same dataset, independence of respondents, avoiding political or other biases etc.

Among NSOs, quality is generally accepted as "fitness for purpose". However, this implies an assessment of an output, with specific reference to its intended objectives or aims. Quality is therefore a multidimensional concept which not only includes the accuracy of statistics, but also other aspects such as relevance and interpretability. Over the last decade, considerable effort has been made to give a solid framework to these definitions in statistics.

For instance, the ABS Data Quality Framework (DQF) 2009 is based on the Statistics Canada Quality Assurance Framework (2002) and the European Statistics Code of Practice (2005). Besides the "Institutional environment", six dimensions have been specifically defined to help getting the best data quality; Relevance, Timeliness, Accuracy, Coherence, Interpretability, and Accessibility. The following table presents some thoughts on how these dimensions can be viewed from an EO perspective, and add two additional definitions from the EO discipline; integrity and utility.

Table 2: Statisticians and EO scientists' definitions: summary

	ABS DQF or NSOs community	Key aspects (How NSOs assess the dimension?)	EO/remote sensing community
Institutional environment	"The institutional and organisational factors which may have a significant influence on the effectiveness and credibility of the agency producing the statistics".	• Impartiality and objectivity • Professional independence • Mandate for data collection • Adequacy of resources (sufficient to meet needs) • Quality commitment • Statistical confidentiality	In principle EO data is impartial, objective and reproducible. The processing must be transparent and open to scrutiny. Space agencies or commercial aerospace companies provide the raw "Top of Atmosphere" data. These same agencies and others pre-process the data to an analysis ready format. Subsequently the ARD needs to be translated into a relevant variable either by or for the NSO. Criteria to look for: comprehensive information about the EO sensor specifications, its calibration (pre-flight, on-board and vicarious); does reliable peer reviewed literature exist? It is essential to have transparent algorithms and documentation, complete metadata and product documentation, open access products, or open access algorithms. The concept of ARD is important here as it solves one aspect of institutional capacity: If world-class experts pre-process the EO data to ARD EO Data Cubes the institutional capacity can focus on applying the right algorithm, parameterisation and validation. It is essential to have geospatial analytics capacity.
Relevance	"How well the statistical product or release meets the needs of users in terms of the concept(s) measured, and	• Scope and average[4] • Reference period[5] • Geographic detail • Main outputs/data items	Reference period =Record life, i.e. EO mission life. Could be one satellite sensor or a suite of sensors such as Landsat (multiple sensors from 1984 onwards).

[4] Purpose or aim for collecting the information, including identification of the target population, discussion of whom the data represent, who is excluded and whether there are any impacts or biases caused by exclusion of particular people, areas or groups

[5] Period for which the data were collected, as well as whether there were any exceptions to the collection period

	ABS DQF or NSOs community	Key aspects (How NSOs assess the dimension?)	EO/remote sensing community
	the population(s) represented".	• Classification and statistical standards • Types of estimates available • Other sources[6]	Geographical detail corresponds to the spatial resolution of the EO sensor which needs to be selected for the intended purpose. Temporal resolution is also important for EO applications and also varies with sensor. Main outputs/data items and types of estimates: see discussion in Chapter 3 on various methods and algorithms. Many EO classification methods exist but there is a need for standards that are widely followed (e.g. GFOI and GEOGLAM). Potentially NSOs could develop classification standards for this type of data. Types of estimates available will be enhanced by increases in: geographic coverage (global mapper, regional, on demand) and sensor resolution considerations; spatial, spectral, temporal, radiometric. Other sources: an issue to consider is whether there is no, minimal or adequate ground reference data available. A related concept in EO is **integrity;** biophysical and scientific integrity. This relates to the ability to relate and interpret EO derived metrics to biophysical processes.
Timeliness	"The delay between the reference period (to which the data pertain) and the date at which the data become available; and the delay between the advertised	• Timing[7] • Frequency of survey	With automated processing systems producing 1) ARD and 2) properly validated algorithms, a near-real time delivery becomes possible i.e. within a few days to a few hours of EO data reception. A related concept in EO is utility: this is a function of accuracy and timing. A high accuracy after the event has less utility than a much lower accuracy early on or before a specific biological period e.g.

[6] www.abs.gov.au/ausstats/abs@.nsf/Latestproducts/1520.0Main%20Features4May%202009?opendocument&tabname=Summary&prodno=1520.0&issue=May%202009&num=&view=

[7] Time lag between the reference period and when the data actually become available (including the time lag between the advertised date for release and the actual date of release)

	ABS DQF or NSOs community	Key aspects (How NSOs assess the dimension?)	EO/remote sensing community
	date and the date at which the data become available".		sowing, flowering of crop or harvesting or e.g. in the case of coral reefs, a bleaching event.
Accuracy	"The degree to which the data correctly describe the phenomenon they were designed to measure". "Should be assessed in terms of the major sources of errors that potentially cause inaccuracy".	• Coverage error • Sample error • Non-response error • Responses error • Other sources[8]	For EO derived information products the validity has to be established first. Thus, it essential to establish a causal relationship between the EO measurement and the phenomenon. Empirical algorithms can run the risk of producing spurious results. EO data have a high spatial and temporal coverage but can have data gaps due to low repeat visits and /or inclement weather or other image conditions. For classification results (products with categorical variables, e.g., land use land cover, vegetation type, benthic type), the users, producers and overall accuracy need to be determined. Note that Kappa statistic is considered defunct. For products with continuous variables (e.g. fractional cover, chl-a concentration), there are numerous statistics used. Common statistics include RMSE and variants thereof, bias, R2, Pearson's R. For RMSE and bias, the results can vary significantly based on which value is put first; EO or ground reference. R2 and R obfuscate how well the data match up (things can be highly linearly correlated and not fall along the one-to-one line). It is essential to assess EO products with independent data. Best practice is all accuracy assessment done with independent data. Note though, that ground reference measurements also contain uncertainties.
Coherence	"The internal consistency of a statistical collection,	Changes to data items Comparison across data items	EO data sets are internally very consistent as they are all based on measurements by the same instrument. However the processing from raw top of atmosphere data to ARD continuously

[8] http://www.abs.gov.au/ausstats/abs@.nsf/Latestproducts/1520.0Main%20Features6May%202009?opendocument&tabname=Summary&prodno=1520.0&issue=May%202009&num=&view=

	ABS DQF or NSOs community	Key aspects (How NSOs assess the dimension?)	EO/remote sensing community
	product or release, as well as its comparability with other sources of information, within a broad analytical framework and over time".	Comparison with previous releases Comparison with other products available	improves. Similarly, the EO algorithms improve continuously. The increased use of EO data, ground reference data and model data improves validity and accuracy but may make comparison with previous version derived data more complex. The coherence issue also occurs when multiple sources of EO data are used.
Interpretability	"The availability of information to help provide insight into the data".[9]	Presentation of the information Availability of information regarding the data	The interpretation of EO data derived information requires several skills in the EO processing domain as well as the geospatial analytics domain. EO data is often reduced to table and graphics destroying some of the interesting spatial and temporal contextual information. Good documentation and record keeping is key. A guide on what the scope and limitations are of using EO data is required.
Accessibility	"The ease of access to data by users, including the ease with which the existence of information can be ascertained, as well as the suitability of the form or medium through which information can be accessed". "The cost of the information may	Accessibility to the public (extent to which the data are publicly available, or the level of access restrictions) Data products available[10]	EO data products are typically very large and complex, which challenges accessibility. EO data products need to be accessible, meaning they need to be delivered in data formats that are standardised and easily openable by a variety of different software, especially open access software. It is also preferred that data products be open access (GEO). It is useful if the EO data is supplied according to open geospatial standards (OGS) and open source geospatial software and data (OSGeo) standards. Another standardisation is through the Geospatial Data Abstraction Library (GDAL) which is a computer software library for reading and writing raster and vector geospatial data formats. There is a joint standards working group of the OGC and the W3C that is developing an approach

[9] Information to assist interpretation may include the variables used, the availability of metadata, including concepts, classifications, and measures of accuracy.

[10] specific products available (e.g., publications, spreadsheets), the formats of these products, their cost, and the available data items which they contain

	ABS DQF or NSOs community	Key aspects (How NSOs assess the dimension?)	EO/remote sensing community
	also represent an aspect of accessibility for some users".		to publishing EO data as "linked data" for easy access, employing a model for Data Cubes that was originally developed by the statistical SDMX community. If ARD is adopted by all prior to the translation of this ARD data to a meaningful information product the interpretability will increase as a growing body of knowledge is more easily created. This will also lead to more standardised products.

As EO use by NSOs is relatively new, pilot and demonstration studies that explore these definitions and refine the table above are recommended. Some pilot studies conducted by members of the UN Satellite Imagery and Geospatial Data Task Team are described in Chapter 4.

In the following section, it will be shown the potential of using EO satellite data is much more than using only time series of MODIS or LANDSAT images. More sources are available, and examples will be presented about which sensors are most suited to get the best expected data quality

2.13 Earth Observation data information sources available

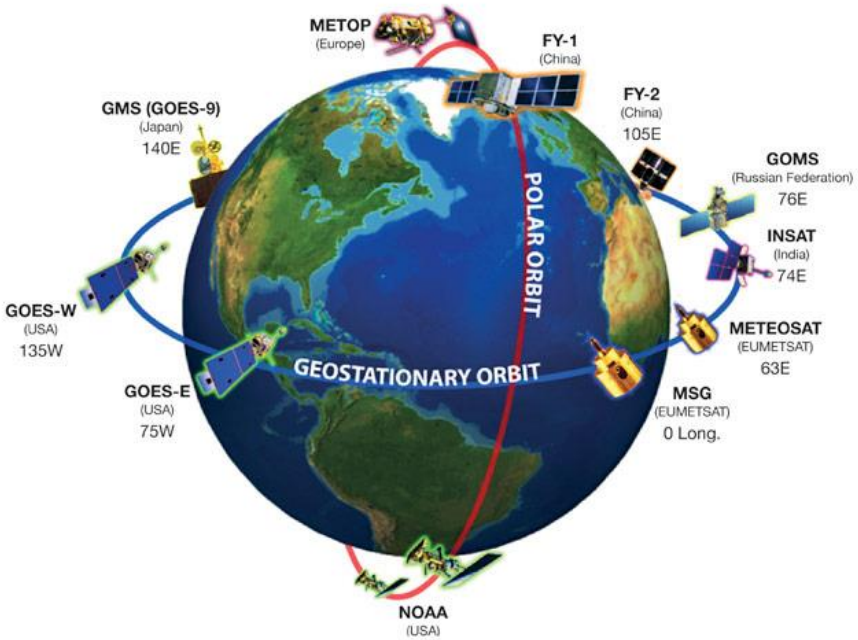


Figure 10: Operational weather satellites

Source: CEOS EO Handbook: http://www.eohandbook.com/eohb2011/climate_satellites.html

A comprehensive list of EO satellites past, present and future exists on the online WMO Oscar database that contains 645 entries (per April 2016). https://www.wmo-sat.info/oscar/satellites

Filters exist for sorting the data on:

1. Acronym of earth observing sensor platform (that may contain multiple payloads: a single payload is the specific earth observing sensor),
2. Launch date and end-of-life;
3. Space agency programme name,
4. List of orbital characteristics and
5. Payload

As an example, look at Sentinel-3 (an important sensor for the next 15 years for land and ocean visible and nearby infrared monitoring; as well as land and ocean surface temperature measurement and with a land and ocean altimeter).

There are two Sentinel-3 A and B satellite platforms in the system; one was launched on 16th February 2016 and one will be launched in 2017. After that Sentinel-3 C and D are already funded and will be similar replacing Sentinel-3 A and B. Sentinel E and F are also planned but will be amenable to enhanced sensor performance based on the results of the preceding 4 satellites. Sentinel-3 A and B both have an expected lifetime of 7 years. Expected lifetime can be exceeded 3 to 4 fold for some EO sensors-space agencies are often cautious about this aspect. It flies in a sun-synchronous orbit, meaning it will pass exactly over the same strip of earth at the same solar time, at 814.5 km altitude. Its status is operational for Sentinel 3 A and Planned for Sentinel 3 B. The payload is composed of 7 sensors: DORIS, GPS, LRR, MWR, OLCI, SLSTR and SRAL. The first four sensors are mainly used for exact positioning and assessment of atmospheric conditions, whereas the last three are the actual earth observing sensors with an application to detecting and monitoring the earth; OLCI (Ocean Land Colour Imager), SLSTR (Sea and Land Surface Temperature Radiometer) and SLAR (Synthetic Aperture Radar Altimeter).

On the WMO Oscar database, by selecting the EO sensor acronym one is transferred to the instrument page where a wealth of information on the sensor is presented. Information is also presented on other satellites this instrument also flies on; its contribution to Space Capabilities and a very informative "Tentative Evaluation of Measurements" containing a list of measurements that can typically be retrieved from this type of instrument. For OLCI this table is as follows below[11].

Variable	Relevance for measuring this Variable	Operational Limitations	Processing maturity
Ocean Diffuse Attenuation Coefficient (DAC)	1-primary	Clouds	Consolidated methodology

[11] Source: https://wmo-sat.info/oscar/instruments/view/374: Tentative Evaluation of Measurements .The following list indicates which measurements can typically be retrieved from this category of instrument. To see a full Gap Analysis by Variable, click on the respective variable. Note: table can be sorted by clicking on the column headers.

Variable	Relevance for measuring this Variable	Operational Limitations	Processing maturity
Colour Dissolved Organic Matter (CDOM)	1-primary	Clouds	Consolidated methodology
Ocean chlorophyll concentration	1-primary	Clouds	Consolidated methodology
Ocean suspended sediments concentration	1-primary	Clouds	Consolidated methodology
Normalised Difference Vegetation Index (NDVI)	1-primary	Clouds	Consolidated methodology
Oil spill cover	2-very high	Clouds	Consolidated methodology
Cloud top height	3-high	Clouds	Consolidated methodology
Short-wave cloud reflectance	3-high	No specific limitation	Consolidated methodology
Aerosol volcanic ash (Total column)	3-high	Clouds	Consolidated methodology
Sea-ice cover	3-high	Clouds	Consolidated methodology
Aerosol Optical Depth	3-high	Clouds	Consolidated methodology
Cloud optical depth	3-high	Cloud not too dense	Consolidated methodology
Fraction of Absorbed PAR (FAPAR)	3-high	Clouds Land use	Consolidated methodology
Integrated Water Vapour (IWV)	3-high	Clouds	Consolidated methodology

Variable	Relevance for measuring this Variable	Operational Limitations	Processing maturity
Earth surface albedo	3-high	Clouds	Consolidated methodology
Upward short-wave irradiance at TOA	4-fair	No specific limitation	Consolidated methodology
Aerosol column burden	4-fair	Clouds	Consolidated methodology
Photosynthetically Active Radiation (PAR)	4-fair	Clouds	Consolidated methodology
Cloud cover	4-fair	No specific limitation	Consolidated methodology
Aerosol type	4-fair	Clouds	Heavily dependent on external info
Aerosol effective radius	4-fair	Clouds	Heavily model-dependent
Aerosol volcanic ash	4-fair	Clouds	Consolidated methodology
Downward short-wave irradiance at Earth surface	5-marginal	Total column only. Clouds	Heavily dependent on external info
Aerosol mass mixing ratio	5-marginal	Clouds	Consolidated methodology

Figure 11: Tentative Evaluation of Measurements

The following list indicates which measurements can typically be retrieved from this category of instrument. To see a full Gap Analysis by Variable, click on the respective variable. Note: the table can be sorted by clicking on the column headers. An interesting feature of this site is the gap analysis page: https://www.wmo-sat.info/oscar/gapanalyses where if one selected e.g. “Land surface” it produces a menu of Land surface applications e.g. “soil type” which then produces a list of instruments, their relevance for measuring the requested variable (colour coded) and below that comprehensive list another list ordered in terms of relevance, processing maturity and operation imitations.

Another satellite mission database can be found at CEOS website:
http://database.eohandbook.com/database/missiontable.aspx

It is organised slightly differently with the mission name being the initial field (equivalent to the earth observing sensor platform in the Oscar database). Next the responsible space agency or commercial operator, status, launch date, end of life data , then the applications, followed by the instruments that do the measurements for these applications and then the orbit details and the URL.

An attractive feature of this database is the ability to search on keywords e.g. "applications" by going to the page of http://database.eohandbook.com/measurements/overview.aspx

There is a quick informative overview of the measurements split into categories of atmosphere, land, ocean snow and ice and gravity and magnetic fields. In each category on the right hand a small graph is visible with timelines and if selected will open a graph showing the full timelines of past, present and planned sensors allowing an estimation of the continuity of that particular data stream. By selecting e.g. under "Land" the category "vegetation" a new page opens with all the vegetation variables that can be measured.

For example if Measurements > Land > Vegetation >Chlorophyll Fluorescence from Vegetation on Land is selected an earth observing instrument overview is presented with a concise summary of the intended applications and showing the planned instruments that are intended for carbon estimation by measuring solar induced chlorophyll fluorescence.

The following is a list of several satellite imagery repositories where data can be downloaded for free.

- USGS Earth Explorer;
- ESA Sentinel Mission;
- NOAA CLASS;
- NASA Reverb;
- Earth Observation Link(EOLi);
- National Institute for Space Research (INPE), specific to South America and Africa; Bhuvan Indian Geo-Platform of ISRO;
- JAXAs Global ALOS 3D World;
- NOAA Data Access Viewer Discover Authoritative Datasets;
- VITO Vision Coarse Vegetation Data;
- NOAA Digital Coast Snorkel the Seashore;
- Global Land Cover Facility Derived Satellite Data
- DigitalGlobe Free Product Samples;
- BlackBridge/Geo-Airbus Tag Team Champions of Satellite Imagery;
- UNAVCO Research Data.

The USGS Earth Explorer is one of the most famous and popular agencies for freely available Landsat data. Users are required to register in order to access the USGS data repository and this registration is free of charge.

For detailed information on suitable EO sensors past, present and future for water resources see the open report written for World Bank[12]. It provides an overview of the issue areas related to water resources management, and discusses the data requirements for addressing these issues, focusing on

[12] García, Luis E., Diego J. Rodríguez, Marcus Wijnen, and Inge Pakulski, eds. Earth Observation for Water Resources Management: Current Use and Future Opportunities for the Water Sector.Washington, DC: World Bank Group.doi:10.1596/978-1-4648-0475-5. License: Creative Commons Attribution CC BY 3.0 IGO

those variables that can be obtained or estimated through EO. Besides the surface characteristics, such as topography, land subsidence, and others, Earth observation can address eight key hydro meteorological variables relevant to water resource management applications; precipitation, evapotranspiration, soil moisture, vegetation, land use, and land cover; groundwater, surface water, snow and ice, and water quality.

2.14 Data product characteristics

Types of Data Obtained from EO (example of Water management)

Data type	Description
Raw data	Sensor measurements as received directly from the satellite, formatted as "digital counts."
Processed data	a) TOA (Top-of-atmosphere) signal. Raw data processed to TOA data: conversion to real-world units, such as radiance (W m-2 nm-1 sr-1) or reflectance (%); signal calibration. b) Surface signal. TOA data processed to surface-equivalent data: corrections applied to remove atmospheric and solar-sensor viewing-angle effects; scene stitching; geolocation and re-projection.
Data products	Conversion of processed data into products that describe real-world (usually biophysical) variables such as chlorophyll concentration, leaf area, rainfall rate, surface temperature, and soil moisture mass.
Information products	Conversion of data products into management-relevant information for decision support, for example, eutrophication state of a lake, flood risk of a river delta, and sustainable irrigation rates in an agriculture area.

2.14.1 Key characteristics of data products

Spatial Resolution (sensor-specific)

The spatial resolution of EO data, sometimes called the spatial frequency or image resolution, refers to the pixel size of an image. The spatial resolution of data determines the precision with which the spatial variation of the observed phenomenon can be captured. A relatively large pixel size will capture less fine-scale spatial variation than a relatively small pixel size. Thus spatial resolution is defined as the size of the smallest individual component or dot (called a pixel) from which the image is constituted. For instance, if a satellite's resolution is stated as "5 meters," each pixel in the imagery has a size of 5 meters by 5 meters.

The other aspect is the swath of a sensor; this is equivalent to the number of pixels across that track direction of the satellite. E.g. if an instrument has 1000 pixels of 5 m its swath width is 5 km. If a satellite sensor has 2000 pixels of 1 km then the swath width is 2000 km. A larger swath width is associated with a higher repeat coverage rate for one sensor on one satellite. By having multiple satellites the coverage rate increases with each sensor on each satellite.

When a pixel straddles two (or more) distinct ground features (such as a water body and adjacent vegetation), the pixel captures a mixture of the signals from both features, and is sometimes referred to as a "mixel". Mixels make image interpretation more difficult and, the larger the pixel size, the more mixels the data are likely to contain. Mixed pixels are further described in Chapter 3.

Temporal frequency (sensor-specific)

The temporal frequency of data (or the temporal resolution) refers to how often a sensor makes observations of a given location. In the case of polar-orbiting satellites, frequency is related to overpass frequency and is typically measured in days. With the current constellations for LEOs sub day capacity can be achieved in some cases. The frequency of imagery by geostationary satellites is much higher, being measured in the order of minutes to hours as the sensor is stationary above a fixed location above the equator The distance of geostationary sensors to the earth (~ 36000 km) means the spatial resolution is low(currently between 05. And 2 km). Relatively high-frequency observations are better able to capture the dynamics in fast-changing processes than are relatively low-temporal frequency observations.

For some applications, the time of observation can be important, either to ensure the observations occur at the same time each day, or because observations need to occur at specific times of the day.

Record length (sensor-specific)

The record length refers to how long the record of data is. This is typically a function of the period of operation of the satellite (or series of similar satellites), and so is determined by the mission launch and end dates. Often, however, satellite sensors acquire data long past their planned mission end dates (e.g. Landsat-5).

Generally speaking, the longer the record length, the older the satellite and its associated technology. Thus, there is usually a trade-off between record length and other data attributes such as accuracy, spatial resolution, and/or number of spectral bands. On the other hand long lasting sensor systems and their data streams have often created a significant opportunity for developing operational information extraction methods, supported by relevant scientific and applied literature.

Field or ground reference data requirement (product-specific)

Some EO data products are generated solely from satellite observations, some from a combination of satellite and field-based observations. The latter have much higher input data requirements, and so are more dependent on the availability of suitable field data. Traditional survey data captured by NSOs may offer suitable field validation data in some cases. EO data generated from a combination of satellite and field based observations are also generally more complex to generate and can become limited to the specific locations and times the field data represent.

- **Low** field-based data requirement products refer to data products that do not use field data, or use them only for initial parameterisation of algorithm or for algorithm output validation purposes;

- **Medium** field-based data requirement products refer to data products that need field data for calibration of the EO data, or use a moderate amount of field data in the derivation of the final EO product itself (such as when river gauge data are combined with satellite-derived flood extent data to estimate flood volumes);
- **High** field-based data requirement products refer to data products that incorporate multiple sources of field data (e.g. most evapotranspiration (ET) and soil moisture data products), sometimes in complex data assimilation systems.

Data product source reliability (product-specific)

Data product reliability refers to the certainty of supply of that product across space and through time. The greater the spatial coverage, the more frequently the product is updated; the greater the number of options for sourcing the product, the higher the reliability of the product.

- **Low** reliability describes a product that is tailor-made for a specific time, region, or application, or is generated by only one organisation;
- **Medium** reliability describes a product that typically has wide (global) coverage and is frequently updated but is provided by just one source organisation;
- **High** reliability describes a product with global coverage that is frequently updated and can be sourced from multiple, independent organisations.

Data product accuracy (product-specific)

The accuracy of data products is an estimation of the uncertainty associated with the data estimates. Accuracy can be described in absolute terms (that is, in physical units such as mm/y) or in relative terms (usually as a percentage). So, for example, if an estimate of evaporation of 200 mm/y has an error of 10 percent (and thus an accuracy of 90 percent), the real value is likely to be between 180 and 220 mm/y but may be lower than 180 or higher than 220 mm/y.

Please note: rarely will the accuracy of an EO data product be as high as that of an equivalent field measurement at that precise location (although this has not been systematically analysed often enough). Although when extrapolating field measurement results through time and space EO observations are likely to become more accurate overall.

The field of quality assurance for EO is in rapid development and standards are being developed. We refer to the GEO activity on "A Quality Assurance Framework for Earth Observation: Principles" (http://wiki.esipfed.org/index.php/Data_Understanding_-_Quality_(ISO-19157) as well as ISO 19157:2013 - Geographic information -- Data quality for detailed information.

In Yang et al (2013) a relevant summary is presented on data quality in earth observation. Fig (below) describes essential aspects of EO data quality assessment

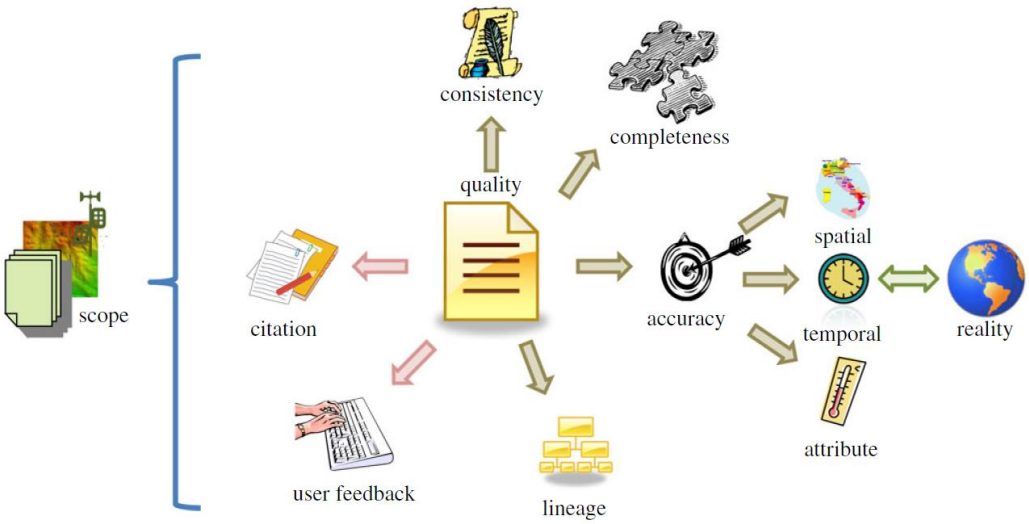


Figure 1. Overview of the key concepts of data quality addressed in this study, including both producer- and consumer-created information. (Online version in colour.)

Figure 12

The Yang paper addresses the following quality aspects known from ISO standards, which might be characterised as *producer data quality elements* because they are known by the data producer:

- *completeness*: presence and absence of features, their attributes and relationships;
- *logical consistency*: degree of adherence to logical rules of data structure, attribution and
- relationships;
- *positional accuracy*: accuracy of the position of features;
- *temporal accuracy*: accuracy of the temporal attributes and temporal relationships of features;
- *thematic accuracy*: accuracy of quantitative attributes and the correctness of non-quantitative
- attributes and of the classifications of features and their relationships; and
- *lineage*: information about the provenance of the dataset, including details of processing applied.

In addition, Yang et al add that good quality metadata records are essential too. An interesting aspect is that end users also desire 'soft' knowledge about data quality—i.e. data providers' comments on the overall quality of a dataset, any data errors, potential data use and any other information that can help to assess fitness-for-use of the data. Finally importance was given to dataset provenance as well as citation and licensing information when assessing whether data are fit for purpose.

Despite their generally lower accuracy, EO products are an important data source as EO imagery can provide information with greater spatial extent, spatial density, and/or temporal frequency than can most field-based (point-based) observation networks. It is for this reason a combination of EO and field data generally provides the best information outcomes. If it is possible to have a model (e.g. deterministic) that sufficiently describes the phenomenon of interest then model, EO and field data assimilation is the most powerful way to derive the required information.

Data product maturity (product-specific)

Product maturity refers to how established a data product is; it can be gauged by the level of validation, acceptance, and adoption of that data product. A mature product is generally founded on well-established science. Data product maturity is evidenced by a body of peer reviewed literature as well as relevant technical reports and applications publications.

- **Low** maturity indicates that the product is still in an experimental stage.
- **Medium** maturity indicates that the product is developmental in the sense that, while the underlying science is mature, the product's conversion to being operational is still in progress.
- **High** maturity refers to a proven, widely tested and adopted, operational product.

Data product complexity (product-specific)

Data product complexity describes the level of complication involved in the process of converting the EO-processed data into the data product. Complexity is a function of, among other things, the number of methodological steps involved, the number and type of input data sources, the level of mathematics involved, the volumes of data to be processed, and/or the required technical expertise.

- **Low** complexity: no function or very simple function for converting processed satellite data into the data product, requiring basic technical expertise;
- **Medium** complexity: moderately complex method;
- **High** complexity: highly complex method for generating the data product, requiring advanced technical and/or computational expertise.

2.14.2 Necessity to define "core data streams": example of GFOI, a GEO initiative

The Global Forest Observation Initiative (GFOI) (http://www.gfoi.org), was founded under GEO, and is currently led by the Governments of Australia, Norway and the USA as well as the Food and Agriculture Organization of the United Nations (FAO) and CEOS. It is supported by an extensive community of international experts and stakeholders, including from the United Nations Framework Convention on Climate Change (UNFCCC) Secretariat, the greenhouse gas inventory programme of the Intergovernmental Panel on Climate Change (IPCC), the World Bank Forest Carbon Partnership Facility, Global Observation of Forest and Land Cover Dynamics (GOFC-GOLD), universities, other specialist international organisations and experts, and of course REDD+ countries.

For such global initiatives which need frequent, regular and global coverage, a baseline data strategy acquisition involves coordination of core satellite data streams that satisfy key criteria consistent with the principles for implementation of the initiative:

- core data streams provide data, at 30 m resolution or finer, free-of-charge and openly shareable for GFOI purposes, consistent with being available in support of any country's information requirements;
- core data stream systems have a sustained and long-term capacity in coverage, processing and distribution which is consistent with the large (global) scale data requirements of the GFOI.

Several years of discussions within CEOS have resulted in consensus on a working list of CEOS agency satellite missions that represent the GFOI Core Data Streams - based on available information regarding known or expected data policies and mission capacities. These include:

Optical, NIR and TIR systems that required clear skies;

- Landsat-7 and - 8 (optical) – USGS /NASA;
- Sentinel-2 series (optical) – ESA/EU;
- CBERS-3 and -4 (optical) – INPE (Instituto Nacional de Pesquisas Espaciais, the Brazilian National Institute for Space Research)/CRESDA (Center for Resource Satellite Data and Applications, China);

Synthetic Aperture Radar missions that have cloud, fog, mist and haze penetrating capabilities;

- RADARSAT Constellation Mission (C-band SAR) – CSA
- Sentinel-1 series (C-band SAR) – ESA/EU (European Union);

Other CEOS agencies' related missions, such as optical high-resolution missions, (e.g.RapidEye and the SPOT series), and radar missions (e.g. ALOS-2, Radarsat-2, TerraSAR-X and TanDEM-X) can supplement the core missions for persistently cloudy areas in addition to supporting validation and technical studies.

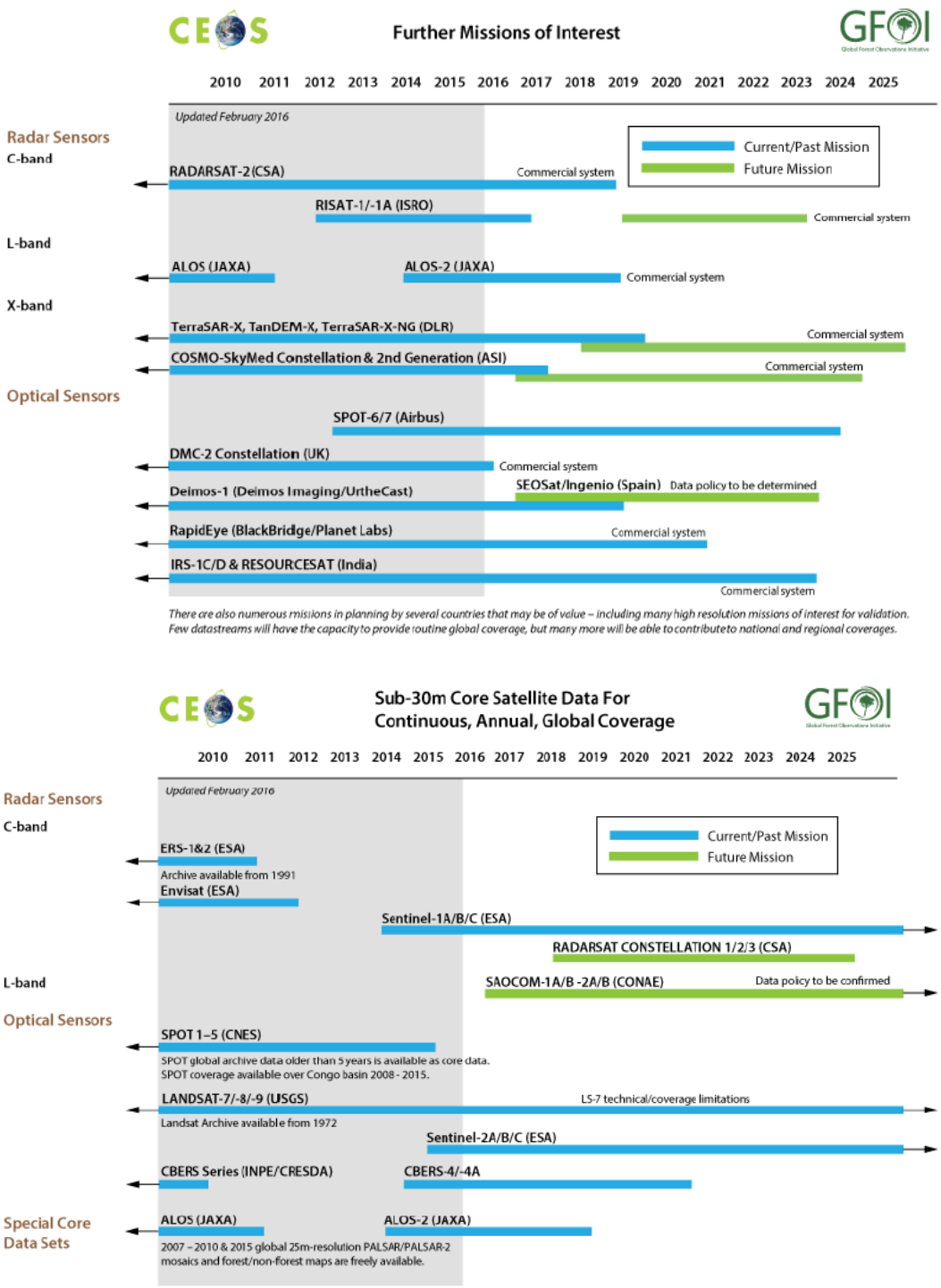


Figure 13: GFOI Initiative: sub-30 Core Satellite Data for Continuous, Annual, Global Coverage

2.14.3 Examples of how to choose sensors data to measure specific variables (water and land cover areas)

Table of existing EO data sources - most "suitable" according to EO scientists

This table shows the ability of each sensor to monitor and detect surface water in floods.

We use different symbols/colours to shows various levels of ability:

❶ Highly suitable ❷ Suitable ❸ Potential ❹ Not suitable

Table 3: ARCHIVAL SOURCES

Sensor functional type	Mission instruments	Mission names (short)	Spatial Resolution (m)	Frequency (d)	Accessibility	Cost effectiveness	Surface water in floods
OPTICAL	TM	Landsat 5	30	16	Open	?	❷
	MSS	Landsat 1-3	80	18	Open	?	❷
	AVHRR/2	NOAA 7-14	1100	1	Open	?	❸
	MODIS	Terra	250	16	Open	?	❷
ACTIVE MICROWAVE	SAR (RADARSAT-1)	RADARSAT-1	25	24	Constrained	?	❷
	PALSAR	ALOS	7-44	14	Constrained	?	❷
	ASAR (stripmap)	Envisat	30		Constrained	?	❷
	ASAR (wide swat)	Envisat	150		Open	?	❶
	AMI-SAR	ERS-1	30	35	Constrained	?	❷
	AMI-SAR	ERS-2	30	35	Constrained	?	❷
RADAR ALTIMETRY	NRA	TOPEX-Poseidon		10	Open	?	❹
	GFO-RA	GFO		17	Open	?	❹
	Poseidon-2	JASON-1		10	Open	?	❹

Table 4: CURRENT SOURCES

Sensor functional type	Mission instruments	Mission names (short)	Spatial Resolution (m)	Frequency (d)	Accessibility	Cost effectiveness	Surface water in floods
OPTICAL	OSA	IKONOS	3.3		Constrained	?	❷
	GIS	GeoEye	1.6		Constrained	?	❷
	MSI	RapidEye	6.5	1	Constrained	?	❸
	Worldview 2 and 3	Worldview 2 and 3	2/1.3	2	Constrained	?	❸
	MSI	Sentinel-2	10/20/60	5	Open	?	❸
	ASTER	Terra	15	16	Open	?	❷
	OLI	Landsat-8	30	16	Open	?	❷
	ETM+	Landsat-7	30	16	Open	?	❷
	MODIS	Aqua	250	16	Open	?	❶
	MODIS	Terra	250	16	Open	?	❷
	AVHRR/3	NOAA-18	1100	1	Open	?	❷
	AVHRR/3	NOAA-19	1100	1	Open	?	❹
	VEGETATION	SPOT-5	1150	26	?	?	❹
	VIIRS	Suomi NPP	1600	16	Open	?	❹
	OLCI	Sentinel-3 A+B	300	1	Open	?	?

Which sensors to use to measure Vegetation and Land Cover metrics (NDVI, Albedo, fPAR and LAI)

Note: NDVI (Normalised Difference Vegetation Index)/ fPAR (fraction of PAR)/ PAR is photosynthetically Active radiation/Leaf Area Index (LAI).

Data Currency	Sensor Functional Type	Mission Instruments	Mission Name (Short)	Spatial Resolution (m)	Revisit Period (days)	Accessibility	Launch Date	End Date	NDVI	Albedo	fPAR	LAI
Archival	Optical	TM	Landsat 5	30	16	Open	Jul-82	Jun-13	1	1	1	1
		MSS	Landsat 1-3	80	18	Open	Jul-72	Sep-83	2	2	2	2
		AVHRR/2	NOAA 7-14	1100	1	Open	Jun-81		1	2	1	4
Current	Active microwave	X-Band SAR	TanDEM-X	16	11	Open	Jun-10		2	4	2	4
		X-Band SAR	TerraSAR-X	16	11	Open	Jun-07		2	4	2	4
		S-Band SAR	HJ-1C	20	31	Open	Nov-12		2	4	2	4
		SAR (RADARSAT-2)	RADARSAT-2	25	24	Constrained	Dec-07		2	4	2	4
	Optical	MSI	RapidEye	6.5	1	Constrained	Aug-08		2	2	2	2

Data Currency	Sensor Functional Type	Mission Instruments	Mission Name (Short)	Spatial Resolution (m)	Revisit Period (days)	Accessibility	Launch Date	End Date	NDVI	Albedo	fPAR	LAI
		MSI	Sentinel-2	10/20/60	5	Open	Jun-15		2	2	2	2
		ASTER	Terra	15	16	Open	Dec-99		1	1	1	1
		OLI	Landsat-8	30	16	Open	Feb-13		1	1	1	2
		ETM+	Landsat 7	30	16	Open	Apr-99		1	1	1	2
		Hyperion	NMP EO-1	30	16	Open	Nov-00	Oct-14	1	1	1	1
		AWiFS	RESOURCESAT-2	55	26	Open	Apr-11		1	1	1	1
		LISS-III (Resourcesat)	RESOURCESAT-2	55	26	Open	Apr-11		1	1	2	2
		MISR	Terra	250	16	Open	Dec-99		2	2	2	2
		MODIS	Aqua	250	16	Open	May-02		1	1	1	1
		MODIS	Terra	250	16	Open	Dec-99		1	1	1	1
		AVHRR/3	NOAA-18	1100	1	Open	May-05		1	2	1	4
		AVHRR/3	NOAA-19	1100	1	Open	Feb-09		1	2	1	4
		VEGETATION	SPOT-5	1150	26	?	May-02	Dec-14	1	2	1	2

Data Currency	Sensor Functional Type	Mission Instruments	Mission Name (Short)	Spatial Resolution (m)	Revisit Period (days)	Accessibility	Launch Date	End Date	NDVI	Albedo	fPAR	LAI
		VIIRS	Suomi NPP	1600	16	Open	Oct-11		1	1	1	1
Future	Active microwave	SAR (RCM)	RADARSAT C-1	50	12	Constrained	2018		2	4	2	4
		SAR (RCM)	RADARSAT C-2	50	12	Constrained	2018		2	4	2	4
		SAR (RCM)	RADARSAT C-3	50	12	Constrained	2018		2	4	2	4
	Optical	LISS-III (Resourcesat)	RESOURCESAT-2A	5.8	26	Open	2015		1	1	2	2
		MSI (Sentinel-2)	Sentinel-2A	10	10	Open	2015		1	2	1	2
		MSI (Sentinel-2)	Sentinel-2B	10	10	Open	2016		1	2	1	2
		MSI (Sentinel-2)	Sentinel-2C	10	10	Open	2020		1	2	1	2
		LISS-IV	RESOURCESAT-2A	23.5	26	Open	2015		1	1	2	2

Data Currency	Sensor Functional Type	Mission Instruments	Mission Name (Short)	Spatial Resolution (m)	Revisit Period (days)	Accessibility	Launch Date	End Date	NDVI	Albedo	fPAR	LAI
		HISUI	ALOS-3	30	60	?	2016		1	1	1	1
		AWiFS	RESOURCESAT-2A	55	26	Open	2015		1	1	1	1
		OLCI	Sentinel-3A	300	27	Open	2015/16		1	2	2	2
		OLCI	Sentinel-3B	300	27	Open	2017		1	2	2	2
		OLCI	Sentinel-3C	300	27	Open	2020		1	2	2	2
		VIIRS	JPSS-1	1600	16	Open	2017		1	1	1	1

Source: Information derived from the Committee on Earth Observation Satellites (CEOS) Earth Observation Handbook (http://www.eohandbook.com/) and WMO Observing Systems Capability Analysis and Review Tool (http://www.wmo-sat.info/oscar/).

2.15 Public and private sensors/satellites

There are three types of providers of satellite data; the national and multinational space agencies, most of which are part of CEOS, commercial private industry providers and some private providers that are linked to national space agencies such as ISRO for India and its affiliated company Antrix.

In tables 3 and 4 “open” and “constrained” satellite data sources are mentioned. Most open sources are from the national and multinational space agencies and most constrained sources are the commercial providers. The reason they are called constrained is because the End User License Agreement is usually quite restrictive for sharing the raw data. Many of the commercial satellite data providers focus on very high spatial resolution for defence, precision agriculture and precision mapping (e.g. cadastral) purposes.

Most EO sources used to monitor ecosystem variables or renewable and non-renewable resources are from the space agencies with an open data policy as that reduces or annuls the cost of data acquisition. However, high value commodity monitoring does use the commercially available very high spatial resolution data.

Although in the past much of the R&D was carried out by space agencies or large technological institutes and academia, the last few years have seen an augmentation of applied research by organisations such as GEO, NGOs, international development banks and the private sector. Thus, it is crucial to adopt a pragmatic approach while entering the Big Data era, and work with all sectors. More companies are getting involved in launching their own satellites or using satellite data products, and some are taking the lead in some areas.

Even if governments used to rely only on their national satellites and sensors, they now understand the urgent need to talk and work with private companies as they can offer satellite data services or products which might be useful to manage Big Data and offer solutions. This section provides some examples of private EO data sources; however this is by no means an exhaustive list.

There are an increasing number of companies that are investing in both satellites and the resulting data, although there is also a wave of consolidation occurring with companies merging. At the same time technology accelerators such as nanosats, cubesats, microsats etc. are evolving rapidly and augmenting the space agencies and companies that have been launching and operating large systems with long lifetimes. Thus, there is now a scale of operation of building and launching satellites of 100s to 1000 kilograms with long lifespans and very accurate measurements to smallsats or cubesats that weigh one to a few kilograms but have limited lifespans.

This chapter provides information on available web based resources for the plethora of satellites available and some guidelines on how to select the right satellite for the job at hand. The CEOS and OSCAR databases focus more on the public sector systems.

Some of the private companies that provide highly relevant services are presented here but only as a snapshot and without the intent of being complete. Some larger companies with a track record of providing high spatial resolution and/or globally relevant data sets are:

- Digital Globe (https://www.digitalglobe.com/)
- AIRBUS Industries (http://www.satimagingcorp.com/satellite-sensors/other-satellite-sensors)
- Planet (https://www.planet.com/)
- Google Terra Bella (https://terrabella.google.com)

Many smaller dedicated companies exist that may have their own satellites such as the hybrid of space agency and industry; the Chinese-Brazilian Earth Resources Satellite Program (CBERS) and the collaboration between ISRO and ANTRIX in India. As a trend, increasingly space agencies are creating joint venture type activities with private companies.

Open data policies are welcomed when it comes to public entities. Private satellite data providers are generally not adopting the same policy because they can profit from selling such data. However, things might change in that sector. In September 2015Will Marshall, CEO of Planet, announced the company would open the access (under CC BY SA 4.0 open licence) to some high resolution satellite data acquired by its constellation of microsatellites. Marshall made the announcement at the UN Assembly, talking about how the data would contribute to the UN SDGs. In other words, their data can be used for free, but whatever is produced using it must be made open in the same way (and this applies to value-added products as well)[13].

DigitalGlobe is a US leading global provider of commercial high‑resolution Earth imagery products and services. It has activated FirstLook, the subscription service that provides emergency management and humanitarian workers with fast, web-based access to pre and post event images of the impacted area. DigitalGlobe provides images to help humanitarian crisis through Tomnod, another project that uses crowdsourcing to identify objects and places in satellite images.

Therefore these companies acknowledge that while satellite imagery on its own is useful, greater benefit comes from extracting meaningful information that can be used by first responder and recovery agencies.

Another type of approach is by companies that have no space assets at all but harvest, harness and display EO data from the actual providers such as Google Earth Engine, Amazon Web Services, Facebook etc. Facebook's Internet.org project (population map) is an example that aims to beam internet access to areas of the world that lack broadband access via drones and satellites. This internet access can then be used access processed EO data providing geospatial information.

2.16 Future sensors and data architectures

The WMO OSCAR and CEOS EO sensors databases also include a comprehensive inventory of future EO sensors.

In general EO sensors are becoming more sophisticated due to technological developments in the actual sensors on the satellite platforms, the platforms themselves, the electronics, on board compression and downlink rates to ground stations etc. These developments also lead to miniaturisation. Miniaturisation leads to either enhanced capabilities in equal sized satellites (typically 500 to 1000 kg) or smaller satellites right down to nano satellites or cubesats weighing only a few kilograms.

Another development in LEO sensors is the race between publicly funded and publicly available EO data streams, and the commercial EO satellite sensors. In general, the coarser resolution sensors (pixel size above 20 m) has been made available for free by most space agencies, and higher resolution data has been provided at commercial rates. However, a gradual shift in publicly available spatial, temporal and spectral resolution is going on: e.g. until the advent of Sentinel-2 in 2015 with freely available 10 m spatial resolution, Landsat with its 30 m pixels was the highest resolution free data. Thus commercial operators now need to provide sub-10 m data to be competitive. The currently highest spatial resolution

[13] http://www.eurisy.org/article-free-and-open-satellite-data-private-companies-join-in-the-game_18#sthash.0VQ20Ubf.dpuf

on offer from a commercial company is the WorldView-3 0.4 m panchromatic and the 1.3 m multispectral and SWIR data.

Temporal resolution and area coverage are other areas of competition. Providing imagery on a 'wall-to-wall" basis, Landsat overpasses once every 16 days whereas Sentinel-2 (once both satellites 2A and 2B are launched) will provide imagery approximately once every 5 days world-wide. Spectral resolution is also increasing, which will culminate in a shift from multispectral sensors (with typically 4 to 13 spectral bands) to imaging spectrometers (with 100s of spectral bands). Commercial operators are providing increased temporal resolution by either having their EO sensors be pointable in all directions in space, or by launching "swarms" of sensors such as the RapidEye constellation and increasingly cubesat and nanosat constellations such as the SkySat constellation of 7 high resolution satellites complementary to Planet's existing medium resolution 60-satellite fleet. The former enable regular, rapidly updated snapshots of select areas of the globe at sub-meter resolution; the latter regular, global coverage at 3-5 meter resolution.

Geostationary sensors, which were exclusively the domain of meteorological coarse scale measurements, are now providing higher spatial resolution imagery with more spectral bands, especially adding bands in the blue and green wavelengths, making them much more useful for non-meteorological use. The thermal bands are also becoming finer in resolution. The most recent type of advanced GEO sensor is the Himawari-8, satellite from Japan which is positioned over Indonesia at 36000 km. It views half of the globe every 10 minutes, with spatial resolution of 500 to 2000 m pixels. Several more Himawari type sensors (known as the GOES-R series, with a first launch for the Americas accomplished late 2016) will be placed in geostationary orbits to cover the Americas and Africa and Europe. There is fast progress in developing non-meteorological use of this advanced type of geostationary EO data.

The potential new data architectures are also critical for the future of EO and the benefits of the use of data. EO programmes of space agencies are facing a number of trends which are driving the need for change in the ways in which data are processed, analysed and distributed. As the change is becoming crucial, the CEOS Chair (CSIRO) for 2016 has proposed to study the issues around next-generation EO data system architectures (CEOS Future Data Architectures (FDA) ad-hoc team), and the opportunities offered by approaches such as the Data Cube (see2.17) and commercial cloud storage and processing solutions. The ad-hoc team looked at the relevant current initiatives undertaken by CEOS; lessons learned from early prototypes, identified the key challenges and expressed some recommendations. An interim report is now available on CEOS website[14]. A more comprehensive report will be delivered in 2017.

Maximising the value of EO is actually a fundamental driver for space agencies. In recent years there has been a steady trend across space agencies toward a greater integration of diverse EO data for various applications in land, water, climate issues. The increased integration produced a more diverse range of applications, which leads to complexity in the value chain when observations are combined with analytics to meet multiple user requirements.

Another key message for NSOs is that, in addition to free and open data, space agencies realise how desirable it becomes now to get free and open access to analysis software and tools that facilitate the

[14] CEOS Future Data Access and Analysis Architectures Study - Interim Report (October 2016): http://ceos.org/meetings/30th-ceos-plenary/ and more precisely here: http://ceos.org/document_management/Meetings/Plenary/30/Documents/5.2_Future-Data-Architectures-Interim-Report_v.1.pdf

use of EO data. The CEOS Data Cube initiative, based on the Australian Geoscience Data Cube (AGDC), see section 2.17) is an example of that trend. The project relies on open source software for the creation of data cubes (ingesting satellite data) and the interaction with data cubes (application programming interfaces= APIs). Open source software would undoubtedly stimulate application innovation and the increased use of satellite data since these advanced technologies can be utilised globally and even by developing countries that are not traditional users of satellite data,

This FDA report stressed that CEOS agencies will need to continue working on that issue given its stakes. "Future work should help users benefit from all relevant CEOS data at all stages – complementing past efforts which have emphasised unity of 'discovery', without fully addressing the significant challenges in the analysis and exploitation of disparate or incompatible data after discovery."

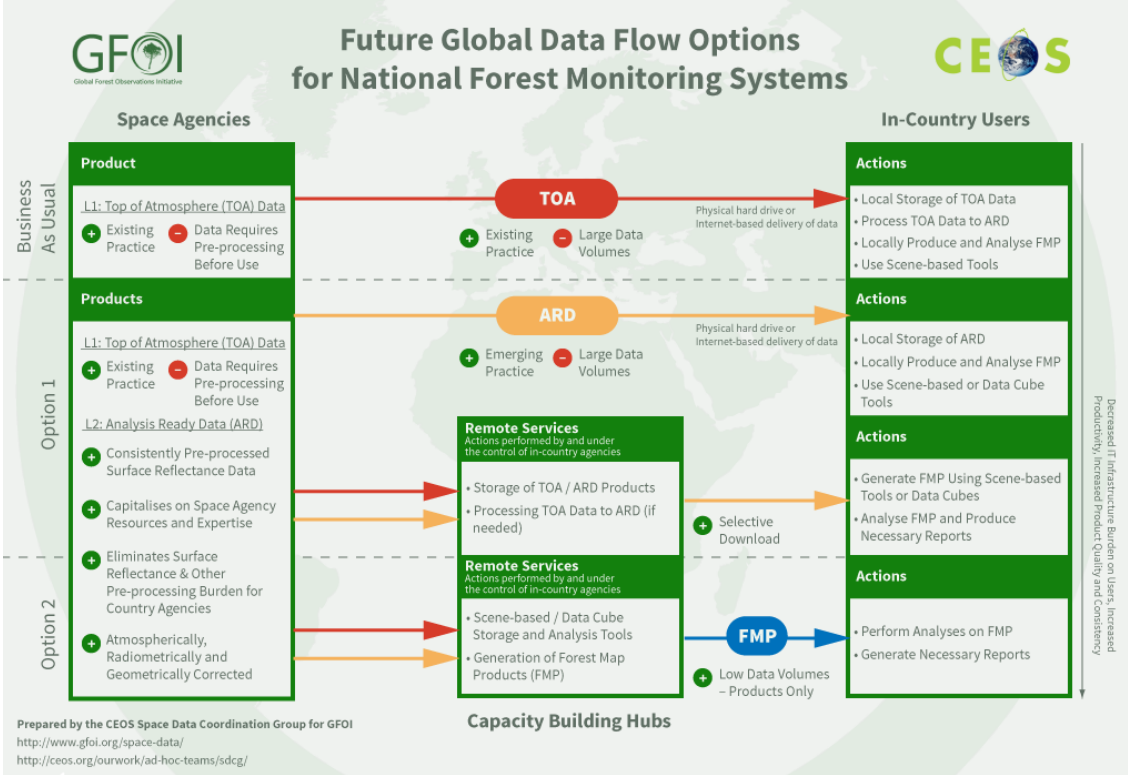


Figure 14: Future Global Data Flow Options for National Forest Monitoring Systems

2.17 Example: Data Cube initiatives

Australian Geoscience Data Cube

The Australian Geoscience Data Cube (AGDC) is a new collaborative approach for storing, organising and analysing the vast quantities of satellite imagery and other Earth Observations, making it quicker and easier to provide information on issues that can affect all Australians. The AGDC is developed and maintained by a partnership between Geoscience Australia, the Commonwealth Scientific and Industrial Research Organisation (CSIRO), and National Computational Infrastructure (NCI).

The AGDC makes standardised and calibrated satellite data available in structures on a range of processing platforms which can be either local, remote or cloud based. The AGDC software is also optimised for use by High Performance Computing facilities, such as the 'Raijin' facility at the National Computational Infrastructure in Australia. The AGDC is composed of a series of data structures and

tools which facilitate the efficient analysis of very large standardised and calibrated gridded data collections, like satellite data, for multiple purposes (Figure 15). This enables a user to easily apply the full potential of satellite data to real-world challenges like agricultural productivity and monitoring of industrial impact on the landscape.

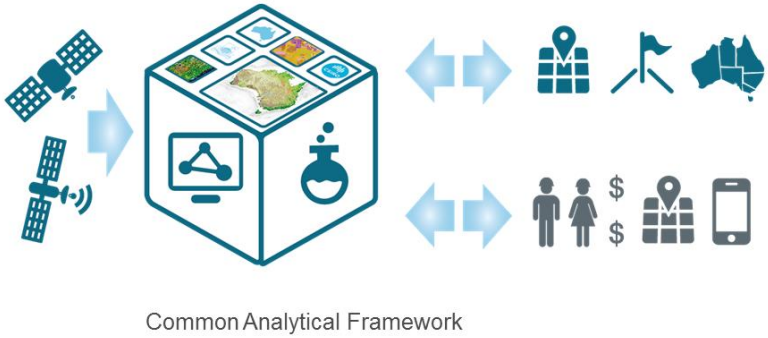


Figure 15: The Data Cube provides a common analytical framework to allow multiple data sources (on the left) to produce information for multiple uses (on the right)

Standardisation and calibration increases the value which can be derived from EO, and other sources of large gridded datasets. It allows for the rapid development of information products to enable informed decision making across government and industry.

This standardisation and calibration is important for another reason. It means that products created by different users to address different problems can be integrated. This ability to integrate information will be critical to solving big national challenges. For example, efforts to improve agricultural productivity are more effective if soil moisture information can be integrated with information on crop health and on forecast precipitation.

Proving the concept

The AGDC has been used to complete analyses that were previously impractical. For example, a recently completed study mapped observations of surface water across all of Australia for the period 1998 to 2012 at a nominal 25 metre resolution. This analysis would have taken 4-8 years under a traditional model, but can now be produced in less than 4 hours using the AGDC. This product is now an information source for the National Flood Risk Information Portal (Figure 16) helping communities understand, and plan for, potential future flooding.

The section of land in Figure 15 shows the channel country adjacent to the Simpson Desert with infrequently observed water in red through to permanent water bodies in blue.

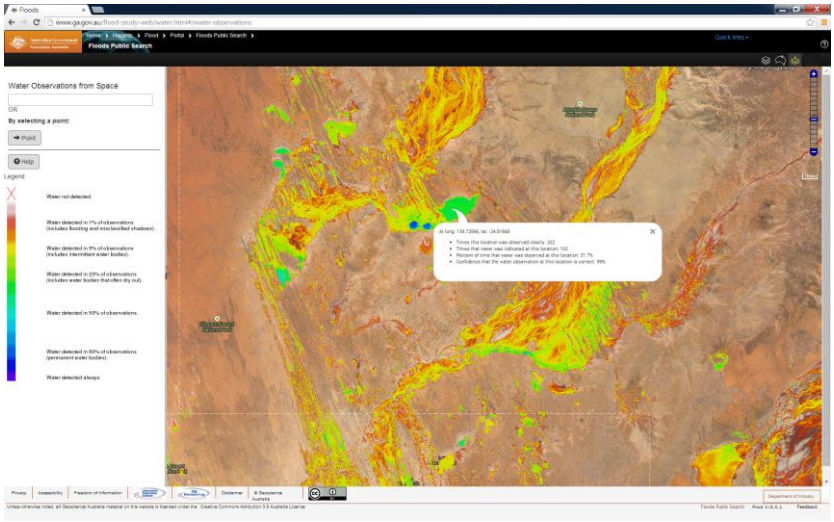


Figure 16: Water Observations from Space (WOfS) mapped surface water observations for all of Australia at 25 metre resolution using data from 1998 to 2012.

Key characteristics

The use of standardised and calibrated data is a key characteristic of the AGDC. In the past the calibration of EO data has been performed on a per-application basis for subsets of data. This can be inefficient and results in large overheads. By calibrating all data to the same standard it becomes immediately usable by many different user groups, eliminating up to 80% of the non-productive 'start up' activity often required in a traditional approach.

Another key characteristic of the data cube is it maintains every unique observation and makes it available for analysis. This contrasts with traditional approaches where technical limitations mean only small subsets are used. This enables the full 'time series', all of the observations acquired by the satellites over many years, to be put to work. This is critical because many important phenomena only become apparent when monitored regularly over time.

The final key characteristic of the AGDC is its ability to deliver 'economies of scale'. The same costly supercomputing facilities and data stores, the infrastructure that enables these levels of performance to be achieved, can be used for multiple purposes. The ability to realise these economies of scale is of increasing importance.

Data volumes that are already impossible to manage on a per-agency basis are scheduled to grow exponentially as new satellites from the USA, Europe, Japan and elsewhere give us access to more data than ever before. An approach which enables investment in shared infrastructure will be critical if we are to benefit from this data.

The unique way in which the AGDC organises data enables it to be rapidly manipulated in a single high performance computing environment (Figure 17) for many different purposes. The AGDC organises images from multiple sources and times, such as the images on the left, into stacks of tiles (on the right). The top of the stack is the most recent observations. As a result, the AGDC can help us embrace the 'data deluge'.

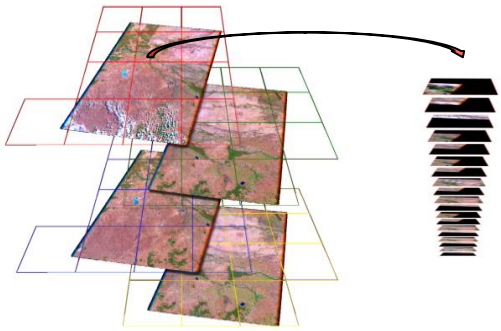


Figure 17: AGDC organisation process

More information can be found at www.datacube.org.au and the source code is available on GitHub at https://github.com/data-cube/agdc-v2.

Role of CEOS and the Data Cube technology

Many countries lack the knowledge, infrastructure, and resources to access and use space-based data. Countries have expressed a desire for support from CEOS by providing search & discovery tools, cloud-based storage and processing, and training & capacity building.

CEOS is leading several projects to demonstrate data services tools and build an architecture that supports a growing volume of data. Some countries (Kenya and Colombia) have already asked CEOS to help them building such an environment to manage Big Data on EO, and making them active pilot projects for the Data Cube. The objective is these pilot projects will provide a solid foundation for future operational systems to be funded and managed by UN organisations and individual countries.

While providing architecture and tools for countries to access and utilise satellite data, and also the training and capacity building necessary to use those tools and manage satellite data, CEOS is developing prototype projects to demonstrate those tools and services. CEOS is evaluating advanced technologies in its architecture and tools, such as Data Services Platforms and Data Cubes based on cloud computing.

Countries and regions with on-going and future Data Cube projects:

- Australia
- Kenya
- Colombia
- Switzerland
- South East Asia

NSOs interested in these future data programs are strongly encouraged to get in touch with the CEOS Systems Engineering Office as they are building a global system to organise the implementation of Data Cubes in countries.

2.18 Recommendations on selecting appropriate EO sources

As EO transforms from relying on a few publicly available well defined EO sensors, such as MODIS and Landsat sources, to a much larger array of sensors with significantly enhanced specifications, the trend will be towards more data, with greater accuracy and precision being a part of the new Era of Big Data.

Before using EO satellite data, NSOs need to consider some key questions (cf. decision tree in Figure 33, Chapter 5) to decide whether or not using EO will assist in achieving their objectives and outputs effectively. The research question can guide the user to decide what EO data sources might be appropriate and useful.

If EO data is chosen as a data source, consider the best sensors to use (cf. CEOS or OSCAR of WMO databases), depending on various previously defined criteria. The global initiative GFOI is a good example of land surface monitoring, as a core data stream that has been well defined and is currently operational.

Even though the accuracy is generally lower for one pixel than with a field data measurement for the same field plot, EO products should still be considered an important alternative data source, as EO imagery can provide information with greater spatial extent, spatial density, and/or temporal frequency than any field-based (point-based) observation networks. The cost per unit area sampled and per variable will significantly reduce, as EO satellite data become more prevalent.

By using smart methods for retrieving more and more valid information from EO data, the emphasis can shift increasingly from field data to EO data. NSOs can benefit from using more EO data, where relevant and appropriate, to replace or complement their results and analysis.

Another point to highlight is the importance of the public data provided by all national space agencies. More and more private companies invest in satellites and launch their own missions to respond to immediate, punctual and operational requests from their users. Despite the great interest in these new activities in space, it is important to stress here the global coverage and continuity in time (missions planned for the next decades); two main characteristics that were only provided by public and national space agencies until now.

This fundamental aspect certainly needs to be taken into account for NSOs if they wish to use EO satellite data in certain situations. For example, if the area of interest is how a relevant process, such as erosion, land degradation, crop types, forest cover, wetlands extent, evapotranspiration, urban expansion has developed over the last 30 years it is evident that the Landsat time series is the only source of data. However, for example if the issue of interest is recent coal seam gas extraction has caused any subsidence, then public or private high resolution SAR images in interferometric mode would be most appropriate. These sources would give accuracies of millimetres deformation at any temporal scale captured since the launch of the satellites. If an environmental or natural resources baseline geospatial map is required, it could be best to opt for the highest spatial resolution imagery accessible.

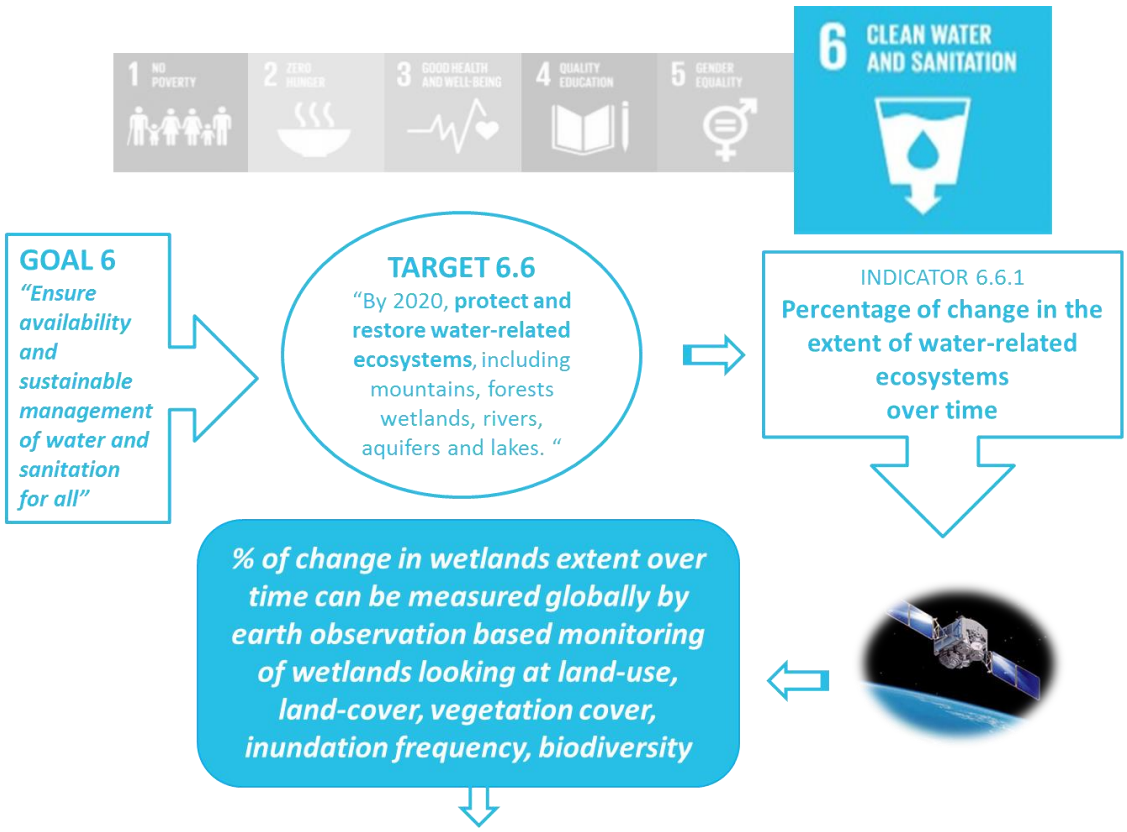
With the concept of ARD global coverage and continuity are important issues that involve a significant amount of resources to create an ARD type EO Data Cube. This is only worthwhile if there will be multiple uses made of the data for the past, present and future.

2.19 Illustrations

The United Nations has identified 17 Sustainable Development Goals (SDGs) to address challenges of economic and social development and environmental sustainability. For each of the SDGs, the UN has identified multiple targets and is developing indicators countries will use to track and report progress. To achieve the SDGs, geospatial information and Earth observations, collected at local, national and global levels, and supported by the best science, tools and technologies, can serve critical, insightful roles in monitoring targets, tracking progress, and helping nations make mid-course corrections. Combined with demographic and statistical data, these sources help enable nations to analyse and model conditions, create maps, and monitor change over time in a consistent and standardised manner (http://www.earthobservations.org/).

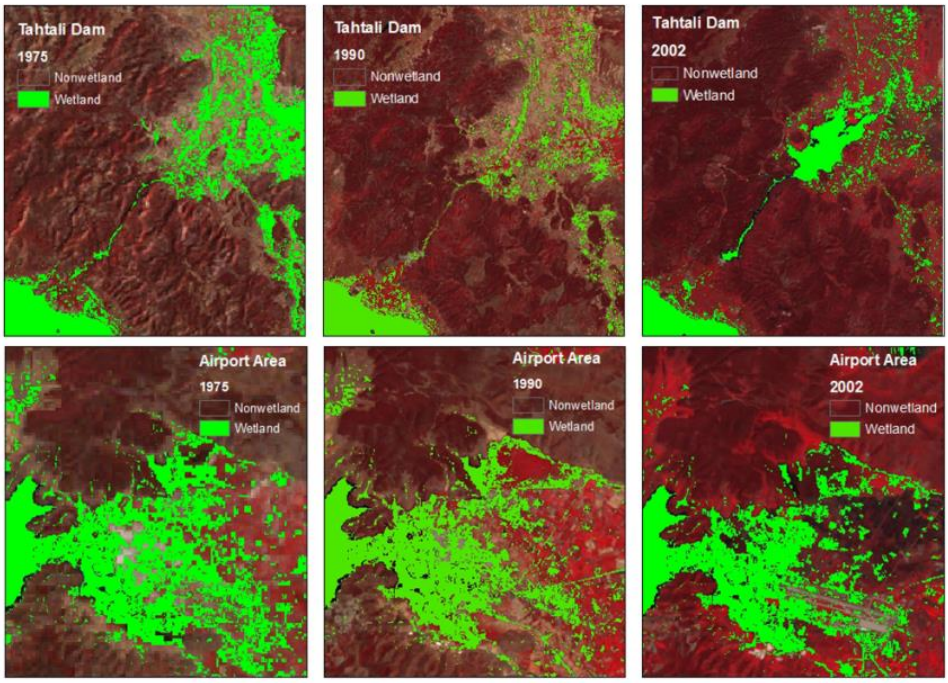
Below 2 SDGs are illustrated, which have an identified earth observation measurable component.

Examples of utilisation of EO satellite data for the UN SDGs (2030 Agenda)



Multi-temporal Wetland Identification and Delineation products (Landsat 1975, 1990, and 2002) for exemplary sites between Izmir and Bodrum (upper part: region around Tahtali Dam; lower part: Bodrum airport area).

http://www.earthzine.org/wp-content/uploads/2011/12/Figure-3.jpg



GOAL 15

"Protect, restore, and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss."

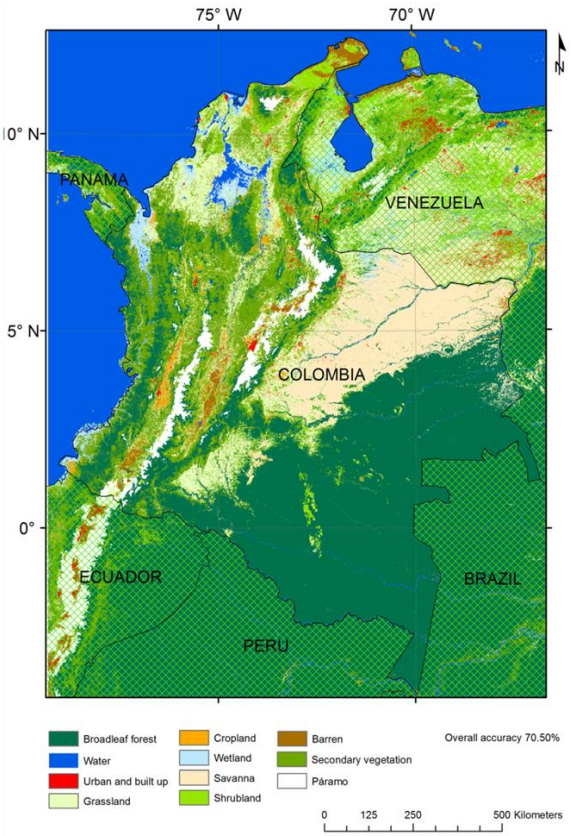
TARGET 15.2

"By 2020, promote the implementation of sustainable management of all types of forests, halt deforestation, restore degraded forests and substantially increase afforestation and reforestation globally"

INDICATOR 15.2.2

Net permanent forest lost

Land cover (time series) to be monitored, such as the global initiative GFOI (to foster the sustained availability of observations for national forest monitoring systems)



Land cover map for Colombia using 2011 ± 2 years of MODIS NDVI and surface reflectance MOD13A1 data, filtered for low-quality observations and adding elevation (TS-F-C2-E)

http://www.mdpi.com/2072-4292/7/12/15833/htm

SDGs and EO data: satellite data used in a varied range of applications (GEO document) [15]

[15] GEO "Supporting Official Statistics in Monitoring the SDGs", March 2016 – 47th UN Statistical Commission in NYC. More here: http://www.earthobservations.org/documents/meetings/201603_eo_sdgs_ny/2016_geo_un_flyer.pdf and here as well: http://www.earthobservations.org/geo_sdgs.php

Sustainable Development Goals

Earth Observations in Service of the *Agenda 2030*

Target *Contribute to progress on the Target yet not the Indicator per se*									*Goal*	*Indicator* *Direct measure or indirect support*				
							1.4	1.5	1 NO POVERTY	1.4.2				
						2.3	2.4	2.c	2 ZERO HUNGER	2.4.1				
					3.3	3.4	3.9	3.d	3 GOOD HEALTH AND WELL-BEING	3.9.1				
									4 QUALITY EDUCATION					
								5.a	5 GENDER EQUALITY	5.a.1				
		6.1	6.3	6.4	6.5	6.6	6.a	6.b	6 CLEAN WATER AND SANITATION	6.3.1	6.3.2	6.4.2	6.5.1	6.6.1
					7.2	7.3	7.a	7.b	7 AFFORDABLE AND CLEAN ENERGY	7.1.1				
								8.4	8 DECENT WORK AND ECONOMIC GROWTH					
					9.1	9.4	9.5	9.a	9 INDUSTRY, INNOVATION AND INFRASTRUCTURE	9.1.1	9.4.1			
						10.6	10.7	10.a	10 REDUCED INEQUALITIES					
	11.1	11.3	11.4	11.5	11.6	11.7	11.b	11.c	11 SUSTAINABLE CITIES AND COMMUNITIES	11.1.1	11.2.1	11.3.1	11.6.2	11.7.1
				12.2	12.4	12.8	12.a	12.b	12 RESPONSIBLE CONSUMPTION AND PRODUCTION	12.a.1				
					13.1	13.2	13.3	13.b	13 CLIMATE ACTION	13.1.1				
		14.1	14.2	14.3	14.4	14.6	14.7	14.a	14 LIFE BELOW WATER	14.3.1	14.4.1	14.5.1		
	15.1	15.2	15.3	15.4	15.5	15.7	15.8	15.9	15 LIFE ON LAND	15.1.1	15.2.1	15.3.1	15.4.1	15.4.2
								16.8	16 PEACE, JUSTICE AND STRONG INSTITUTIONS					
17.2	17.3	17.6	17.7	17.8	17.9	17.16	17.17	17.18	17 PARTNERSHIPS FOR THE GOALS	17.6.1	17.18.1			

Source: CEOS/GEO EO4EDGs Initiative, 2017

3. Methodology

3.1 Introduction

This chapter presents an overview of methodology for using spectral bands or frequencies generated from earth observation (EO) data to estimate quantities of interest to NSOs. The chapter follows on from Chapter 2, which describes the sources of EO data, and addresses the question, 'now that we have the data, how do we use it?'.

EO images, and the data that are extracted from them, fall into the category of 'big data'. This term is generally used to describe large datasets that are challenging to store, manage and analyse. For many NSOs, traditional data management and analysis tools are inadequate. Other issues include choice of appropriate statistics, consideration of the quality and accuracy of the data and results, and validation and interpretation of the outputs.

The development of techniques and tools for the analysis of EO data has been occurring for over a decade. However, the increasing resolution and availability of EO data has meant that it is now feasible for organisations and agencies such as NSOs to consider including this data source in their systems.

This chapter commences in Section 3.2 with a discussion of the types of estimates relevant to NSOs that can be derived from EO data. These include official statistics for use at a national level, as well as statistics related to the 2030 Agenda for Sustainable Development. An overall description of the approach to analysing EO data is provided in Section 3.3. Three broad steps involved in this approach include pre-processing the images and data, analysing the data to obtain the required estimates, and validating the results. These steps are described in more detail in Sections 3.4 to 3.7. The chapter closes with a summary in Section 3.8.

3.2 EO data and official statistics

Sustainable Development Goals

The use of EO data for official statistics conforms to the 2030 Agenda for Sustainable Development, through the use of a wider range of data to support implementation of the Sustainable Development goals, targets and indicators (http://unstats.un.org/sdgs/indicators/indicators-list/). As described in Section 2.19, EO data can contribute to many of the SDG targets and indicators. Examples of SDG targets and indicators that are directly relevant to EO data include the following:

- 2.4 By 2030, ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters and that progressively improve land and soil quality.
    - 2.4.1 Proportion of agricultural area under productive and sustainable agriculture.
- 6.3. By 2030, improve water quality by reducing pollution, eliminating dumping and minimising release of hazardous chemicals and materials, halving the proportion of untreated wastewater and increasing recycling and safe resuse globally.
    - 6.3.2 Percentage of bodies of water with good ambient water quality.
- 6.6 By 2020, protect and restore water-related ecosystems, including mountains, forests, wetlands, rivers, aquifers and lakes.
    - 6.6.1 Change in the extent of water-related ecosystems over time.

- 15.1 By 2020, ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services, in particular forests, wetlands, mountains and drylands, in line with obligations under international agreements.
    - 15.1.1 Forest area as a proportion of total land area.
    - 15.1.2 Proportion of important sites for terrestrial and freshwater biodiversity that are covered by protected areas, by ecosystem type.
- 15.2. By 2020, promote the implementation of sustainable management of all types of forests, halt deforestation, restore degraded forests and substantially increase afforestation and reforestation globally.
    - 15.2.1 Forest cover under sustainable forest management.
    - 15.2.2. Net permananet forest loss.
- 15.3 By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world.
    - 15.3.1 Proportion of land that is degraded over total land area

Anderson *et al.* (2017) provide a number of examples that illustrate the use of EO in the service of the 2030 Sustainable Development Goals. The following advantages are highlighted: enablement of informed decision-making and monitoring of the expected results; improvement of national statistics for greater accuracy; assurance that the data are "spatially-explicit"; fostering of synergy between the SDGs and multilateral environmental agreements by addressing cross-cutting themes such as climate and energy; and facilitation of countries' approaches for working across different development sectors.

3.2.1 Environmental and agricultural statistics

A current major focus of EO data analysis is on deriving environmental and agricultural statistics. Three specific examples of statistics that can be derived from EO data are land cover, land use and land cover change. These are defined in the FAO Global Strategy[16] report as follows: land cover is the observed (bio) physical cover on the Earth's surface; land use is the use made of land by humans; and land change studies attempt to describe where and what change is occurring over time, at what rate and perhaps why.

Other agricultural statistics include crop identification and crop yield. Crop identification and crop yield case studies are detailed in Chapter 4. For further information about using EO data for crop identification and crop yield, refer to the FAO Handbook on Remote Sensing for Agriculture Statistics.

These statistics can be tabulated or displayed graphically, as illustrated in Figure 18 for Chiapas, Mexico.

[16] Global Strategy 2017. Handbook on Remote Sensing for Agricultural Statistics. Rome, www.gsars.org, 250pp.

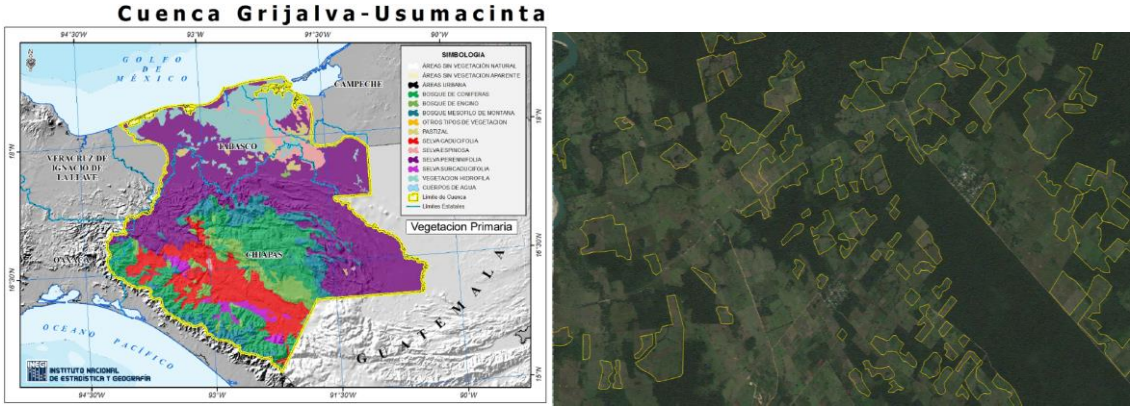


Figure 18: Examples of geographic display of statistics relevant to the SDG indicators that can be obtained in full or in part by EO data. Use of INEGI's Land Use and Vegetation Map Series in the Digital Map of Mexico (various scales available). Left: Indicator 15.2.1 Progress towards sustainable forest management. Right: Indicator 15.2.2 Net permanent forest loss, estimated changes in tropical broadleaf evergreen forest in Chiapas based on satellite images from 2006 to 2013.

Source: Figures extracted from Integrating Statistical and Geospatial Information: Experience in Mexico. Presentation by Mr. Rolando Ocampo, Vice President, INEGI, Mexico. Meeting organised by UNSD on Geospatial Information and Earth Observations: Supporting Official Statistics in Monitoring the SDGS, New York, 7th March 2016.

Another example of graphically displaying environmental and agricultural statistics derived from satellite imagery is the Global Forest Change map by Hansen, Potapov, Moore, Hancher et al (2013). Forest loss, forest cover loss and gain and percentage of tree cover are identified from time series analysis of Landsat images and depicted on an interactive global map in Google Earth Engine. A section of the map is below in Figure 19.

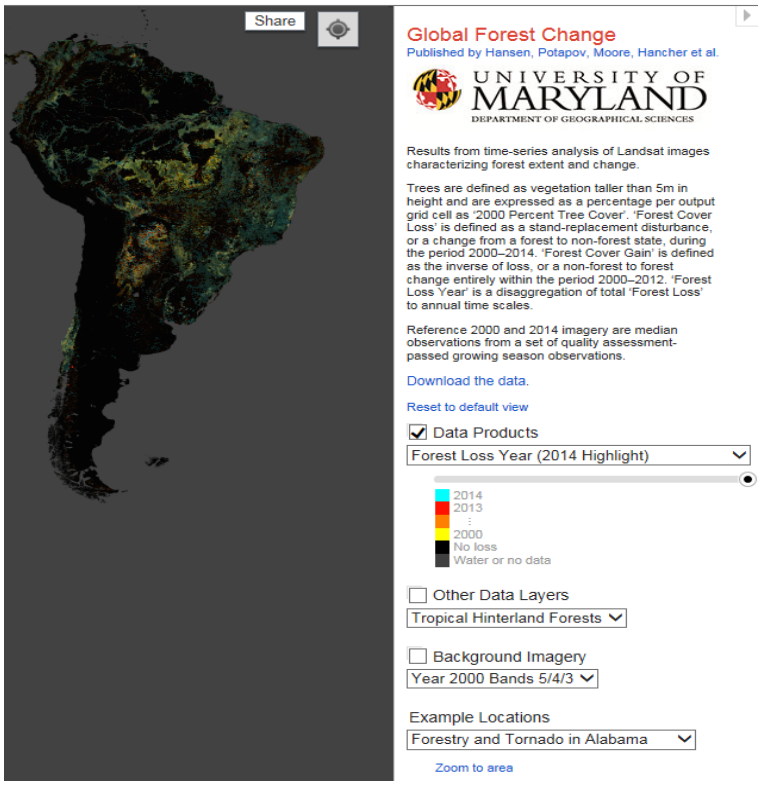


Figure 19: Global Forest Change map view of South America

See https://earthengineparnterns.appspot.com/science-2013-global-forest for more information and to view the map.

3.2.2 Other statistics

Many other statistics of interest to NSOs can be obtained from EO data. Examples that address the SDGs include water quality detection (Dekker *et al.*, 2016), urban change (Taubenboch *et al.*,2012; Esch *et al.*, 2012) and natural disaster risk assessment (Geib and Taubenboch, 2013). Anderson *et al.* (2017) also describe examples of global crop monitoring (by GeoGLAM), electricity access (visualised using night time satellite imagery to assess the location and spread of electric lighting) for SDG 7.1, air quality (by monitoring aerosols, hot spots and forest fires , SDG11.6) and biodiversity (by EO monitoring of protected areas and potential criminal activity, SDGs 14 and 15).

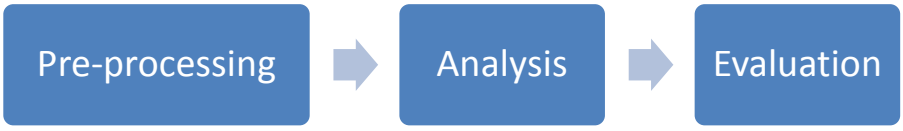
Different forms of EO data can be combined to provide relevant statistics. For example, drones are now being used extensively as EO data sources in their own right and in combination with satellite and radar data. They are also being used in combination with traditional data sources such as surveys, and with other big data sources such as mobile phone and social media data. For example, Steele *et al.* (2017) give an example of combining EO and mobile phone data to obtain poverty estimates.

It is important to note that different definitions of quantities of interest can affect the calculation of the estimates. This is described in the FAO Global Strategy report for the case of land cover change: substantial differences were found in 11 cover classes derived from four different global databases. The report notes (p. 23) that "this does not mean that the figures are inaccurate (as they relate to different definitions of class membership); rather, they are inconsistent, especially where few classes are used." For this reason, a common Land Cover Classification System (LCCS)[17] has been developed by the FAO and UNEP, as detailed in the report[18]. The SEEA Central Framework[19] is a useful international standard for environmental accounting and its land cover classification is based on the set of rules and classifiers set out in the LCCS.

3.3 General approach to analysing EO data

3.3.1 Steps in the analysis of EO data

The analysis of EO data can be divided into three broad steps, as follows:



The **Pre-processing** step is critical to successful analysis of big data, and the quality and integrity of the obtained estimates. This step involves the following considerations:

[17] Also refer to the LCCS2 http://www.fao.org/docrep/008/y7220e/y7220e00.htm and LCCS3 http://www.fao.org/3/a-i5232e.pdf)

[18] Report reference: (http://gsars.org/wp-content/uploads/2016/08/TR_Information-on-Land-in-the-Context-of-Ag-Statistics-180816.pdf, Information on Land in the Context of Agricultural Statistics, Technical Report Series GO-15-2016).

[19] SEEA Central Framework https://unstats.un.org/unsd/envaccounting/seearev/seea_cf_final_en.pdf

- *Data storage:* This includes storage of the EO images and/or extracted data, and of the statistics and derived products obtained from the analysis of the data.
- *Data management:* This includes management of the EO images and extracted data.
- *Data quality:* This includes critical evaluation of the data extracted from the EO images with respect to its overall capacity for analysis and ability to provide reliable, accurate statistics.
- *Other information sources:* This includes identification, collation, storage, management and evaluation of other supporting data that can be used in the analysis step.
- *Software:* Based on the above considerations, this includes identification of appropriate, available software products that can be employed to help with the pre-processing step.

The **Analysis** step involves the following considerations:

- *Overall aim:* This includes defining the overall aim, such as provision of particular national statistics or a SDG indicator; and defining the corresponding statistical estimates, predictions or inferences that are to be obtained from the analysis.
- *Data:* This includes determining which subset of the stored data will be used in the analysis, and whether the analysis will be based solely on the EO data or in combination with other data sources.
- *Analytic method:* This includes selection of a general approach and specific technique for extracting the required quantities, based on the aim and available data.

The **Evaluation** step involves the following considerations:

- *Critical assessment of the results:* This step involves collating, assessing and interpreting the results of the analysis.
- *Accuracy assessment:* This includes a comparison between observed values and predicted estimates where possible, assessment of the uncertainty or precision of the results, and evaluation of the replicability of the results.
- *Other concerns:* This includes consideration of any other potential biases or concerns with the results and their interpretation.

These steps are described in detail in Sections 3.4 to 3.7.

3.3.2 Implementation of methodology

Various NSOs have devised plans for implementing the analysis of EO data. These plans incorporate the above steps in different ways.

As illustration, Figure 20 shows the template proposed by Denmark to facilitate the pathway from EO data collection to estimation of relevant statistics and integration into NSO operations.

Suggested geospatial data integration
GAP analysis: *"Reliable methods for estimating emissions from forest degradation are still lacking. We suggest using a common input source (Sentinel 2) to monitor the world's forest, thus eliminating the need for a Tier system. This will also standardize reporting methods and create enhanced transparency – building on a close partnership with national forest authorities".*
List required geospatial data: *"Need for high-resolution multispectral imagery (including NIR) for detailed images of land and vegetation, with frequent revisit times to provide frequent images".*
Data quality requirements: *"This indicator requires high repetition rates to acquire large data coverage in short time periods (short repetition cycle), high spatial resolution (10-20m) to assess also forest stands with low canopy closure, 10, 20 and 60m, and high spectral resolution to discriminate between forest and spectrally similar vegetation types".*
Data availability: *"Sentinel data are globally available, downloadable from ESA. Access to Sentinel data is free, full and open for the broad Regional, National, European and International user community. User registration is based on a user account pre-registration, with a dedicated single account per Agreement".*
Data collection: *"Sentinel data access infrastructure for International Agreements (International Agreements Data Hub), can provide access to a rolling on-line archive covering the last month(s) of Sentinels core products, available within their specific timeliness. Furthermore, access to off-line archived data is available on-request".*
Data interpretation: *"Forest cover change assessment procedure: Acquire EO data, site image control and pre-processing, preliminary labeling of objects and changes, verification and adjustments of labels, validation and adding forest and land use dimension".*
Method of integration: *"1) A governance structure is agreed nationally and internationally, 2) A global reference data set is created, 3) Monitoring cycles are agreed, 4) Methods for change detection are developed, and the centrally established dataset is revised, 5) An online portal like the Forest Resources Information Management System "FRIMS" is used as channel for interaction between FAO and each national authority".*

Figure 20: Template proposed by the Agency for Data Supply and Efficiency in Denmark.
Source: Presentation by Mr. Morten Nordahl Moller, Head of Division. Meeting organised by UNSD on Geospatial Information and Earth Observations: Supporting Official Statistics in Monitoring the SDGS, New York, 7th March 2016.

3.4 STEP 1: Pre-processing

The considerations to be addressed in the Pre-processing step include (1) storage of the EO data, (2) management of the data, (3) assessment of data quality, (4) identification of other information sources and (5) choice of software products to assist in this step. These considerations are now discussed in detail.

3.4.1 Storage of EO data

Traditionally, NSOs have collected sample data to produce statistical outputs and make inferences about broader populations. Big data sources, such as EO, present opportunities to access larger volumes of data that are timelier, and often at a lower cost. However, EO data sets are large and therefore appropriate storage approaches are necessary. Guidance on storage solutions and approaches is beyond the scope of this report, so a few options are briefly mentioned here.

Storage options for NSOs include:

- storing the data onsite;
- outsourcing the data storage.

Storage of data onsite will usually require some form of High Performance Computing (HPC) environment. HPC clusters and distributed computing techniques allow large datasets to be split into

blocks and run simultaneously on multiple nodes for faster computational time. Results from each node are then combined in statistically sensible ways.

Setting up a HPC system that is capable of dealing with current – and future – EO data can be expensive in terms of infrastructure, training, upkeep and currency. For these reasons, outsourcing data storage is an appealing alternative. For example, there are various cloud-based storage solutions such as those offered by Microsoft and Amazon Web Services, or local trusted companies can be considered.

Another option is to use third party or open data. Open EO data are becoming increasingly prevalent and are now part of the remit of many EO data sources (e.g., Copernicus). Using analysis-ready data can further simplify the process by eliminating not only problems of storage but also most of the pre-processing burden. Data Cubes described in Chapter 2, for example, have HPC capability, and make standardised and calibrated satellite data available in structures available on a range of processing platforms which can be either local, remote or cloud based. Online and free data catalogues combined with on-line modelling platforms such as the GEE – Code Editor may also be applicable.

3.4.2 Management of EO data

Management of EO data typically involves processing images to analysis ready data (ARD).

As described in Chapter 2 and in the previous section, some countries have a Data Cube or other sources of ARD available. This can usually be analysed without further pre-processing. However, it is important that other considerations, such as assessment of bias and validation of results, are still undertaken. These issues are described in more detail in subsequent sections of this chapter.

For many NSOs, ARD data may not yet be available. As discussed in Chapter 2, raw EO data are not able to be used for analysis unprocessed because this would lead to inaccurate results based on varying sun-angles and sensor geometries, noise, haze and distortion of the underlying imagery data. Different pre-processing levels are conducted in order to increase the quality of the imagery data.

The goal of the pre-processing is to extract the pure spectral information reflected from the surface of the earth and recorded by the sensor without any obscuring aspects. This is done through so-called correction algorithms, namely, geometric correction and radiometric correction. These algorithms filter out and correct for specific and defined noise parameters. The goal of the geometric correction is to improve the accuracy of surface spectral reflectance, emittance, or back-scattered measurements obtained using a remote sensing system. This pre-processing step is also known as detector error correction, or atmospheric and topographic correction. The radiometric correction deals with atmospheric particles which can obscure spectral information.

In addition to these Top of Atmosphere satellite imagery corrections, "masking" of data is also required. Masking refers to the process of detecting and then "masking" out obscuring artefacts such as cloud cover, cloud shadow, fire clouds, water, and so on. All these corrections are an integral part of creating Analysis Ready Data (ARD).

With some investment of time and skills, NSOs can set up a system to process raw satellite imagery data to the ARD stage using either proprietary or open-source software.

Open-source software is potentially less expensive to set up and has the advantage of providing independence from proprietary systems. This has advantages of allowing the software to be customised and linked to a broader range of software products and systems that are already embedded in the

organisation. Moreover, there is often a large open source community that can provide support and solutions to problems. On the other hand, proprietary software can be seen to be more reliable from the client or consumer's perspective, and may have the advantage of greater technical support. (Trevithick and Gillingham, 2009). Software products are discussed further in Section 3.4.5.

A detailed system that uses open-source software to process raw satellite imagery data to ARD is described in Section 3.4.6. This system was developed by the Remote Sensing group in the Queensland Department of Science, Information Technology and Innovation (DSITI) in Australia. The system was developed prior to the creation of the Australian Data Cube and has been actively used for more than a decade. It uses Landsat data available from the United States Geological Survey (USGS) website and applies a number of open source software packages that translate data formats, make atmospheric corrections and program the image-processing. An example of how this processed data is used to identify cropping activity and land use is outlined as a case study in Chapter 4.

3.4.3 Quality assessment of EO data

Traditionally, NSOs have collected sample data to produce statistical outputs and make inferences about broader populations. Big data sources, such as EO, present opportunities to access larger volumes of data that are timelier, and often at a lower cost.

There is a misconception that big data sources, such as EO, will be statistically valid simply due to the magnitude of data available. Although increasing sample size can reduce sampling errors, it does not reduce other sources of statistical bias such as measurement error. Further, data sets derived from these sources are not necessarily random samples of the target population NSOs want to make inferences about, therefore increasing the size of the dataset may not reduce sampling error or improve the quality of the estimates.

In addition, big data sources have their own specific issues which can impact on statistical validity. These include accumulation of errors (noise) and potential spurious correlations, as well as algorithmic instability that can lead to inaccurate estimates. The different sources of data, and their aggregation, can also lead to statistical biases (Fan, Han and Liu, 2014).

Some of these challenges of using big data for statistical purposes can be addressed by using appropriate methodologies, depending on the data source and intended outputs. Examples of different methodological techniques for EO data specifically are described in this chapter. However, it should be noted that these methodologies will not counter issues related to data quality, data representativeness or other related issues. This is discussed further in Section 3.7.3.

3.4.4 Other information sources

EO data can be analysed on its own, or with other datasets. The choice of other datasets depends on the following considerations:

- *Aim:* Different datasets will be required for different purposes, based on the required estimates, selected method for analysis, spatial and temporal resolution and scope of the analysis, quality of the available EO data, and so on.
- *Access:* Datasets can include existing resources held by the NSO and/or they can be obtained from external parties. Access considerations also include intellectual property, confidentiality, cost, reputation, and continuity of access.

- *Content:* A wide range of data can potentially complement EO data in an analysis, such as censuses, household or agricultural surveys, administrative data, environmental and meteorological data.

The FAO report on a Global Strategy for Improving Agricultural and Rural Statistics (2016) provides advice about constructing and maintaining a Minimum Set of Core Data (MSCD) that includes EO and other spatial and non-spatial information in a Master Sample Frame (MSF) database. The MSF is constructed by combining satellite images classified by geo-referenced land use and digitised administrative data, digitised enumeration areas, and overlaying this with population and agricultural census data, other relevant data such as a register of commercial farms, and an area frame.

(http://gsars.org/wp-content/uploads/2016/08/TR_Information-on-Land-in-the-Context-of-Ag-Statistics-180816.pdf, Information on Land in the Context of Agricultural Statistics, Technical Report Series GO-15-2016)

Many NSOs are in various stages of implementing systems to integrate EO data with other data for official statistics and SDGs. For example, Table 5 shows how Mexico envisages the use of different resolutions of satellite imagery for national statistics and to support the related SDGs. These statistics can be geographically displayed as illustrated in Figure 18.

Table 5 Integrating Statistical and Geospatial Information: Experience in Mexico.

GEO-STATISTICAL INTEGRATION to MONITOR NATIONAL PRIORITIES & SDGs			
Satellite Imagery	**Other sources**	**National Uses**	**SDG / other applications**
High resolution (2.5 m) **SPOT ERMEX** Very high resolution (0.5 m) **GEOEYE EVISMAR**	**Population Census** **National Housing Inventory** **Economic Census** **Technical Standard on addresses** **COA-Web** ***In situ* validation**	**Geo-statistical framework** **Updating of:** Topographic charts **Visualization of:** Population, Economic, Housing, Gender, Health, Education & public services Urban & rural development Water and sanitation Infrastructure GHG emissions/hzd waste	**1. No poverty** **2. Zero hunger** **3. Health and well-being** **4. Quality education** **5. Gender equality** **6. Water and sanitation** **7. Affordable & clean energy** **8. Decent work & economic growth** **9. Industry & infrastructure** **10. Reduced Inequalities** **11. Sustainable cities & communities** **12. Life on land**
Medium resolution (5-30m) **RAPIDEYE LANDSAT**	**Natural resources & topographic charts** **Forestry & water data** ***In situ* validation**	**Land Use & Vegetation map series** Deforestation, land use changes **Monitoring crops**	**2. Zero hunger** **16. Clean water and sanitation** **13. Climate action** **14. Life below water** **15. Life on land**
Low resolution (250 m) **MODIS**	**Topographic maps** **Land use & vegetation**	**Disaster monitoring** Fires, large flooding	**Sendai Framework** **Climate action**
Radar **RADARSAT**		**Disaster monitoring** Flooding, digital models in foggy areas	**Sendai Framework** **Climate action**

Source: Presentation by Mr. Rolando Ocampo, Vice President, INEGI, Mexico. Meeting organised by UNSD on Geospatial Information and Earth Observations: Supporting Official Statistics in Monitoring the SDGS, New York, 7th March 2016.

3.4.5 Software products

There is a range of proprietary and open source software products available for working with EO data. The products can be used to assist with preparation, storage and management of data. This chapter does not make recommendations on software product because the most appropriate tool will vary for individual NSOs.

When choosing a product, NSOs should consider the capabilities and experience of their staff using different software, cost if choosing a commercial product, and long term accessibility if choosing an open source product. For example, if the NSO built a statistical collection around data produced using an open source product, how would they be impacted if the provider started charging for access and have contingency plans in place.

The list of software available is increasing rapidly. Some popular products that are available now are briefly described here.

Hadoop is a popular technology related to big data management (Scannapieco, Virgillito and Zardetto (2013). It is an open-source software project, developed by the Apache Software Foundation, targeted at supporting the execution of data-oriented application on clusters of generic hardware. The main components of Hadoop are HDFS, which sends tasks to multiple cores for processing, and MapReduce, which keeps track of the data packets and combines the results of the processes. Many products are now available that use Hadoop as a platform and provide improved interfaces for easier engagement by end-users. Popular current examples include Spark and its derivatives (such as Sparkling Water and Steam), and Tensor Flow.

GDAL/OGR - Geospatial Data Abstraction Library (reading and writing raster and vector geospatial data formats) - most of the commonly used geospatial software applications use GDAL/OGR.

GDAL supports more than 140 raster formats; OGR supports over 80 vector formats (see Warmerdam *et al.* (2016) for more information).

Some software packages (e.g. raster in R (R Core Team, 2016)) allow manipulation of data too large to load into memory in its entirety by only creating structure information about the data, and processing in chunks when manipulating the data itself.

GIS - System for Automated Geoscientific Analyses (SAGA) SAGA is open source software which is intended to give scientists an effective but easily learnable platform for implementing geoscientific methods and enables the user to perform vector and raster based spatial analysis, edit and manipulate diverse data and store it in a format which allows sharing with other GIS communities and commercial software packages. Further, it can perform interpolations using triangulation, nearest neighbour, inverse distance and other metrics. SAGA GIS can be downloaded at http://www.saga- gis.org/en/index.html.

SAGA has a fast-growing set of geoscientific methods and is written in C++. It was developed at the Department of Physical Geography at the University of Gottingen, Germany and is now being maintained and extended by an international developer community. The initial release was in February 2004.

Google Earth Engine

As described in Section 3.2.1, Google Earth Engine can be used to display and interpret EO data. Landsat data is now available in Earth Engine through collaboration with USGS and NASA. Earth Engine provides this data in its raw form, as a TOA-corrected reflectance and in various ARD computed products such as NDVI and EVI vegetation indices. See https://earthengine.google.com/datasets.

Extensions to existing software products

A growing number of software products that traditionally dealt only with databases are now providing big data capability and data management tools. Examples include SAP (Hana) and HPE (Vertica). Similarly, statistical and mathematical modelling packages such as R, Matlab, Stata and SAS now provide big data management tools, often based on Hadoop and similar frameworks.

Bespoke data management tools can also be found, and/or written in programming languages such as R (see, for example, RStoolspack) and Python.

Further examples of software used to pre-process EO data are discussed in the case study described in the next section.

3.4.6 Case Study: Data Pre-Processing

In Australia, the Queensland Department of Science, Information Technology and Innovation (DSITI) created a system using open-source software to process raw satellite imagery data to ARD. This was prior to the creation of the Australian Data Cube.

The software packages which are crucial to the process are GDAL, 6S and Python. These programs are open source. GDAL is a translator library for raster and vector geospatial data formats. 6S is atmospheric radiative transfer modelling software which is used to make atmospheric corrections. Python is a programming language used for the majority of the image-processing in this study.

First, raw Landsat data is obtained for the entire state of Queensland from the United States Geological Survey (USGS) website. The Landsat data is included if it has <80% cloud cover. The data in the files is then unpacked into reflective, thermal and panchromatic components and saved as ERDAS Imagine (.img) files. Other GDAL software readable formats could also be used. The processing for the thermal, panchromatic and reflective components is briefly described below, in no particular order.

Thermal component

The thermal component is adjusted for temperature, and cloud and shadow masks are automatically applied. Next, snow, cloud and cloud shadow masks are automatically applied. This masked data is then included in the automatic seasonal fractional cover step in the reflective component process. It is an input to the cloud and cloud shadow masks that are applied to produce the ARD.

Panchromatic component

This is a one step process in which the raw data is processed in python to produce a panchromatic image. This component is not used further in analysis.

Reflective component

From the raw Landsat data, a scaled top-of-atmosphere radiance image is automatically produced. This top-of atmosphere radiance image is then corrected for atmospheric effects and saved as an .img file.

According to Flood et al (2013) “atmospheric effects on the signal include a range of scattering and absorption processes, and are a function of the various angles relating the sun, surface and satellite. These effects are assumed to be well modelled by widely available atmospheric radiative transfer models” (p. 86).

In the DSITI process, the Second Simulation of the Satellite Signal in the Solar Spectrum (widely known as 6S) model is used to apply atmospheric corrections and produce the atmospherically corrected .img file. For further details on the 6S model application, see Flood et al (2013) section 2.2.

The atmospherically corrected .img file, with various cloud cover, cloud-shadow, incidence, topo-shadow and water masks applied, is the resulting ARD used in analysis.

Once these processes are completed the data is ready for analysis. Note that only the reflective component is included in the ARD, and within that only a subset of reflectance images with <60% cloud cover.

3.5 STEP 2: Analysis

Prior to undertaking the analysis, the following questions should be considered:

1. What measures are required?
2. What statistics will be used to estimate these measures?
3. What data are required to obtain these statistics?

The first two questions have been addressed above in the context of NSOs and SDGs; see, for example, Section 3.2. In addressing the third question, it is important to recognise that not all of the available data are required for a particular analysis. A good data management structure will allow either the aggregation of relevant data for analysis, or alternatively provide the tools to access datasets from different databases stored in different (virtual) locations. There are advantages and disadvantages of both of these approaches. Identifying only relevant data for the analysis helps to guard against the generation of spurious results due to the inclusion of superfluous information.

3.5.1 Analytic Approach

In addition to identifying the type of analytic problem, it is necessary to choose an analytic approach (or combination of approaches). As discussed in Section 2.4, analytic approaches can be categorised into five types of methods:

Figure 21: Analytic approaches for analysis of EO and other data

The choice of analytic approach depends on the available data and degree of understanding of the physical processes underlying the relationship between the EO inputs and the target estimates. For example, if there is a strong understanding of the biological or physical processes, then a physics-based approach is appropriate, otherwise an empirical or machine learning approach may be adopted. If data are available and there is knowledge of the process, then semi-empirical methods can be used.

Although the five methodological approaches have distinct characteristics, there is substantial overlap. For example, although empirical approaches focus more on the model and machine learning approaches focus more on the algorithm, both approaches aim to create relationships based on the observed data and they share a common set of methods to achieve this. Similarly, mathematical and statistical models tended to be treated as distinct, but it is now common to merge mathematical or physics-based methods with statistical models and simulation where this is relevant. For example, a mathematical representation of a process can be combined with statistical descriptions of less well known parts of the process and/or uncertainty in input parameters. Simulation can then be included to describe more complex components or further evaluate uncertainty in inputs and outputs, or evaluate 'what if' scenarios.

Empirical methods

Empirical methods are defined in Chapter 2 as cases where a statistical relationship is established between the spectral bands or frequencies used and the variable measured (field-based) without there necessarily being a causal relationship. This relationship can be parametric, semi-parametric or nonparametric.

The main advantages of empirical (statistical model-based) approaches are they provide a mathematically rigorous way of describing sampling and model error, estimating and predicting outcomes of interest and relationships between variables, and quantifying the uncertainty associated with these estimates and predictions. They can also be used to test hypotheses under specified assumptions. Disadvantages are they often include assumptions about the data generating process (unlike many of the machine learning methods) and require in-situ data (unlike the physics-based models). This reliance on in-situ data also means they may be difficult to extrapolate or transfer to other contexts (Dekker *et al.* 2013).

Beyond the spatial scope, many forms of remotely sensed data (particularly from satellites) are collected over time. Although adding a temporal dimension increases the data size substantially, this can be managed by careful selection of data (for example, based on *a priori* knowledge regarding particular crop growth cycles). Including a temporal dimension in the analysis can add a wealth of useful insights, such as substantially more accurate crop classification as well as estimation and prediction of and crop yield.

Semi-empirical methods

Semi-empirical methods combine knowledge about the process with statistical models. This knowledge can be about the process itself or about the variables that are included in the process.

These methods have been used for EO data analysis for over a decade. For example, Phinn *et al.* (2005) used Landsat 7 Enhanced Thematic Mapper image data to map selected water quality and substrate cover type parameters. More recently, Dekker *et al.* (2013) describe a semi-empirical approach to water quality detection, in which knowledge about the spectral characteristics of some of the parameters is

used to refine the statistical model. In their example, only a subset of variables is used in the model, with well-chosen spectral areas and appropriate wavebands or combinations of wavebands. The authors highlight the popularity and utility of these approaches, but also caution that they still require in-situ data. Thus while they are arguably more transferable than purely empirical models (since they contain information about the process), they can still be limited by the generality of the data used to build them.

Tripathy et al. (2014) also use a semi-empirical method which incorporates physiological measures, spectral measures and spatial features for estimating wheat yield. The authors note that while spectral (empirical) and physics-based (mechanistic) models based on vegetation indices are widely used, they are respectively limited by being data-intensive and complex. Their semi-empirical approach is proposed as an intermediate method.

Physics based methods

As outlined in Chapter 2, physics based models are based on detailed knowledge of the system that is being modelled. They can be built without data, or data can be used to calibrate the model parameters. This method is suitable for automation across large areas, provided the model is appropriately and accurately parameterised.

Biophysical and geophysical models that utilise EO data have been developed and applied to a wide range of problems for over 15 years. An early example is the extension of a PHYSGROW plant growth model to include NOAA and NASA satellite data products in order to create forage production maps for a large landscape. The EO derived inputs were gridded daily temperature, rainfall and a Normalised Difference Vegetation Index (NDVI), with cokriging to take advantage of spatial autocorrelation (Angerer et al., 2001). The authors concluded that the mapped surfaces of the cokriging output could successfully identify areas of drought and argued these maps could be used as part of a Geographic Information System (GIS), 'which could then be linked to economic models, natural resource management assessments, or used for drought early warning systems'.

Phinn et al. (2005) pioneered the use of these methods in a marine context, using Landsat 7 Enhanced Thematic Mapper image data to map selected water quality and substrate cover type parameters. A more recent physics-based method for detecting water quality using EO data is described by Dekker *et al.* (2013). There are now many examples of these types of models. For instance, Watts et al. (2014) extended a terrestrial flux model that allows for satellite data as primary inputs to estimate CO2 and CH4 fluxes, and Gow et al. (2016) combined satellite observations of land surface temperature with a surface energy balance model to estimate groundwater use by vegetation.

These physics-based approaches are typically based on sophisticated algorithms that take into account sensor performance, multiple environmental impacts from the atmosphere and sea surface, as well as the optical properties of the water body and seafloor. For more information, see Wettle et al (2013).

Object based image analysis

Two types of object based image analysis are field-based aggregation approaches and contextual classification approaches.

The simplest approach is field-level aggregation. This method aggregates pixels up to "fields" (per-field classification) or "objects" (object- oriented classification) and then estimates or classifies at this new, aggregated level. These approaches spatially smooth the data by averaging over all pixels within a field or object. This is computationally efficient and has also been shown to produce more accurate and robust outputs than pixel-based approaches, particularly with fine resolution spatial data. For

example, Hoque et al. (2016) and Hoque et al. (2017) employ field-level approaches for modelling cyclone impacts, with the latter paper evaluating cyclone risks for present and future climate change scenarios.

Contextual techniques explicitly acknowledge and incorporate spatial dependencies between neighbouring pixels. They may make use of spatial smoothers, Markov Random Fields, and spatial statistics and models in combination with classification techniques. Estimation or classification occurs either after spatial dependencies are accounted for (pre-smoothing) or before (post-smoothing).

Artificial intelligence and machine learning methods

Machine learning methods, also called artificial intelligence (ML) methods, use algorithmic models to analyse data. These methods treat the way in which the data were generated or relationships between the variables as unknown (Breiman, 2001).

There are many ML algorithms that perform different tasks. Some of the algorithms that are relevant to EO data applied to SDG targets are listed in the following figure, and are grouped according to four main analytic aims: classification, clusting, regression and dimension reduction. These aims are described in Sections 3.5.2 and 3.5.3. Details of the algorithms are presented in the Appendix.

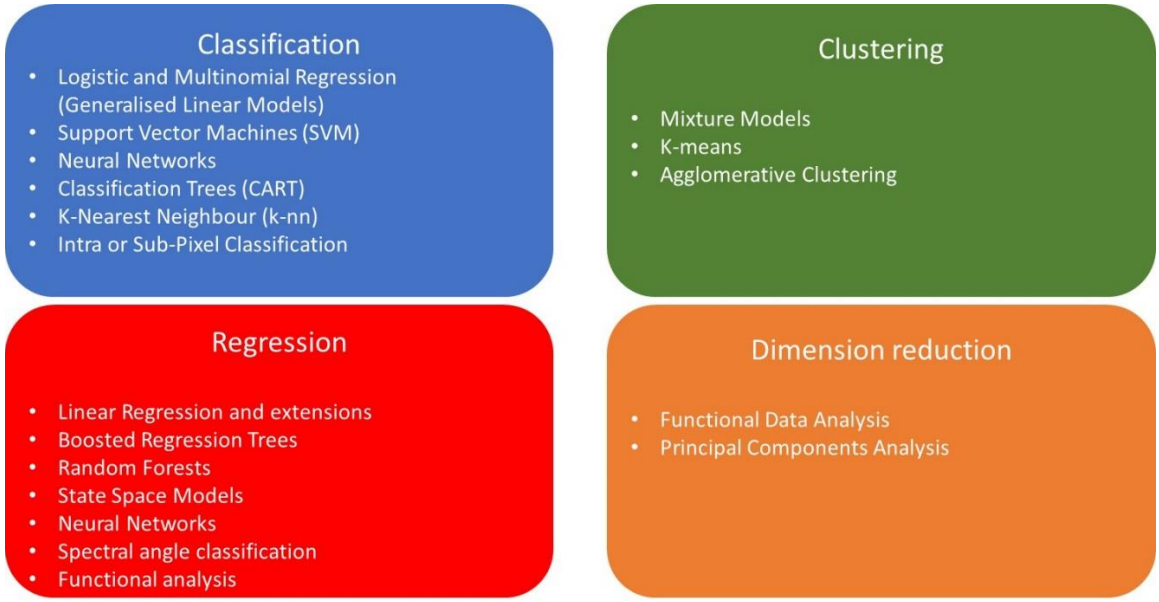


Figure 22: Empirical and machine learning methods for analysis of EO and other data, collated according to the analytic aim.

Ensemble Approaches

Recent trends in ML and remote sensing analyses centre around the combination of multiple ML and empirical methods to form hybrid approaches. These ensemble approaches are also known by other names, such as Multiple Classifier Systems for classification problems (Du et al., 2012; Woźniak et al., 2014). Ensemble methods fall into two categories: serial (or concatenation) and parallel.

Serial combination refers to the methods being combined in a serial fashion - the results of the first analysis are used as inputs into the next analysis, and so on. The final output (classification, estimate, clustering, dimension reduction, etc) is determined by the output of the final method in the series.

Parallel combination refers to the approach that applies multiple methods to the data simultaneously; with the final output determined using some kind of decision rule. The most popular decision rule for continuous outcomes is the simple average of all of the methods. For Multiple Classifier Systems, the most popular rule is the majority vote, whereby the final class membership is the one which the majority of classifiers predict. The output of the methods can also be weighted by its estimated accuracy using a training set. Other decision rules include Bayesian averaging, fuzzy integration, and consensus theory (Due et al., 2012).

Examples of recent work in the remote sensing literature utilising a Multiple Classifier Systems approach include: Briem et al. (2002), Huang and Zhang (2013), Zhang et al. (2015b), Li et al. (2012b), Roy et al. (2014), Bigdeli et al. (2015), Wu and Gao (2012), Samat et al. (2014), Clinton et al. (2015), Han and Liu (2015), Li et al. (2014), Zhang and Xie (2014).

3.5.2 Analysis of static data

Static data refer to data obtained for a single time period (dynamic analyses, which refer to analysis of data over time, are discussed in Section 3.5.3.) As indicated in the figure above, four of the most common aims of static analyses are classification, clustering, regression and dimension reduction.

Classification is applicable if the overall aim is to accurately allocate objects to a discrete (usually small) set of known classes, or groups. This allocation is based on a set of input variables (also called explanatory variables, factors, predictor variables, independent variables, covariates or attributes). A set of data containing input variables and the output variable (the corresponding classes are used to develop or 'train' the model). This model can then be applied to test datasets that contain only the input variables.

An example is the categorisation of pixels in an image into crop types, based on a training dataset that contains variables extracted from the images (the input variables) and ground-truth crops (the output variable) at a set of sites. The crop classification model that is developed can then be applied to the rest of the image where ground-truth data are not available.

Clustering is applicable if the aim is to combine objects into groups or classes based on a set of input variables. Unlike classification, we don't know the output variable, or classes, even in the training dataset. Therefore we need to work out a measure of similarity between the objects and a way of grouping them according to these similarities. We can specify the number of groups (clusters), or also make this unknown and estimate the number of groups as part of the analysis. The analysis can be used to make decisions about the objects that were clustered, or to predict cluster membership for new objects. An example is the allocation of pixels into groups based on a set of input variables extracted from an image. These groupings can then be inspected, described and compared in terms of their characteristics.

Regression is applicable if the aim is estimation or prediction of a response (output) variable based on a set of covariates or explanatory (input) variables. This is similar to classification methods, but the response is continuous instead of categorical. Like classification methods, the regression model is developed or trained based on set of input variables for which the response is known. The model can then be used to predict responses for test datasets (with input variables but no response variable), identifying which input variables are most important in providing good estimates or predictions, or inspecting the relationships between the input variables. An example of regression is accurately

estimating or predicting crop yield based on variables extracted from an EO image. In this case, crop yield is a continuous variable, rather than the crop type classes described as in the above classification example.

Dimension reduction is applicable if there are many variables that can be extracted from EO data (and other data sources), and the aim is to construct a small set of new variables that contain all (or most) of the information contained in the original (large) set of input variables. These new variables can be used as inputs into other analyses, or they can be end products in their own right. For example, they may be inspected to gain a better understanding of important variables, or interpretated as 'features' or 'indices' (e.g., two satellite reflectance variables are combined to give a single Vegetation Index variable, VI). This is an unsupervised learning process, since there is no response variable to estimate.

3.5.3 Analysis of dynamic data

Dynamic data are data collected over time. Analysis of dynamic data is important for measuring progress of SDG targets. The number of time periods might be small or large, depending on the analytic aim. Examples of these aims are:

- Comparison of before-after outcomes, for example comparing water quality or forest cover as a result of an extreme weather event.
- Estimation and/or comparison of trends over time, for example, monitoring annual land use change over decades or crop growth over a number of seasons.

If the aim is the comparison of before-after outcomes, then it is typical to have a small number of (EO and other relevant) datasets corresponding to a small number of time periods. For these types of data, two common approaches are as follows.

- Analyse the data for each time period separately using the methods described in Section 3.5.2 and compare the results.
- Take the difference in pixel or object values between the EO (image) data for two periods of interest, and analyse the differences using the methods described in Section 3.5.2.
- Include time period as a covariate (input) in the methods described in Section 3.5.2.

If the aim is to estimate or compare trends over time, then it is typical to have a larger time series of datasets. For example, the aim may be to monitor land use changes or urban expansion over a decade, changes in water bodies during and after an extreme weather event, and so on.

There are many approaches to analysing time series data. Fulcher et al (2013) analysed over 9000 time-series analysis algorithms and annotated collections of over 35,000 real-world and model generated time series. They developed a resource which automates selection of useful methods for time-series classification and regression tasks. Examples of the types of questions that can be answered using this resource are shown in the figure below.

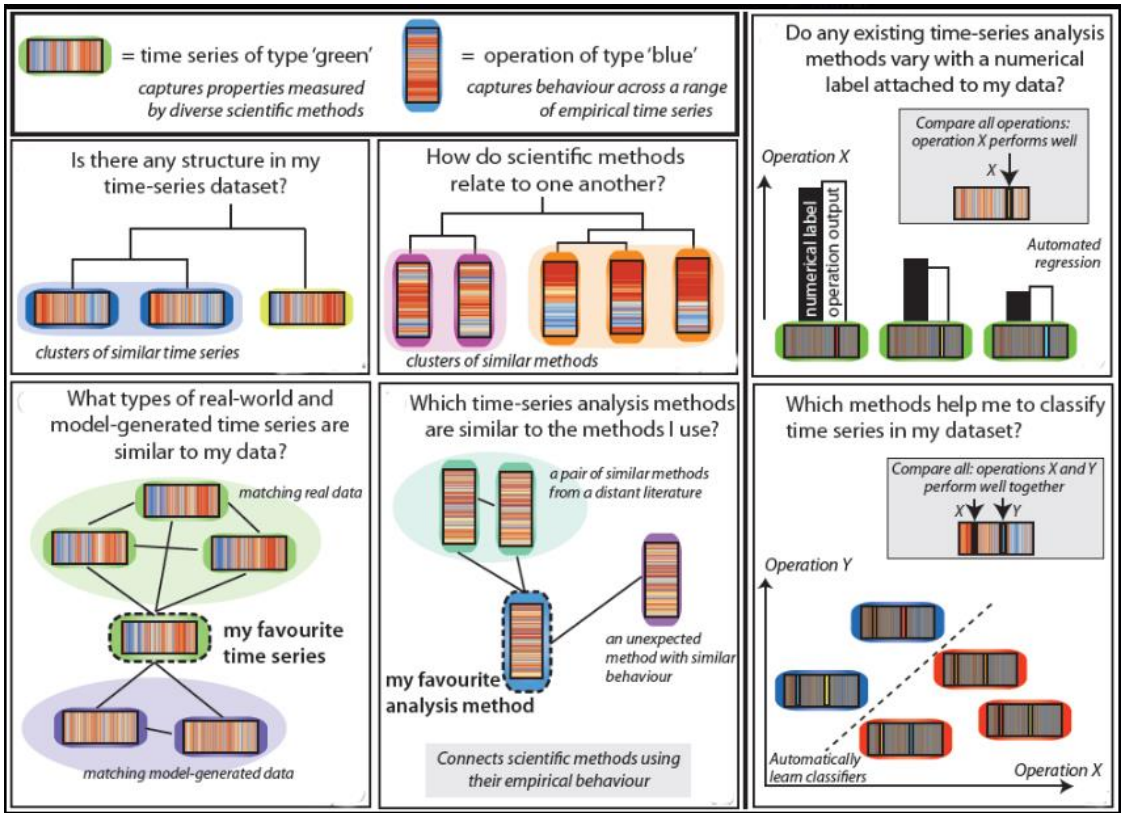


Figure 23: Types of analysis questions answered by Fulcher et al (2013)

Source: Fulcher et al (2013). A compound methodological eye on nature's signals. Retrieved from http://systems-signals.blogspot.com.au/2013/04/a-compound-methodological-eye-on.html

The different methods for analysing dynamic data can also be classified according to whether the aim is classification, clustering, regression or dimension reduction.

Classification In order to classify dynamic series, it is necessary to establish how to compare them. A common approach to comparing curves is through alignment matching. Two methods for alignment matching is instance-based comparison, which involves computing the distance between the series at a set of points along the series, and feature-based comparison, which involves comparing a set of features such as those obtained by principal components analysis.

Other approaches for classifying curves can be categorised as comparative approaches and model based approaches.

- Comparative approaches, e.g. cluster analysis and principal components analysis;
- Model-based approaches, e.g. cubic splines, harmonic analysis and state space models.

These methods and published examples of their application to EO data are described in the appendix.

Clustering As previously described in Section 3.5.2, the overall aim is to combine objects into groups or classes based on a set of input variables. Three main groups of methods for clustering time series data are as follows (Rani and Sikka, 2012):

- Work directly on time series data either in frequency or time domain.

The most common similarity measures used for direct comparison of time series include correlation, distance between data points and information measures. Hierarchical clustering and k-means methods are then applied to these measures.

- Work indirectly with features extracted from time series.
  The most common features extracted from time series data include points identified visually, via transformations of the data, or via dimension reduction. The most common distance measure is the Euclidean distance, although Kullback-Liebler and geometric distances are also used.
- Work with models built from the time series.
  The most common time series models include moving average (MA), autoregressive (AR) and autoregressive moving average (ARMA) models and variants, hidden Markov models (HMM) and fuzzy set methods.

Regression Time series regression aims to predict a future response based on the response history from relevant predictors. Two common methods that are used for this purpose are parametric time series models that capture temporal dynamics are listed above (MA, AR, ARMA and HMM) and nonparametric convolutional neural networks which are an extension of static neural networks, adapted to describe data over time.

Another common aim for time series regression is interpolation of missing data within the spatial and temporal span of the data. For example, cloud cover is a common reason for missing data in EO images. Splines are widely used for both spatial and temporal interpolation.

Dimension reduction A common approach to dimension reduction of temporal data is principal components analysis (PCA). This approach is described in the Appendix. An example of PCA applied to a time series of Enhanced Vegetation Index (EVI) values is described in Potgieter et al (2007). EVI from 16-day MODIS satellite imagery within the cropping period (i.e. April–November) was investigated to estimate crop area for wheat, barley, chickpea, and total winter cropped area for a case study region in North East Australia. The PCA classification method, and others used in the study, were trained on ground truth data collected from the study region. In this study, principal component analysis was used to reduce the EVI time series at each pixel from the 23-image sequence into a smaller set of transformed variables or principal components (PC), which explained 90% or more of the temporal variability in the series. Overall, PCA correctly classified 98% of pixels as wheat, barley, chickpea or non-cropping. This example is discussed further in the Appendix.

3.5.4 Choice of method

The choice of method used for analysis of EO data depends on a number of factors:

- The nature and amount of training data
- The amount of calibration (ground-truthed, in-situ) data
- The type of estimates and inferences required
- The availability of software for modelling and analysis
- The expertise of the team performing the modelling and analysis

The following overall statements can be made:

- Empirical methods are useful if there is sufficient training and calibration data, if a model-based approach is required, and if the assumptions of the models are tenable.

- Semi-empirical methods are useful if the conditions for empirical methods are fulfilled and if there is some expert knowledge about the input variables and system.
- Physics-based methods are useful if there is a deep knowledge about the system under consideration and/or if there is a lack of calibration or training data.
- Machine Learning models are useful if there are data available to train the models and evaluate their fit, but there is an inability or unwillingness to make model-based assumptions or develop physics-based processes.

A review of studies that have compared different statistical and machine learning algorithms for the analysis of static EO data is provided in the Appendix.

For dynamic EO data analysis, the Australian Bureau of Statistics (ABS) has recommended the use of state-space models for the analysis of dynamic EO data. See Tam, S-M. (2015). A Statistical Framework for Analysing Big Data for more information. These are described in the Appendix.

3.6 STEP 3: Evaluation

The considerations to be addressed in the Evaluation step include (1) critical assessment of the results, (2) assessment of the accuracy of the results, and (3) assessment of other potential biases or concerns with the results or their interpretation.

3.6.1 Critical assessment of results

As with any statistical analysis, it is essential to critically review the results with respect to whether they are sensible from both statistical and domain-knowledge perspectives. This is particularly important with estimates derived from big data or multiple data sources. Evaluations can include:

- Inspection of the overall magnitude of the results, and identification of results that are outside expected ranges, etc.;
- Inspection of the precision of the estimates, the size of the prediction intervals and other measures of variability of the results;
- Comparison of the results with other relevant results;
- Evaluation of whether any assumptions in the model or the modelling process have been met.

3.6.2 Accuracy assessment

Accuracy "is a relative measure of the exactness of an estimate and accounts for systematic errors also referred to as bias. Therefore, an accurate estimate does not systematically over or underestimate the true value" (FAO 2016, p. 1).

When considering accuracy assessment, it is important to recognise that sampling effort (accuracy and representativeness of sampled data used for training) as well as the analytical technique(s) utilised play important roles. These issues have been described above.

Good practice involves reporting details of these processes, as well as details of the model fit, the accuracy of the estimates or predictions obtained from the model, and quantification of uncertainty of these estimates and predictions (Olofsson et al., 2014). These issues are now discussed in more detail.

Model assessment

Regardless of the type of model (empirical, semi-empirical, physics-based, machine learning), the goodness of fit of the model is typically assessed by comparing the estimated or predicted values obtained from the model with the observed values, if available.

Statistical models are typically subjected to further goodness of fit evaluations using criteria such as AIC, BIC, likelihood ratios for nested models, and traditional hypothesis tests (if available and applicable). Where possible, estimates obtained from the model are typically compared with the observed data, using measures such as misclassification rates for categorical responses and mean squared error of prediction for continuous responses.

Depending on the available data, a typical statistical practice is to define complementary training and testing datasets by randomly partitioning the original data (for example, randomly splitting the dataset into a 75% training set and a 25% testing set). A model is then built using the training data, which is then assessed for accuracy in various ways on the test dataset. For example, for classification models, misclassification rates and/or positive predictive value (PPV) could be used to assess how well the training data predict the test data, and hence how well the trained model may be expected to perform on new, unknown samples.

Another commonly used approach is cross-validation techniques. Cross-validation is often used in situations where partitioning the data as described above would significantly hamper the training and/or testing of the model (for example, smaller datasets where partitioning would leave either the test or training data sample size too small). The idea of cross-validation is to repeat the validation procedure described above, using different data subsets each time. The measured fit (for example, the misclassification rate) is then averaged across these repeats to provide a more accurate measure of the predictive capabilities of the model under investigation. Cross-validation techniques can generally be classified into two groups: Exhaustive (all possible splits of the data are undertaken – for example leave-one-out and leave-k-out cross validation) and Non-exhaustive (not every partition of the data is computed – these cross-validation approaches can be considered approximations to the leave-k-out cross-validation technique). Which approach is taken often simply comes down to computational burden.

Accuracy assessment of map data

An example of accuracy assessment practices for EO data analyses is given by the FAO Map Accuracy Assessment and Area Estimation Practical Guide (FAO, 2016, http://www.fao.org/3/a-i5601e.pdf). The following information is extracted from the FAO report, pp. 6, 17.

In an accuracy assessment of map data, the map is compared with higher quality data. The higher quality data, called reference data, is collected through a sample based approach, allowing for a more careful interpretation of specific areas of the map. The reference data is collected in a consistent manner and is harmonised with the map data, in order to compare the two classifications. The comparison results in accuracy measures and adjusted area estimates for each map category. This process is broken down into four major components: (i) a map, (ii) the sampling design (iii) the response design and (iv) the analysis.

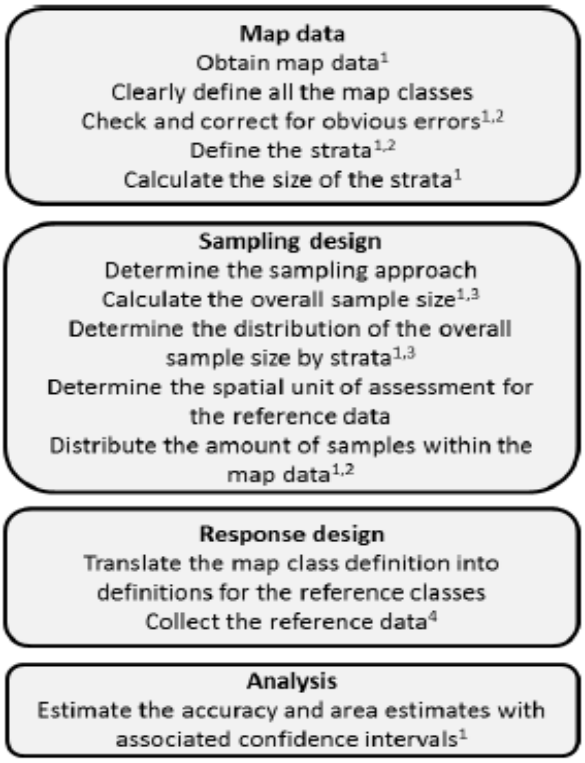


Figure 24: The main four steps of an accuracy assessment: Obtaining and finalising the map data, sampling design, response design and analysis. The symbols show the software that can accomplish that step: [1] is *R*, [2] is *QGIS*, [3] is Excel, and [4] is *Collect Earth*.

In an analysis step, an error matrix is produced. The error matrix is a cross-tabulation of the class labels allocated by map and reference data. It is derived as a q x q matrix with q being the number of classes assessed. The elements show the number of data points which represent a map class i and reference class j (nij). Usually the map classes are represented in rows and the reference classes in columns. The diagonal of the matrix contains the correctly classified data points, whereas the cells off the diagonal show commission and omission errors.

The accuracy measures are derived from the error matrix and reported with their respective confidence intervals. They include overall accuracy, user's accuracy and producer's accuracy. The overall accuracy is the proportion of area classified correctly, and thus refers to the probability that a randomly selected location on the map is classified correctly (see equation 3). User's accuracy is the proportion of the area classified as class i that is also class i in the reference data (see equation 4). It provides users with the probability that a particular area of the map of class i is also that class on the ground. Producer's accuracy is the proportion of area that is reference class j and is also class j in the map (see equation 5). It is the probability that class j on the ground is mapped as the same class.

$$A = \sum_{j=1}^{q} p_{jj} \quad (3)$$

$$U_i = p_{ii}/p_{i\cdot} \quad (4)$$

$$P_j = p_{jj}/p_{\cdot j} \quad (5)$$

For all three accuracy measures, the confidence intervals need to be derived as well. The formula for the variance are presented in equations 5, 6 and 7 in Olofsson et al. (2014), and the 95% confidence interval can be calculated by multiplying the square root of the variance by 1.96.

FAO has applied these accuracy assessment steps to measure forest area and forest area change. These measures are important for countries with reporting requirements to access results based payments for reducing emissions from deforestation and forest degradation.

Interpretation of accuracy estimates

For map accuracy judgement on the validity of the data depends on the purpose of the map and should be assessed on a case by case basis. The following discussion is extracted from the FAO (2016) report, pp. 20, 21.

For example, for land cover change, it is necessary to look at the accuracy of change and not at the accuracy of two single land cover maps. Even if both land cover maps have high accuracy measures for a single point in time, it does not provide any information about the accuracy for change classes. A new change analysis using remote sensing images is necessary rather than comparing maps from different times.

The overall map accuracy is not always representative of the accuracy of individual classes (GFOI, 2013). High overall map accuracy does not guarantee high accuracy for forest loss. Therefore, both producer's and user's accuracy for all single classes need to be considered.

Additionally total sample size, the number of strata and the allocation of the total sample size to the strata can favour one accuracy measure over the other. Accuracy is usually higher for stable classes than for change classes. Furthermore, accuracy is variable in different landscapes. The steps of the accuracy assessment described in the FAO practical guide need to be considered when assessing accuracy value.

Reporting accuracy assessment results

Again, extracting from the FAO (2016) report, p. 23:

When reporting the results of accuracy assessment, the report should not only include the estimates of accuracy assessment, adjusted area and their respective confidence intervals but also the assumptions implied by several elements of the accuracy assessment. The assumptions can influence the level of accuracy, and include, but are not limited to:

1. the minimum mapping unit and the spatial assessment unit
2. the sampling design
3. the forest definition
4. the source of reference data
5. the confidence level used for calculating the confidence intervals (typically 95 %).

The estimates always need to be reported with their respective confidence intervals. Additionally, it is recommended to present the error matrix in terms of estimated area proportions instead of absolute sample.

For details of the practical application of accuracy assessment, see the Global Forest Change (GFC) example in the FAO Map Accuracy Assessment and Area Estimation Practical Guide 2016.

3.6.3 Other concerns

Other concerns about the results of EO data analyses can include:

- bias in the data used to generate the model estimates.
- assumptions underlying the adopted model.
- influence of the choice of method of estimation of the quantities of interest.
- potential misinterpretation of the results.
- bias of area estimates directly computed from classified images.

The first two points have been addressed earlier in this chapter, and the last point has been discussed above. The concern about the choice of estimation method is important since it raises the question of the margin for subjectivity of the results. Given the wide range of image classifiers and analytic methods, there is a concern that they can be 'tuned' to get the 'right' results, for example a desired proportion between classes, and hence that an analyst could choose/tune the algorithm to obtain the figure that better corresponds to their a priori belief.

Another concern is the accuracy of the bias correction depends on the sample size of the field data used. A consequence of this is the value added of remote sensing is generally proportional to the effort put on the field survey, with the exception of some classes for which identification in the image is particularly reliable.

These issues can be resolved in large part by following good practice guides – see, for example, the GEOSS guide by Gallego *et al.* (2008) – and by promoting transparent reporting, open data,open models and results and replication of results by independent groups.

3.7 Summary

This chapter has described a range of methodologies for analysing EO data. Following a discussion about the type of estimates that can be obtained from EO data, the focus turned to the three broad steps of pre-processing the data, techniques for analysing the data, and the critical evaluation of the analysis results.

A range of references has been provided to indicate the relevance of the methods described and their practical application to EO data. The areas of application range across agricultural and environmental statistics to other fields such water quality detection and urban growth. The relevance of these estimates for the 2030 Sustainable Development Goals is a focus of the chapter, as described in Section 3.2.

References have also been provided for the technical details of the methods described here. Further details are provided in the Appendix for selected methods.

In addition to providing references, the chapter has also highlighted a case study for each of the three broad steps. These include details of a practical approach for pre-processing the data (developed and used by DSITI, Australia, for over a decade), a state space model for analysing time series of remotely sensed images (recommended by the Australian Bureau of Statistics) and good practice guidelines for accuracy assessment based on FAO (2016), and GEOSS (2008). More detailed case studies that employ the methods described in this chapter are presented in Chapter 4.

4. Pilot Projects and Case Studies

A number of pilot projects were formulated under the umbrella of the Task Team, covering a range of applications. These projects are aligned with the mission and strategies of the Task Team; to contribute to the improvement of official statistics through the use of satellite imagery data, as well as supporting the monitoring of SDGs.

Pilot projects can be considered examples of how the Task Team is working on its four specific activities:

- Identify reliable and accurate statistical methods for estimating quantities of interest;
- Suggest approaches for collecting representative training and validation data of sufficient quality;
- Research, develop and implement assessment methods for the proposed models including measures of accuracy and goodness of fit;
- Establish strategies to reuse and adapt algorithms across topics and to build implementations for large volumes of data.

Naturally, progress achieved to date is not homogeneous. Pilot projects show different levels of development. Three of the more mature projects are showcased in this chapter:

Pilot Project 1: Application of satellite imagery data in the production of agricultural statistics, undertaken by the Australian Bureau of Statistics (ABS).

Pilot Project 2: Study on Skybox Commodity Inventory Assessment, led by UNSD and undertaken by Google.

Pilot Study 3: Study on the use of satellite images to calculate statistics on land cover and land use, undertaken by DANE, Colombia.

Each report describes the processing techniques, data sources, selection criteria, and quality issues associated with data, as well as the analyses and results obtained at the time of this report.

In addition to the pilot projects, five case studies are included in this chapter to complement the Task Team Pilot Projects. The case studies are as follows:

Case Study 1: an evaluation of the implementation of various machine learning techniques for analysis of EO data for crop classification, undertaken by the Department of Science Information Technology and Innovation (DSITI) Australia and Queensland University of Technology (QUT) Australia.

Case Studies 2 and 3: two published implementations of EO data analyses for estimation of crop yield.

Case Studies 4 and 5: two fully operational methods developed for the analysis of EO data to derive official statistics. These have been developed by the National Statistics Office in Canada and the DSITI in Australia, respectively.

4.1 PILOT PROJECT 1: Application of satellite imagery data in the production of agricultural statistics (Australia)

The Australian Bureau of Statistics Pilot Study for the application of satellite imagery data in the production of agricultural statistics outlines the outcomes for the study to be: "(…) to assess the feasibility of statistical methodology for classifying satellite surface reflectance data to crop type and estimating crop production". This project was based on an empirical approach. The full paper is available on request through the Australian Bureau of Statistics (Marley et al 2014).

Data specifications

ABS acquired Landsat 7 imagery data from Geoscience Australia (GA) since this was the active Landsat satellite collecting data during the period for which they had ground truth data. Since the pilot was conducted, it would be recommended to use Landsat 8 or Sentinel 2 data as sources. The Landsat imagery data in the Australian Geoscience Data Cube (AGDC) is stored in one-degree latitude and longitude tiles. Each tile is approximately 100km x 100km, with each pixel representing a 25m x 25m area of land. Each pixel has six reflectance measurements associated with it, corresponding to six distinct bandwidths on the electromagnetic spectrum, namely red, green, blue, near infra-red (NIR), short-wave infra-red (SWIR) 1 and SWIR 2. Landsat 7 revisits the same area of land, on average every 16 days, meaning that most pixels have a set of six reflectance measurements every 16 days.

ABS acquired satellite imagery data from the AGDC for the 2010-12 calendar years. The Landsat data was used for crop classification. The extent of missing data in Landsat 7 imagery is a key quality issue, which is described in 4.1.4. For future projects this issue could be overcome by using Landsat 8 or Sentinel 2 data. Since there is a significant amount of missing data, a possible line of future research is to investigate possible methods for adjusting or imputing for the missing data. A possible solution is the use Model Data Assimilation approaches described in Chapter 2.

Several MODIS data products are available at the Commonwealth Scientific and Industrial Research Organisation (CSIRO) and those that were of particular interest to the pilot study are listed in Table 6. Data from the MOD13Q1.005 product was used to investigate the feasibility of crop detection, which is measuring the presence or absence of crops, regardless of crop type. Product MOD13Q1.005 contains the Enhanced Vegetation Index (EVI) layer and the two main quality layers of interest; namely, the pixel reliability layer and Vegetation Index (VI) quality layer.

The EVI is an example of the semi-empirical algorithm type referred to in Chapters 2 and 3, as the spectral bands used are known for having a relationship with chlorophyll and thus a measure of photosynthesis in plants, as well as the nearby infrared reflectance peak caused by healthy leaves.

Product	Description
MOD09A1.005	500m pixels 8 day composites[20] Band 1 to band 7 plus quality layers
MOD09GA.005	500m pixels Daily

[20] Products described as being 8 or 16 day composites indicates that the data provided for each image pixel are the best quality measurements from an 8 or 16 day period. In these cases, an additional variable is included, specifying the exact day of the year that the data was measured.

	Band 1 to band 7 plus quality layers
MOD09Q1.005	250m pixels 8 day composites Band 1 and band 2 (red and NIR)
MOD11A1.005	1000m pixels Daily Land surface temperature/emissivity
MOD11A2.005	1000m pixels 8 day composites Land surface temperature/emissivity
MOD13Q1.005	250m pixels 16 day composites Vegetation indices (EVI, NDVI) plus quality layers

Table 6: MODIS data products used in the ABS pilot study

Data processing

This investigative pilot study develops various processing techniques to prepare data for use in accurately classifying satellite imagery as different crop classes and producing quality crop area statistics. The technical tasks were preparation and exploration of training data for crop type classification and preparation of training data for crop detection.

Training data is the data used to build classification models; it is the product of integrating satellite imagery data and ground truth data and matches satellite land surface reflectance measurements to land cover or land use classes.

Starting with the ground truth dataset from the Queensland Department of Science, Information Technology and Innovation (DSITI) the technical tasks, the preparation of training data for crop type classification consisted of two parts. Firstly, determine the field boundaries and secondly, the estimation of field-level sowing and harvest dates.

Field boundaries were determined around the observed latitude and longitude points, to capture within field variation. Manual inspection of satellite imagery data and drawing of boundaries using geo-spatial software was the most accurate and time-efficient means for determining field boundaries for this small scale feasibility study.

For each pixel within the manually derived field boundaries, the Landsat 7 reflectance measurements were extracted for all the time points available from 2010 to 2012 using an internally developed R code. From this integrated dataset, the next task was to determine the sowing and harvest dates that define the growing season for each field.

The estimation of field-level sowing and harvest dates was as follows;

- Calculate the median pixel-level EVI value for each field, at each observed time point;
- Fit a smoothing spline to the irregular time series of field-level median EVI values; then the dates associated with the nearest local minima either side of the date when the ground truth data was observed were labelled as the sowing (left side) and harvesting (right side) dates.

A number of business rules were incorporated for fields for which the ground truth data had insufficient satellite imagery data (due to missing data, poor quality data and cloud cover) to support confident

estimation of sowing and harvest dates. Out of 962 ground truth sites, this automated method determined the sowing and harvesting dates for 414 sites. These 414 fields only included those with a seasonal reflectance pattern that showed distinct peaks and troughs. For future studies, the variance of the fitted spline could be calculated.

To create the final training dataset, these estimated sowing and harvest dates were used to strip down the intermediate, integrated dataset to only those pixel reflectance measurements that corresponded to the growing season of the crop that was observed. A second training dataset was also created, which contained the smoothed median EVI values at regular intervals over the estimated growing season of each observed field.

Exploratory data analysis was undertaken on the training data to identify suitable covariates that would enhance the predictive power of a crop classification model, using repeated measures ANOVA on EVI and other measurements. Repeated measures ANOVA at the pixel level, with random effects for crop class and field, was conducted to test the variation of reflectance measurements and the EVI between crop classes (namely, maize, sorghum, barley and wheat). In the absence of random field effects, an ANOVA analysis showed that mean reflectance measurements were significantly different between crop types. However, when random field effects were included, these differences dissipated. While there was significant variation within and between fields, the variation between crops was not statistically significant.

The strength of relationships between soil and landscape characteristics available in CSIRO's Soil and Landscape Grid (SLG) data and EVI values were explored via various visualisation techniques including density plots, box plots and scatter plots. The visualisations demonstrated there is not enough evidence to indicate the SLG variables have significant relationships with the satellite reflectance measurements. Random forests were also considered for variable selection. As a result of this brief investigation, only a small number of significant relationships were found. For example, wheat crops require deeper soils with higher levels of clay. However, the results showed the inclusion of the soil and landscape variables actually increased prediction error; hence this was not considered further.

A number of phenological characteristics were derived from the field-level smoothed EVI curves, to use in crop classification models, including length of a crop growth cycle in days, number of days taken to reach maximum EVI since sowing, areas under the curve in different growth phases and within field EVI distributional measures such as range, maximum, minimum, kurtosis, skewness and variance. A major limitation of crop growth curve characteristics for statistical modelling is a potential high degree of multi-collinearity between variables. Multi-collinearity can be overcome by dimension reduction techniques, such as principal component analysis (PCA). An alternative methodology, functional data analysis, was also trialled which created functional forms from the entire (smoothed) EVI series for the growing season. This approach avoided problems in model variable selection of suitable phenological characteristics and the issue of multi-collinearity.

Next training data was prepared for crop detection. It started with building a crop detection model, which served to create a crop mask. To create a crop mask, ground truth data containing sites that have been and have not been used for cropping is required. The north-west region of Victoria was chosen as the pilot region for this exercise, for which ground truth data was available from the Australian Ground Cover Reference Sites Database (AGCRDS) and the ABS 2010-11 Agricultural Census.

The ground truth dataset included 18 unique sites in the AGCRSD within the north-west region of Victoria, and nine sites from the 2010-11 Agricultural Census respondents in the study area. Additional

sites that were used for non-cropping land use (such as bodies of water, national parks, forests, etc.) were required to give balanced ground truth data, and these were selected manually by eye using Google maps. The bounding latitudes and longitudes of the selected sites were recorded in the ground truth dataset, along with the crop status and the season; only the year that the ground truth data was collected, in which the ground truth observation occurred.

Data selection

To satisfy the project purposes, different data sources were included; satellite imagery (mainly MODIS and Landsat); ground truth data (agricultural census, reference sites and roadside observation data collected by DSITI). In future work, these datasets may be complemented with additional data sources such as Sentinel-2, VIIRS, Sentinel-3, Synthetic aperture radar data from Sentinel-1, SLG data, and meteorological and climate data.

Nevertheless, there is a key issue concerning the availability and suitable quality of EO data sources; freely and commercially available data have restrictions related to missing values, periodicity and quality. Two ways to overcome these issues were considered. The first was validation and standardisation. This involved comparing data from the same source at different times, and/or comparing between several sources. The AGDC Landsat data for Australia has been pre-processed and calibrated to the same standard across time. CSIRO's MODIS data has been similarly standardised, however other satellite imagery sources would need to be standardised before usage in crop detection and classification analysis. The second issue was capacity. Even freely available data and tools require qualified personnel (e.g. data scientists) to properly extract the wealth of information contained in them. This process may nevertheless be quite resource intensive and needs to be planned for in any Big Data undertaking.

4.1.4 Quality issues

Missing data was a key quality issue for this pilot project. There are two main sources of the missing data:

1. Landsat 7 images are plagued with stripes of missing data, caused by a malfunction of the scan line corrector on board the satellite since May 2003. The stripes are regularly spaced following the edge of Landsat's scan and should not be correlated with the type of agriculture grown in the pixels affected; hence it should not lead to statistical bias except in terms of reducing the effective sample size. This is not a problem for other satellites, in particular Landsat 8 which is now in use and retrieving data and Sentinel-2 which is now collecting more frequent data at 10 m resolution.
2. GA supplied a quality layer with the satellite imagery data, treating any pixels labelled as poor quality as unusable. The main causes of poor quality are cloud cover or cloud shadow. This approach prevents poor quality pixels affecting results.

There is also significant variation in satellite reflectance patterns between different fields growing the same crop type. Obtaining additional predictor variables that explain these variations from one area to another might help improve the classification model's prediction accuracy, however this has proved to be a significant hurdle to obtaining more statistically accurate results. This problem is associated with the empirical approach, but potentially could be overcome by using biophysical approaches which were not in scope of this pilot project.

4.2 PILOT PROJECT 2: Skybox Commodity Inventory Assessment- now part of Planet (UNSD and Google)

The Google pilot project explored the estimation of crude oil inventory using analytics derived from satellite imagery as a means to promote economic transparency.

The pilot specifically focused on quantifying volumes of base commodities, namely crude oil, using satellite imagery. The trade of this commodity, though vital to the global system and central to the economies of numerous emerging countries, is often inaccessible or inaccurate.

By measuring the shadows on floating lid crude oil tanks, Skybox attempted to assess the volume of inventory present in a given tank. This was done using fairly straightforward trigonometry, taking into account the target's latitude & longitude, the time of day, and the satellite's collection angle.

To assess the accuracy of the core methodology, Google conducted analysis of the Cushing, Oklahoma, USA oil storage site. This is the largest oil storage facility in the world, and the EIA conveniently publishes weekly data on oil inventory stored there. By analysing the difference between Google estimates and official reporting, one should be able to assess the accuracy of approach.

Data specifications

Panchromatic	**450 – 900nm**
Blue	450 – 515 nm
Green	515 – 595 nm
Red	605 – 695 nm
NIR	740 – 900 nm
Panchromatic GSD	90 cm at nadir
Multispectral GSD	2 m at nadir
Swath Width	8 km at nadir
File Format	16 – bit Geo TIFF

Table 7: Imagery specifications

Colour	**Panchromatic**
Duration	Up to 90 seconds
Frame Rate	30 frames per second
GSD	1.1 m at nadir
FOV	2 km by 1,1 km
File Format	MPEG – 4 (H 264 encoding)

Table 8: Video specifications

Data processing

Normal issues such as cloud cover were presented and solved by a combination of human and automated processing. Further details about data processing techniques were not included due to commercial sensitivities related to the project.

Data selection

Data were adequate to fit the purpose of the project. In this case, a single source has been used; SkyBox (now Planet) imagery sub-meter accuracy.

The data used by Google focused on monitoring specific targets with high economic importance; the major refineries, metropolitan areas, mines and maritime ports, among others.

Quality issues

Google used images from Skybox. Regarding the crude inventory assessment, Skybox leveraged a proprietary combination of fully-automated and human-refined processes. The error in the measurements is being researched on an ongoing basis, but potential sources include relatively high solar angle during summer months, image processing methodology, signal to noise ratio, facility and infrastructure idiosyncrasies, and satellite collection angle.

In some cases there were gaps in collection due to cloud cover. However, with a full constellation of 24 satellites, Skybox will be able to observe any location on earth between five and seven times per day. This could help significantly to overcome missing data issues.

4.3 PILOT PROJECT 3: Use of satellite images to calculate statistics on land cover and land use (Colombia)

DANE conducted a pilot project with the aim to propose a method to calculate SDG indicator 68 "Ratio of land consumption rate and population growth rate", and seeks to obtain an estimation of land use efficiency, through monitoring the relationship between land consumption and population growth (SDSN, 2016):

"(…) this indicator benchmarks and monitors the relationship between land consumption and population growth. It informs and enables decision-makers to track and manage urban growth at multiple scales and enhances their ability to promote land use efficiency. In sum, it ensures that the SDGs address the wider dimensions of space and land adequately and provides the frame for the implementation of several other goals, notably health, food security, energy and climate change".

The objectives of the project were;

- To assess the feasibility of applying remote sensing methods for the estimation of land consumption rate, and Geographic Information Systems (GIS) based spatial analysis for the calculation of the relationship between land consumption and population growth in metropolitan areas;
- To evaluate the methodology by its application to the Barranquilla metropolitan area, through satellite images and population data for the years 2005, 2010 and 2015.

Data Specifications

To calculate the indicator, the time interval of five years was chosen. This criterion was considered appropriate to see the evolution in the population and to have adequate imagery coverage. The years included in the analysis are 2005, 2010 and 2015.

The criteria to choose the images were:

- Availability
- Cloud coverage under 10% of the study area
- Same month for each year to minimise the changes generated by rainy or drought seasons, phases of crops and others
- Full coverage of the metropolitan area to avoid image mosaics
- Similar spectral bands.

Free Landsat images were used, and were downloaded from the United States Geological Survey (USGS) Earth Explorer website (http://earthexplorer.usgs.gov/). The study area is covered by the Landsat path-row 9-52. Table 10 shows mission, date and file name for each image used in the pilot project.

Path-Row	Mission	Capture date	File
9-52	Landsat 7	January 7 2005	LE70090522005007ASN00
9-52	Landsat 7	February 8 2005	LE70090522005039EDC00
9-52	Landsat 5	January 29 2010	LT50090522010029CHM01
9-52	Landsat 8	January 11 2015	LC80090522015027LGN00

Table 10: Landsat images included in the pilot project

For 2005, two scenes were collected. This was necessary to perform an enhancement on the image. The process is described in the processing section.

Data processing

Processing techniques involved two steps; imagery pre-processing and change detection (image segmentation and classification). Imagery pre-processing included procedures to prepare the images for the classification process; filling the gaps (for the year 2005 image), radiometric resolution scaling (for the year 2015 image), cartographic projection, subset image creation and layer stacking. To fill the gaps, the USGS Gap-Fill Algorithm was used to improve 2005 images Landsat 7 ETM+ due to lack of Scanning Line Corrector (SLC). A radiometric resolution scaling was carried out for the 2015 Landsat 8 image.

Subsets of the images were generated covering a buffer of 500 meters around the metropolitan area of Barranquilla. This distance is a compromise between the coverage of the surrounding areas and the spatial limitation of the 2010 Landsat 5 image, which is smaller than those from the other missions. The transition from Landsat 5 to Landsat 7 and then to Landsat 8 included the addition of new bands (layer stacking) and some previously defined were sub-divided. Even so, most of them are comparable.

The second process carried out was change detection. It was used for post-classification comparison. In this method, each date of rectified imagery is independently classified to fit a common land type schema (equal number and type of land-cover classes). The resulting land cover maps are then overlaid and compared on a pixel-by-pixel basis. The result is a map of land-cover change. This per-pixel comparison can also be summarised in a 'from-to' change matrix, also called a transition matrix. The 'from-to' change matrix shows every possible land cover change under the original classification schema.

Image classification is the process used to produce thematic maps from imagery. Since one of the objectives in the pilot project was to identify urban settlements and given their spectral response is very similar to that from barren or minimal vegetation, the OBIA method was used in order to include additional features to the spectral ones and to improve the thematic accuracy. To perform the process, the open-source INTERIMAGE was used (no license payment). The image to be classified, and the semantic network (hierarchical entities that will be identified in the image) were entered to INTERIMAGE as input. Then, the methods and operators that allow the generation of objects and their classification were defined.

Figure 25 describes the components of the interpretation process on INTERIMAGE. The system implements a specific interpretation control strategy, guided by a structured knowledge model through a semantic net (hierarchical entities that will be identified in the image). The interpretation control is executed by the system core, which uses as input a set of geo-referenced images, SIG layers, digital elevation data or other geo-registered data. Through the interpretation of the scene, input data are processed with the help of top-down and bottom-up operators.

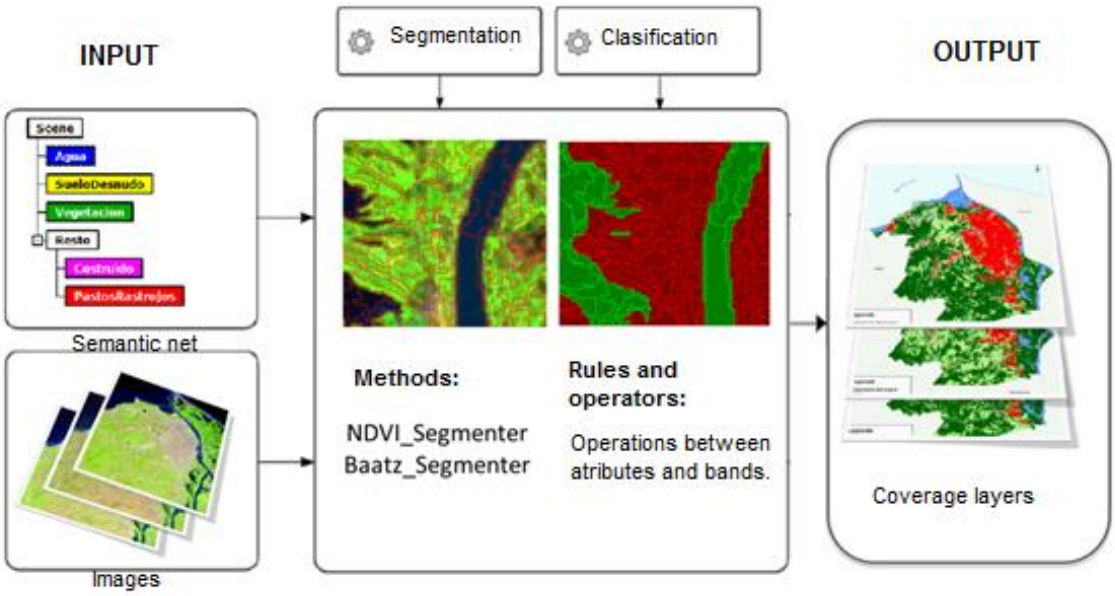


Figure 25: INTERIMAGE flow chart for object-based classification.

Top-down operators are responsible for the partition of the scene into regions, considered as object (segmentation). This process creates objects by grouping similar pixels. It starts with each pixel forming one image object, which is sequentially merged to form bigger ones. The Normalised Difference Vegetation Index (NDVI) numerical indicator and TA Baatz Segmenter algorithms were used to obtain the image segmentation.

After defining the segmentation algorithms, decision rules were introduced for each node of the semantic network. These rules allow filtering, from the set of objects, those that belong to the class of interest. In a decision rule, it is possible calculate a variety of attributes based on spectral values, shape, texture and topological characteristics of image segments. These attributes can be used to select objects within a set, with a user-defined threshold. Objects that are not within a threshold are evaluated in a different class according to the order defined in the semantic network. If an object meets the criteria for more than one class, it is assigned to that with the higher reliability.

Top-down operators are responsible for the partition of the scene into regions, considered as object hypotheses (segmentation). This is a preliminary classification which identifies segments with the potential to belong to each class. The bottom-up operators refine the classifications produced in the top-down step (confirming or rejecting) and solving possible spatial conflicts between them. At the end of the interpretation process, the hypotheses become validated object instances (classification).

The image to be classified, and the semantic network (hierarchical entities that will be identified in the image) are entered to INTERIMAGE as input. Then, the methods and operators that allow the generation of objects and their classification are defined.

The project's semantic net was created based on the previous knowledge of the study area and taking into account the Landsat imagery land cover classification from the project GeoCover[21].

[21] http://www.mdafederal.com/geocover

Finally, the Normalised Difference Vegetation Index (NDVI) numerical indicator and TA Baatz Segmenter algorithms were used to obtain the image segmentation

Data selection

Despite some quality issues, the Landsat data was fit for the purposes of the project because it was freely available and there are several tools to solve quality issues. For future projects using EO data sources such as Landsat 8 and Sentintel-2 could overcome quality issues associated with Landsat 7 data.

The second source of data was population data. Considering that 2005 was the last year a census was carried out in Colombia, population projections were used. This could affect the quality of the results, but is the most common available option to have population information during inter-census periods. This data source was adequate to meet the project´s goals.

Criteria to select data were related to free availability and opportunity. In this sense, they were appropriate. A possible search of additional sources can be done in future exercises with MODIS, Sentinel-2 Landsat 8, Sentinel-3 VIIRS imagery, for instance, and emerging processing tools like Google Earth Engine.

Quality issues

After using the USGS Gap-Fill Algorithm, the improved Landsat 7 images showed enough quality for the study purposes. A confusion matrix was calculated using Google Earth images and orthophotos for reference. This matrix, as mentioned previously in Chapter 3, allows assessment of the classification quality.

4.4 CASE STUDY 1: Application of machine learning techniques to satellite imagery data in the production of agricultural statistics (Australia)

As an extension of the ABS pilot project for the task team, researchers at the Queensland University of Technology (QUT) in Australia applied a range of machine learning techniques to the problem of crop classification, using the same data that were acquired for Pilot Project 1. The aim was to evaluate the ease of application of the methods and compare the resultant estimates.

The machine learning methods included neural networks, boosted regression trees and regularised multinomial regression. These methods are described in the Appendix. Two types of regularisation were used as forms of variable selection, with Ridge regularisation shrinking the coefficients of ineffective variables substantially, and Lasso regularisation shrinking them to zero and hence effectively excluding them from the analysis.

Data specifications

This case study used the Landsat data from the ABS pilot project. Data specifications are described in Section 4.1.1.

The response variable was crop type. The ground truth dataset comprised seventeen (17) crop types: bare soil, barley, barley, cotton, leucaena, lucerne, maize, millet, mungbean, oats, improved pasture, natural pasture, peanut, sorghum, forage sorghum, sunflower, wheat and woody vegetation.

The six spectral bands from the Landsat data, as well as the month and year of the observation, were used to predict the crop type. As no time series method was incorporated here the data set was reduced to only those months known to have ground truth values (March 2011, September 2011 and February 2012). A ground referenced dataset of land cover categories for 1186 sites was available to construct and evaluate the models.

Data processing

Ground referenced observations of land cover typically were for areas spanned by multiple pixels of Landsat 7 imagery. Thus the 1186 ground referenced observations of land cover categories expanded to 247 210 pixels of satellite imagery. These ground referenced pixels are referred to as observations.

The proportion of pixels corresponding to each crop type in the ground referenced dataset varied widely. Dominant crop types were cotton (28%), sorghum (22%), natural pasture (13%) and wheat (11%). Nine (9) crop types had less than 1% of the total number of ground referenced pixels.

An 80/20 training/validation split was used for all analyses (i.e., a random sample of 80% of the ground referenced observations was used to construct the model and the predictive capability of the model was then assessed using the remaining 20% of the data). The number of repetitions (runs) with different training/validation samples varied for the different machine learning methods, and was generally small because the large volume of data meant that runs were computationally prohibitive and that the variance in results between runs was minimal.

Various vegetation indices (VIs) were calculated as functions of the Landsat imagery data. As described earlier in this chapter, VIs are designed to highlight the contrasts between bands that may be indicative of vegetation characteristics. The functions that define VIs can be more complex than the products and polynomial terms typically used for covariates in regression analyses. There is a range of software to calculate VIs from reflectance data; see, for example, the R packages ‘hsdar’ Meyer and Lehnert (2016) and ‘RStoolbox’ Leutner and Horning (2016). However, given the apparent internal inconsistencies in the ‘hsdar’ package and the requirement of the ‘RStoolbox’ package of reflectance data in raster format,

selected vegetation indices were calculated by hand using the formulae in the RStoolbox package and constants provided by Ahmadian et al. (2016) and She et al. (2015).

Implementation of Methods

All analyses were undertaken using the R statistical software. The parameters of the neural network and boosted regression trees were tuned by hand to provide optimal results. The neural network was fitted using the H2O package with the 'rectifier' activation function and hidden layer layout of 200 nodes in layer 1, 100 nodes in layer 2 and 15 nodes in layer 3. The boosted regression tree was fitted using the 'gbm' package. Both ridge and LASSO regularised multinomial logit regression models were fitted using the R package 'glmnet' with 100-fold cross validation. Since cross validation on data with extremely rare categories is problematic, the regression models were restricted crops with at least 10,000 observations (bare soil, cotton, maize, natural pasture, peanut, sorghum and wheat).

For the regression methods, since there was considerable collinearity among the original imagery bands and vegetation indices, the design matrix was filtered to enforce a maximum correlation coefficient magnitude between remaining covariates of 0.85. The retained variables were Landsat bands 1, 3, 4 and 5, the Normalised Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index, Modified Normalised Difference Water Index (MDWI) and Simple Ratio Vegetation Index (SR). All covariates were re-centred and re-scaled (to column means of zero and column Ll norms of one). Linear, pairwise interactions and polynomial terms up to polynomial order four were included in the regression models.

Two different approaches were used to assess the results, namely a confusion matrix and a Receiver Operating Characteristic (ROC) curve. In the confusion matrix, the predicted crop classes are compared with the actual classes. The ROC shows the correct classification rate of a binary classifier as the discrimination threshold is varied.

Results

The neural network configuration resulted in an overall misclassification rate of approximately 26% averaged over 10 iterations. The variance for these iterations was less than 8.3e-06. However, the misclassification rates for specific classes were far worse. There was a fairly clear correlation between the accuracy for a given class the overall proportion of that class in the sample. One potential method to address this would be to use a more even sample distribution by class which is non representative of the true ratios. Alternatively, a small proportion of classes could be dropped or combined into a single 'other' class.

The boosted regression tree approach revealed the domination of one variable, band 5 of the Landsat imagery, in discriminating between the crop types. The relative influence of this band compared with the other five bands is shown below. Band 5 (1.55 - 1.75u m) is sensitive to the turgidity or the amount of water in plants. In other environmental studies band 5 has separated forest lands, croplands, and water bodies. Forests have appeared as a comparatively darker tone than croplands (light grey) and grass lands (lighter tone). No improvement was gained by including the derived vegetation indices. It is likely that any complex relationship captured by a pre-processed VI could be similarly represented by the original variables in the boosted regression tree analysis and therefore adds little value.

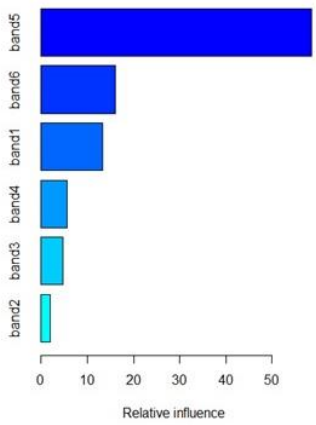


Figure 26: Relative influence of Landsat imagery bands, obtained from the boosted regression tree analysis.

The Lasso regularised multinomial logistic regression models were able to correctly categorise 78% of the Landsat pixels. The nonlinear and interaction terms contributed less than half a percent to overall classification accuracy, but they improved the classification of particular crop types. For example, under the Lasso models the inclusion of these terms provided much better classification of maize.

The Ridge models achieved an overall correct classification rate of 68.5% using only linear effects. In contrast to the Lasso models, the Ridge models assigned no pixels to maize and very few to wheat, and were also substantially less accurate in classifying peanut and natural pasture. The addition of nonlinear and interaction terms increased the overall correct classification to 75%, with substantial improvement in classification of wheat, maize and peanut. In contrast to the Lasso models which by construction eliminates uninformative variables, all covariate terms are retained in the Ridge models.

Discussion

This study achieved its aim to implement a range of machine learning methods for analysis of EO data. For all methods, there were challenges in managing large datasets and correctly classifying a large number of crop types, some of which are very small. While the methods are readily available in software such as R, these challenges meant that considerable time and effort was required to implement and tune the methods. Nonetheless, the study confirmed the conclusions of other published papers, that these methods hold great promise for automatic crop type identification.

Some improvements to the implementation of the methods were noted. First, in the current analysis the cross validation folds were constructed by random subsetting of the full data set using the default method supplied in the 'glmnet' package. A better strategy would be to use a set of folds constructed to ensure that each fold contains approximately the same proportion of observations of the different response categories as are present in the complete data. Second, the challenge of identifying rare responses could be better addressed by artificially inflating the number of observations in these categories using bootstrapping or subsampling techniques, or by enforcing different degrees of coefficient shrinkage for the various response categories. Third, additional model diagnostics could assist in better understanding the misclassification rates for different crop categories and hence reducing them. Fourth, additional covariates could be considered, such as MODIS derived variables and tasselled cap indices. Fifth and last, other regularisation methods for the regression models, such as elastic net, could be evaluated, taking into account the different computational burdens.

4.5 CASE STUDY 2: Crop yield prediction (USA)

This study, reported by Gao et al (2017), aimed to derive crop growth stage and predict yield from remotely sensed data, to contribute to more efficient management of irrigation, improved food security and efficient commodity trading.

The EO data were intended to supplement ground based observation on crop progress and condition currently published by USDA NASS. Under this system, reporters provide visual observations and subjective estimates of crop progress, which are published weekly in the NASS Crop Progress reports.

Gao et al extend the application of data fusion down to sub-field scales for phenology mapping over agricultural landscapes. The main objective was to test the ability of this Landsat-MODIS data fusion methodology to map crop phenology at 30-m resolution, where crop growth stages for different crops can be distinguished. Maps of crop progress were produced across an intensively cropped area in central Iowa.

Data specifications

The study area was in central Iowa, in a rain-fed agricultural area in the U.S. Corn Belt region. Corn and soybean are the major crop types.

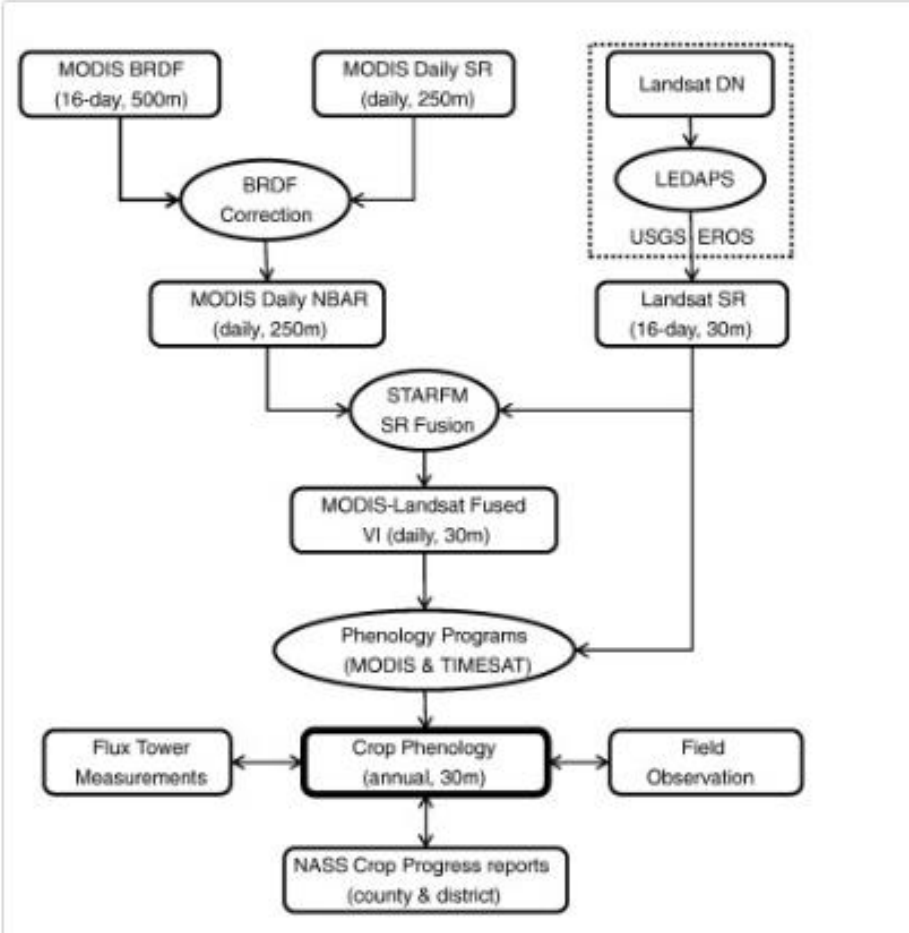
Nine years of Landsat and MODIS data from 2001 to 2014 were chosen to generate the fused Landsat-MODIS reflectance time-series for crop phenology mapping.

Other data sources included in the study are briefly summarised here:

- *The cropland data layer (CDL).* NASS CDL 30-m resolution data from 2001 to 2014 were downloaded and used to analyse the crop phenology patterns for major crop types over the study area.
- *Flux tower data*. In-situ meteorological and surface flux measurements were collected over a pair of adjacent agricultural fields north of Ames (near Buckeye), IA in Hardin County.
- *Field biophysical data.* Field observations of crop progress were conducted during growing seasons from 2010 to 2013, sampling two observation sites in Dallas County, Iowa located within the study area.

Data processing

The analyses conducted in this study include two core components: data fusion and phenology extraction. The entire processing flow chart is shown below. For further details see Gao et al (2017).



Crop phenology data processing and analysis flow chart. Rectangles indicate data products and ellipses represent processing steps/modules

Source: Gao et al (2017). Toward mapping crop progress at field scales through fusion of Landsat and MODIS imagery. Retrieved from: http://www.sciencedirect.com/science/article/pii/S0034425716304369

Data selection

Only mostly clear Landsat scenes were used as fine resolution images to pair with MODIS data as input to STARFM. Partially clear Landsat images were not used in the data fusion process. Landsat 7 images that suffer SLC failure after May 2003 were not used as input pair images since SLC-off gaps will remain in the fused images and affect the subsequent phenology mapping. However, all valid and clear pixels (as identified in the cloud mask) from all available Landsat images, including partially clear and Landsat 7 SLC-off images, were used in the phenology mapping itself.

Method

The STARFM approach was used to produce multi-year daily 30-m surface reflectance and NDVI time-series which captured spatial and seasonal variability between the corn, soybean and forested vegetation classes that characterise this region. The STARFM data fusion approach has been described in detail in Gao et al. (2006).

Two approaches (MODIS and TIMESAT) were applied to extract crop phenology from the daily time-series NDVI. The TIMESAT approach relies on a pre-defined threshold (percent change of the seasonal amplitude between minimum and maximum NDVI values) to determine the start of the season, the end of the season, and the length of the season. The MODIS phenology approach uses curvature analyses to identify inflection points in the fitting curve. A double logistic function was selected to fit time-series NDVI for both approaches.

Crop phenology metrics retrieved from the fused Landsat-MODIS data were compared to crop growth stages reported at district and county levels from the NASS CP reports. Observations at the field scale were examined using the corresponding Landsat pixels.

The figure below shows the fitted NDVI curves from 2011 for corn and soybean pixels at the two South Fork flux tower sites, overlaid with the crop growth stages from NASS county-level CP reports. Also shown are daily NEE and GPP estimates derived from eddy covariance measurements during the growing season in 2011. The general correspondence in the time behaviour of the NDVI and crop carbon uptake curves demonstrates that the NDVI time-series appears to be behaving reasonably in these two fields in relationship with the NASS CP stages.

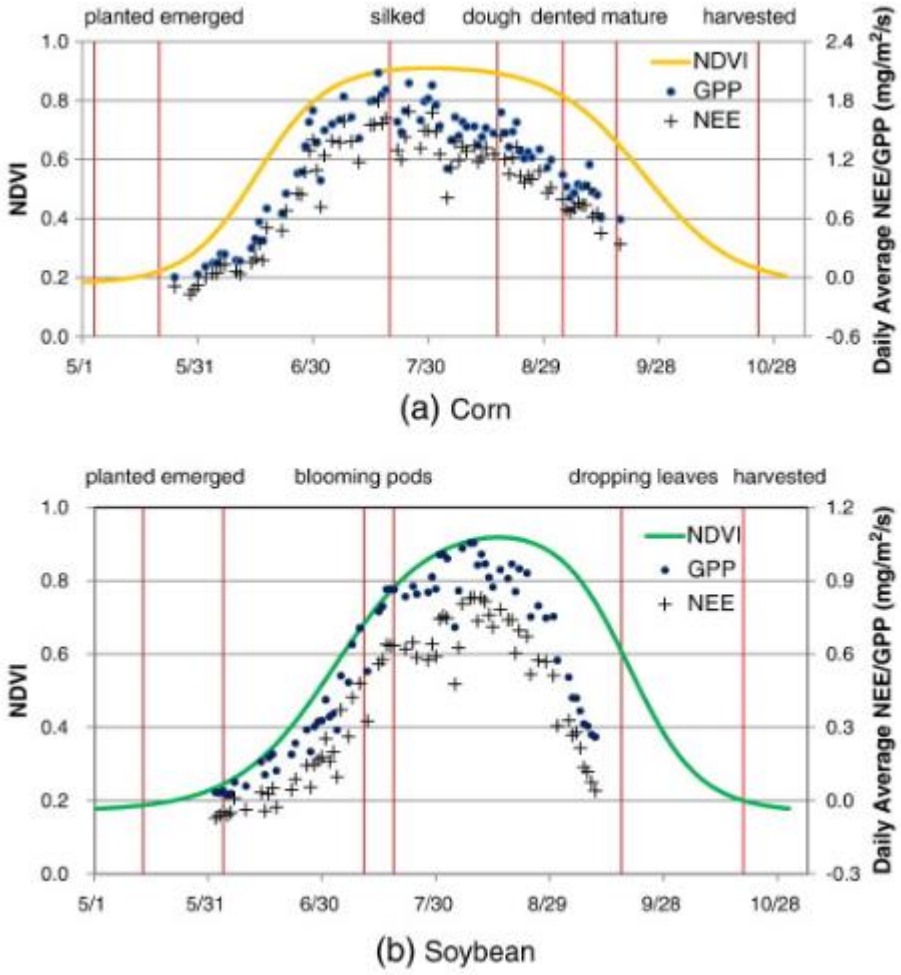


Figure 27: NDVI curves for corn (a) and soybean (b) pixels compared to daily NEE and GPP (secondary axis, only measured during vegetative growing season) and crop growth stages from NASS county-level reports in 2011 (red vertical lines). Clear correspondences can be identified among time-series NDVI, NEE and GPP during crop vegetative stages at the Landsat pixel resolution.

Source: Gao et al (2017). Toward mapping crop progress at field scales through fusion of Landsat and MODIS imagery. Retrieved from: http://www.sciencedirect.com/science/article/pii/S0034425716304369

Quality issues

Application of these methods in real-time is another area that requires additional research. Operationally, crop growth stages and conditions need to be reported weekly throughout the current growing season. The phenology programs used in this paper were not designed to map within-season crop phenology using partial years of data. However, the growth-shape model approach of Sakamoto et al., 2010 and Sakamoto et al., 2011 may be adaptable for real-time field-scale applications using fused Landsat-MODIS time series.

Results

The STARFM approach was used to produce multi-year daily 30-m surface reflectance and NDVI time-series which captured spatial and seasonal variability between the corn, soybean and forested vegetation classes that characterise this region. Biases between fused and observed Normalized Difference Vegetation Index (NDVI) were between − 0.011 to 0.028 and mean absolute differences were < 0.083 for all years from 2001 to 2014. These biases are due in part to sensor, waveband, and view angle differences between Landsat and MODIS acquisitions, and it was demonstrated that it is important to characterise these biases to fully understand performance of the fusion output.

Using time-series of 30-m resolution NDVI maps derived from Landsat-MODIS data fusion, crop phenological metrics were extracted using two established phenology programs (MODIS and TIMESAT). While both approaches generated comparable metrics, the MODIS curvature approach was deemed most practical for operational applications because it does not necessitate specification of pre-defined thresholds, as required by the TIMESAT approach.

The results of the study suggest there is utility for robustly backcasting emergence from remote sensing, e.g. as input to crop simulation models. This study demonstrated that time-series data from multiple remote sensing sources can be effectively integrated and used to detect major crop physiological stages at the field scale. At 30-m resolution, the phenology for corn and soybean crops can be clearly separated and quantified for field sizes typical in the United States. This capability has applications in farmland management and yield prediction. However, routine mapping of crop growth stages within the season is still challenging due to the fact that only a partial year of data is available for near real-time mapping. Real-time applications will require an appropriate phenology approach and frequent clear-sky remote sensing imagery. Satellite image data fusion can play a significant role in achieving this goal.

4.6 CASE STUDY 3: Monitoring crop development (South Korea)

The aim of this study was to investigate the applicability of high-temporal-resolution Geostationary Ocean Colour Imagery (GOCI) satellite data for monitoring the development of paddy rice in South Korea. The monitoring measures included spectral analyses and vegetation index profiles. GOCI launched successfully on 27 June 2010. It is designed to detect, monitor, and predict regional ocean phenomena around Korea and is equipped with eight spectral bands (six visible, two near infrared).

Data specifications

In this study, two paddy rice areas were selected; one was located in Kyehwa and corresponds to a GOCI pixel with coordinates of 35°46′37N and 126°41′03E (Figure 1b). The other was in Kimjae and corresponds to a GOCI pixel with coordinates of 35°44′59N and 126°52′15E (Figure 1c).

The study site at Kimjae represents the double cropping of barley and early maturing rice cultivars, and the site in Kyehwa represents the most popular paddy rice agriculture with an intermediate-late-maturing rice cultivar. As these study sites are relatively homogeneous, despite the small paddy units, the temporal dynamics of different crops should be recognisable in the daily satellite image data analysis.

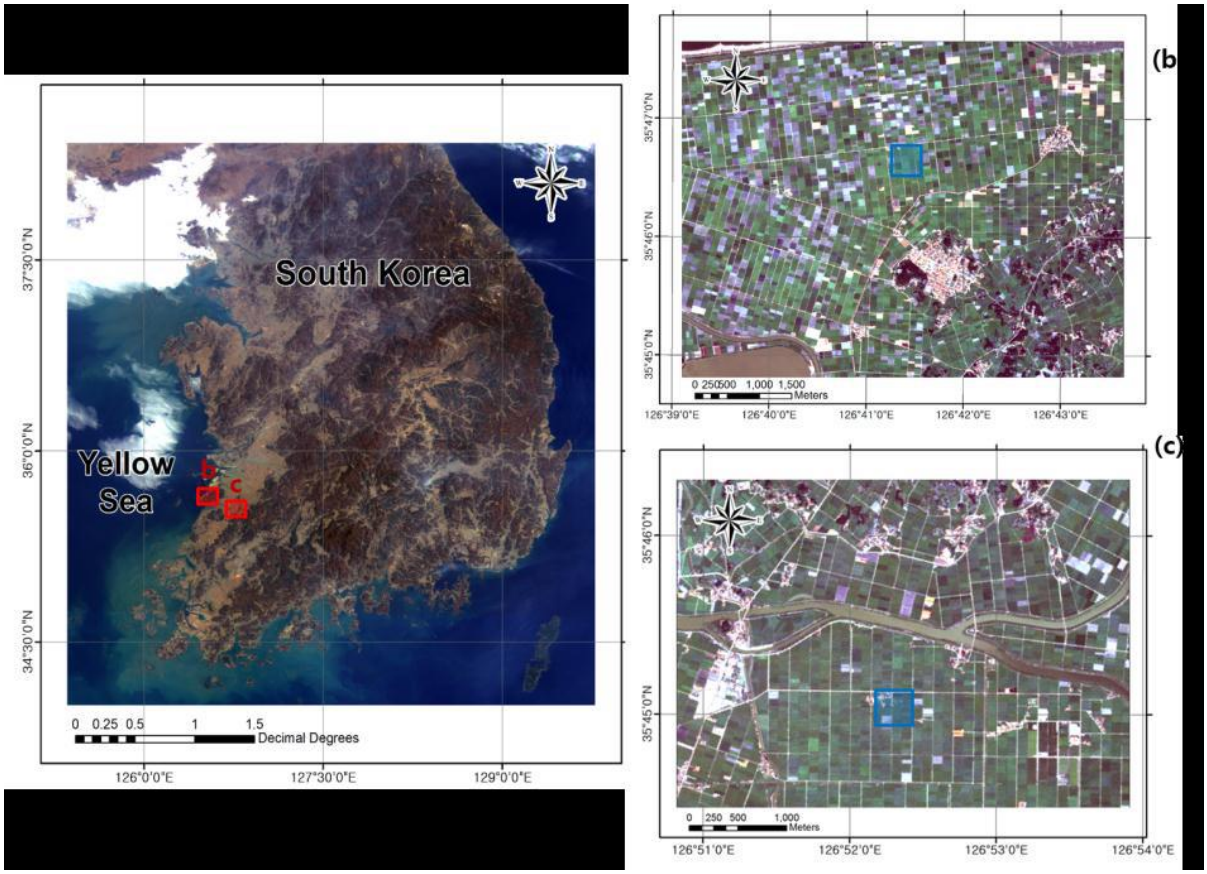


Figure 28: Study area. (a) Red Green Blue (RGB) colour composite image from the Geostationary Ocean Colour Imager (GOCI) acquired on 1 April 2011. The red rectangles, (b) and (c), in (a) are shown in (b), and (c), respectively, giving detailed views using high-resolution RapidEye multispectral data obtained on 5 August 2011 (b), and 11 October 2011 (c). The blue rectangles in (b), and (c) are geometrically matched with corresponding satellite observation pixels.

Source: Yeom, J-M., and Kim, H-O. (2015) Comparison of NDVIs from GOCI and MODIS Data towards Improved Assessment of Crop Temporal Dynamics in the Case of Paddy Rice. Remote sensing (7), 11326 – 11343.

Ground measurements were performed using the multispectral radiometer (MSR) to evaluate satellite-based vegetation profiles for comparative analysis. Field measurements were carried out from June to October 2014. To obtain the crop development characteristics of the paddy rice, measurements were made on eight dates based on the cultivation schedule, including transplantation and harvest.

Data processing
For the GOCI satellite image, further pre-processing, including conversion of digital numbers (DN) to radiance, cloud masking, and atmospheric correction, was performed to calculate surface reflectance. See Yeom and Kim (2015) for further details.

Data selection
The study compared two sets of optical earth observation satellite data with the same spatial resolution of 500 m; one was from a geostationary (GOCI) and the other from a sun-synchronous satellite (MODIS). The fifth and eighth GOCI bands were used for calculating the normalised difference vegetation index (NDVI). For comparison, MODIS NDVI products were applied as a reference. This study analysed the data for the years 2011 to 2014.

Quality issues
For the comparison of the NDVI calculated using moderate-resolution satellite data with the field measurements, it is necessary to consider the mixed-pixel problem. Because the paddy units in South Korea are relatively very small, it is very difficult to observe a non-mixed spectral value for rice paddies on the moderate spatial resolution GOCI data.

Method
A vegetation index was calculated from GOCI data based on the bidirectional reflectance distribution function (BRDF)-adjusted reflectance, which was then used to visually analyse the seasonal crop dynamics. These vegetation indices were then compared with those calculated using the Moderate-resolution Imaging Spectroradiometer (MODIS)-normalised difference vegetation index (NDVI) based on Nadir BRDF-adjusted reflectance.

Results

The results show clear advantages of GOCI, which provided four times better temporal resolution than the combined MODIS sensors, interpreting subtle characteristics of the vegetation development. In general, GOCI and MODIS displayed similar temporal variation in NDVI under benign weather conditions, because they can secure enough cloud-free observations for full inversion BRDF modelling. During the monsoon season, however, with its long periods of rain and many cloudy days, GOCI was found to be more useful for extracting cloudless or less cloudy areas by arraying its eight images to calculate representative daily data.

The study also found the GOCI BAR NDVI was more useful for crop signal monitoring than the widely used MVC NDVI. The authors concluded the very high temporal resolution of GOCI is very beneficial for monitoring crop development, and has potential for providing improved information on phenology.

4.7. CASE STUDY 4: An Operational Framework for Large-Area Mapping of Past and Present Cropping Activity Using Seasonal Landsat Images and Time Series Metrics (Australia)

In Queensland, Australia, the Department of Science, Information Technology and Innovation (DSITI) have been using satellite imagery for statistical analysis for many years. Although DSITI is not formally part of the Task Team, their study is included in this chapter as a case study for NSOs.

Managing land resources to support the needs of the population is a mandate common to all levels of government in Australia, and this study by DSITI uses satellite imagery data to identify actively growing crops in Queensland, Australia.

For the major broadacre cropping regions of Queensland, Australia, the complete Landsat Time Series (LTS) archive from 1987 to 2015 was used in a multi-temporal mapping approach, where spatial, spectral and temporal information were combined in crop-modelling process, supported by training data sampled across space and time for the classes Crop and No-Crop.

Temporal information within summer and winter growing seasons were summarised for each year, and combined with various vegetation indices and band ratios computed from a pixel-based mid- season synthetic spectral image. All available temporal information was spatially aggregated to the scale of image segments in the mid-season synthetic image for each growing season and used to train a number of different predictive models for a Crop and No-Crop classification.

The results suggest that, with appropriate training and validation data, the approach developed and applied in this study is suitable for large-area mapping of cropping activity using the Landsat archive. This approach would be transferable to other satellite imagery with sufficient spatial, spectral and temporal resolution to generate the explanatory variables used in this study.

Data specifications

The study area was the Western Cropping Zone (WCZ) in the State of Queensland, Australia (see Figure 29).

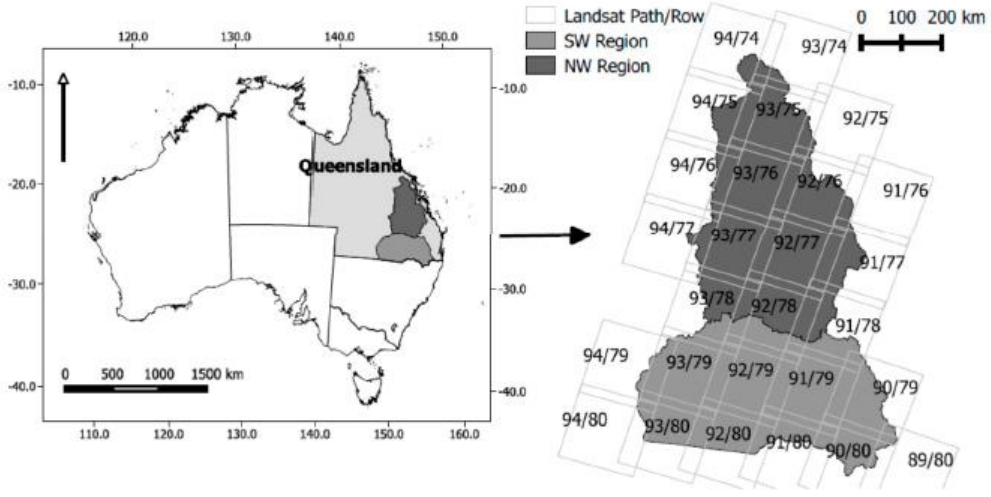


Figure 29: Regional subdivision of the WCZ of Queensland into north and south regions: "NW" and "SW". Superimposed is the Landsat data coverage based on the World Reference System 2 (WRS2).

Source: Schmidt, M., Pringle, M., Rakhesh, D., Denham, R. and D. Tindall. 2016. A Framework for Large-Area Mapping of Past and Present Cropping Activity Using Seasonal Landsat Images and Time Series Metrics (http://www.mdpi.com/2072-4292/8/4/312).

All available Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 OLI data across 27 footprints with cloud cover of less than 60% were used. This criterion was chosen to reduce the potential for noise in the data due to imperfect cloud/cloud shadow masking and water vapour variations.

All images were cloud-masked with a regionally adapted version of Fmask[22] then NBAR-corrected[23]; this latter step converts the units of the imagery to bottom-of-atmosphere reflectance, scaled to the interval (0, 1). The high internal geometric consistency of the USGS-based Landsat imagery allows further data processing and analysis without further geometric adjustment.

Data processing

All archived images were used to generate a synthetic spectral image for each season and year. These images were generated per pixel and per spectral band, excluding the thermal band, based on a statistical model. Figure 30 provides an example contrived to demonstrate, for a single pixel, how synthetic reflectance values for a Landsat band were generated for the midpoint of a growing season, t0, within a particular year. Outliers were Winsorised, then the 4 nearest neighbours to t_0 were used in a linear regression to predict reflectance at t_0. For further details see Schmidt et al (2016).

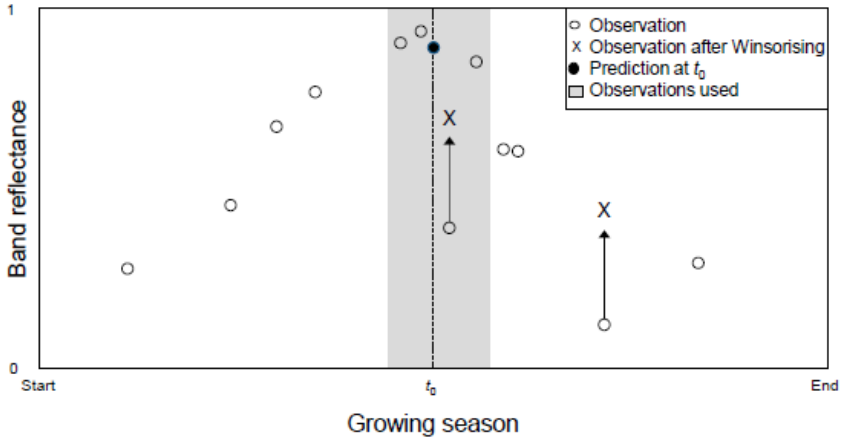


Figure 30: Example of synthetic reflectance value generation process

Source: Schmidt, M., Pringle, M., Rakhesh, D., Denham, R. and D. Tindall. 2016. A Framework for Large-Area Mapping of Past and Present Cropping Activity Using Seasonal Landsat Images and Time Series Metrics (http://www.mdpi.com/2072-4292/8/4/312).

The most recent Queensland Land Use Mapping Program (QLUMP) mapping was used to mask areas from each synthetic image that were associated with land uses that were not of interest for this study, such as conservation areas, forestry and intensive uses. Water bodies and travelling stock routes were also masked for each synthetic image.

[22] Flood, N. Continuity of Reflectance Data between Landsat-7 ETM+ and Landsat-8 OLI, for Both Top-of-Atmosphere and Surface Reflectance: A Study in the Australian Landscape. Remote Sens. 2014, 6, 7952–7970.

Frantz, D.; Roder, A.; Udelhoven, T.; Schmidt, M. Enhancing the Detectability of Clouds and Their Shadows in Multitemporal Dryland Landsat Imagery: Extending Fmask. IEEE Geosci. Remote Sens. Lett. 2015, 12, 1242–1246.

Zhu, Z.; Woodcock, C.E. Object-based cloud and cloud shadow detection in Landsat imagery. Remote Sens. Environ. 2012, 118, 83–94.

[23] Flood, N. Continuity of Reflectance Data between Landsat-7 ETM+ and Landsat-8 OLI, for Both Top-of-Atmosphere and Surface Reflectance: A Study in the Australian Landscape. Remote Sens. 2014, 6, 7952–7970.

To reflect the fact that land is managed in discrete parcels the synthetic images were segmented into homogeneous areas using the open-source software package RSGISLib with Python bindings.
The segmented image was stored in the GDAL-supported KEA image format where the image segments are linked with a raster attribute table (RAT) and used as the basis of all further analysis. This step is a method of data reduction by moving away from a pixel-based analysis to spatial medians per segment for all classification variables. A final step used a 1-s digital elevation model to mask out segments with a slope of greater than 10% as cropping is generally not undertaken in steep terrain within the study region.

A subset of the mid-season synthetic image for winter 2014 is in Figure 31.

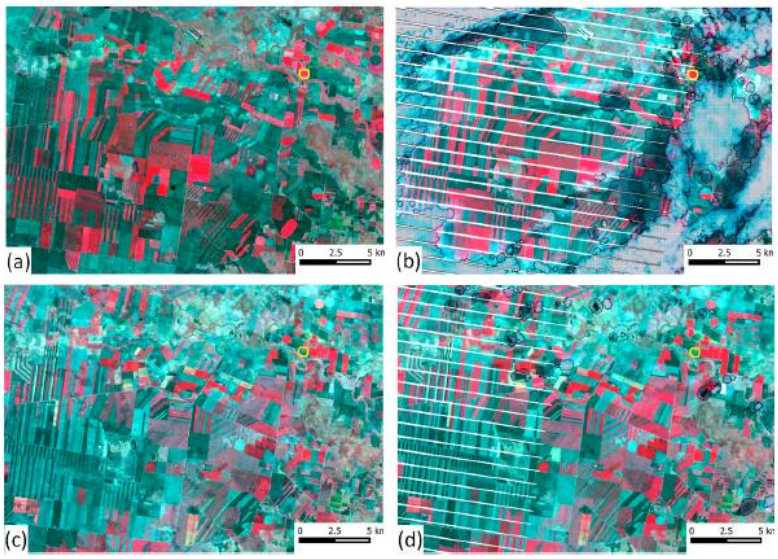


Figure 31: Subset of the mid-season synthetic image (R/G/B with Landsat TM bands 4/3/2) for winter 2014 (a) scene 90/79 and the closest Landsat image (ETM+) (b) to the mid-season interval for winter on 20 September 2014. Panel (c) displays the summer 2014 mid-season synthetic image; and (d) the closest Landsat image on 8 February (ETM+). Fmask cloud and cloud shadow masks are shown as black hatching, the yellow circle in (a) marks a centre pivot irrigation field.

Source: Schmidt, M., Pringle, M., Rakhesh, D., Denham, R. and D. Tindall. 2016. A Framework for Large-Area Mapping of Past and Present Cropping Activity Using Seasonal Landsat Images and Time Series Metrics (http://www.mdpi.com/2072-4292/8/4/312).

Classification variables

A range of variables were calculated in order to capture reflectance signatures and temporal characteristics, which were used to classify the image segments (Table 11).

Table 11: Remote sensing variables, computed on a per-pixel basis, that were spatially aggregated and added to the raster attribute table of the segmented synthetic images.

	Vegetation Indices, Temporal Variables and Band Ratios
1	Normalised Difference Vegetation Index (NDVI)
2	Modified Chlorophyll Absorption in Reflectance Index (MCARI)
3	Renormalised Difference Vegetation Index (RDVI)
4	Triangular Vegetation Index (TVI)

5	Modified Simple Ratio (MSR)
6	Normalised Difference Burn Ratio (NDBR)
7	NDVI seasonal variance (ndviTsVr)
8	NDVI seasonal minimum (ndviTsMn)
9	NDVI seasonal maximum (ndviTsMx)
10	NDVI seasonal coefficient of variation (ndviTsCV)
11	NDVI seasonal range (ndviTsRng)
12	NDVI gradient up (first minimum to maximum) (ndviTsGr1)
13	NDVI gradient down (maximum to second minimum) (ndviTsGr2)
14	NDVI day of time series maximum (ndviTsDyMx)
15	b7 _ b3/(b7 + b3) (nr73)
16	b7 _ b2/(b7 + b2) (nr72)
17	b5 _ b7/(b5 + b7) (nr57)
18	b4 _ b5/(b4 + b5) (nr45)
19	b5 _ b3/(b5 + b3) (nr53)
20	b5 _ b2/(b5 + b2) (nr52)
21	b4 _ b2/(b4 + b2) (nr42)
22	b2/b3 (r23)
23	b4/b3 (r43)

Source: Schmidt, M., Pringle, M., Rakhesh, D., Denham, R. and D. Tindall. 2016. A Framework for Large-Area Mapping of Past and Present Cropping Activity Using Seasonal Landsat Images and Time Series Metrics (http://www.mdpi.com/2072-4292/8/4/312).

Field-based training data, collected between September 1999 and February 2012, were used in the study. All records were recoded as either Crop or No-Crop. An additional set of records were generated through desktop interpretation of seasonal synthetic images sampled at random over space, growing season and years.

Four classification algorithms were applied to the same training data; SVM, multinomial logistic regression, decision-tree classifier and RF, all implemented with the R software. Validation revealed that the predictive accuracy varied by growing season and region and a random forest classifier performed best, with $_K$ = 0.88 to 0.91 for the summer growing season and $_K$ = 0.91 to 0.97 for the winter growing season, and are thus suitable for mapping current and historic cropping activity.

Data selection

All available Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 OLI data since 1987 across 27 footprints with cloud cover of less than 60% were used. For the majority of seasons there are 10 or more Landsat images with less than 60% cloud cover. This threshold was applied to reduce the risk of image artefacts from imperfect cloud and cloud-shadow masking, thin undetected clouds and water vapour variations which can influence an individual pixel's reflectance values. High levels of cloud cover also impacted the geometric accuracy of Landsat 5 data. The data were fit for purpose for the study.

Quality issues

A relatively minor issue is the image segments for the cropped field may not always be sharp on the field boundaries so some discrepancies with the true field outlines are apparent. Also, the comparison of the mid-season synthetic image is effective if the crops are greening-up during the particular time, but if the crop is planted late it might not appear green in the synthetic image. This could lead to misclassification of segments as no crop in some cases.

Recently, the authors have used a similar framework and expanded the mapping approach to broad crop types (Pingle et al, 2018). This approach includes all available Landsat imagery dating back to 1987 until current, and incorporates additionally Sentinel-2 imagery (from 2015 onwards). In case of large temporal gaps where also MODIS imagery used as a backup option. In this updated approach a temporal adaptive seasonal image composite at the time of the maximum EVI was used as input for GEOBIA, followed by a tree based image classification algorithm of phenological metrcis. The crop types of (i) Cereal crop (wheat, barley, oats), and (ii) Pulse crop (chickpea) for winter, as well as (i) Coarse-grain & Pulse (sorghum, maize, mungbean, soybean), and (ii) Cotton crop for summer were compared with values of official statistics (Figure 32).

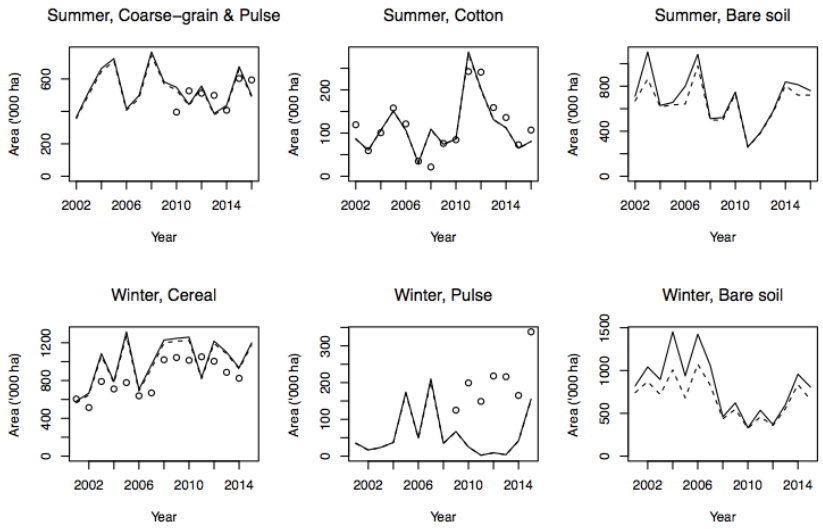


Figure 32: The area devoted to the different groups in each growing season, as predicted by the DSITI model (lines). When available, independent Queensland-wide values are presented (points). The solid line is the total for the entire study region; the broken line is the total associated soley with a land-use cropping.

Source: Pringle, M., Schmidt, M. and Tindall, D. (2018): Multi season, multi sensor time series modelling based on geostatistical concepts - to predict broad groups of crops. Submitted to Remote Sensing of Environment.

For the summer cropping season appears to be an excellent correspondence between state-wide averages of the crop type maps and official commodities data (ABARES, 2016). The over-prediction of of the class 'Cereal' seem to be a similar to the under-predction of the class 'Pulse'. The authors have found little difference between the crop-related summations for their study region.

4.8 CASE STUDY 5: An Operational Approach to Integrated Crop Yield Modelling Using Remote Sensing, Agroclimatic Data and Survey Data (Canada)

Statistics Canada is an NSO which has used remote sensing data since the early 1980s for applications such as census and survey validation, crop mapping and area estimation and support program development. In 2016 they became the first NSO to replace a statistical survey with a remote sensing model-based approach. The goal of the model was to produce a preliminary estimate of the expected harvest yield of the crops in late summer using information from existing data sources.

Although Statistics Canada did not produce a pilot project as part of the Task Team, their case study is included as an example of an NSO using EO data to produce official statistics in practice.

Statistics Canada investigated the use of remote sensing, agroclimatic and survey data to model reliable crop yield estimates as a preliminary estimate to the November Farm Survey estimates, an occasion of the Crop Reporting Series at Statistics Canada.

Initially these estimates were made available before the September Farm Survey estimates were released. However, since 2016 the farm survey has not been conducted and only the model based estimates are published. The process prior to 2016 is described in this case study to demonstrate the process Statistics Canada used to achieve replacing survey collected estimates with model based estimates. The work was completed by the Remote Sensing and Geospatial Analysis Section, Agriculture Division, and by the Business Survey Methods Division at Statistics Canada in collaboration with Agriculture and Agri-Food Canada (AAFC).

Data specifications

A methodology for modelling crop yield was developed and tested on the crops that are typically published at the provincial and national levels by the September Farm Survey, as shown in Table 12. The five provinces listed account for approximately 98% of the agricultural land in Canada, across a diverse range of climate zones and soil types. The crops that account for approximately 85% of the revenue for the 19 crops listed are referred to as the seven major crops.

Table 12: Crops typically published in the results of the September Farm Survey, by province

Table summary

Crops typically published in the results of the September Farm Survey. The information is grouped by Crop type (appearing as row headers), Province (appearing as column headers).

Crop type	Province				
	Quebec	Ontario	Manitoba	Saskatchewan	Alberta
7 major crops					
Barley	X	X	X	X	X
Canola	X	X	X	X	X
Corn for grain	X	X	X		
Durum wheat				X	X
Oats	X	X	X	X	X
Soybeans	X	X	X		
Spring wheat	X	X	X	X	X
12 additional crops					
Canary seed				X	
Chickpeas				X	X
Coloured beans		X	X		
Fall rye		X	X	X	X
Field peas			X	X	X
Flaxseed			X	X	X
Lentils				X	
Mixed grains	X	X	X	X	X
Mustard seed				X	X
Sunflower seed			X		
White beans		X	X		
Winter wheat	X	X	X	X	X

Note: Fodder corn is typically published in the September Farm survey. However, it was not modelled due to a lack of July Farm Survey yield estimates.

Source: Statistics Canada (2015). Integrated Crop Yield Modelling Using Remote Sensing, Agroclimatic Data and Survey Data. Retrieved from: http://www23.statcan.gc.ca/imdb-bmdi/document/5225_D1_T9_V1-eng.htm

The modelling methodology used three data sources: 1) the coarse resolution satellite data used as part of Statistics Canada's Crop Condition Assessment Program; 2) Statistics Canada's Crop Reporting Series data, and 3) agroclimatic data for the agricultural regions of Canada.

Data processing

Normalised Difference Vegetation Index (NDVI)

A spectral vegetation index, the NDVI, was used as a surrogate for photosynthetic potential. NDVI is the normalised ratio of the Near-Infrared (NIR) to Red (R) reflectance ($NDVI = (\rho NIR - \rho R)/(\rho NIR + \rho R)$) and varies from −1 to 1, with values close to one indicating high vegetation content and values close to zero indicating no vegetation over bare ground.

The NDVI data were processed on a continuous basis throughout the agricultural growing season (April to October) for the entire land mass of Canada. Statistics Canada has a time series of NDVI data from 1987 to present, which includes years of severe drought and record production. The daily NDVI images were processed into seven-day composites as described by Latifovic et al. (2005) and the methodology was further refined by Statistics Canada to minimise or eliminate NDVI errors introduced by the presence of clouds (Bédard 2010).

Cropland NDVI statistics by census agricultural region (CAR) were computed and stored in a relational database for each weekly NDVI composite. Only NDVI picture elements, or pixels, that geographically coincide with an agriculture land cover database produced by AAFC as part of an annual crop inventory were extracted to generate the mean NDVI value for cropland within each of the CARs. The agriculture land cover file and the associated metadata file produced by AAFC were accessible at www.geobase.ca/geobase/en/data/landcover/index.html.

After the mean NDVI values were computed they were imported as one of the input variable databases to the crop models as three-week moving averages from week 18 to 36 (May to August).

Survey area and yield data

Statistics Canada's Field Crop Reporting Series surveys were another dataset used in the model. These surveys obtain information on grains and other field crops stored on farms (March, July, September and December Farm Surveys), seeded area (March, June, July, September and November Farm Surveys), harvested area, expected yield and production of field crops (July, September and November Farm Surveys). These data provide accurate and timely estimates of seeding intentions, seeded and harvested area, production, yield and farm stocks of the principal field crops in Canada at the provincial level.

For abundant crops, CAR level crop yield estimates from the July and November Farm Surveys from 1987 to present were used as input variables for the models while yield estimates from the September Farm Survey and the November Farm Survey were used to verify the accuracy of the yield model results. For less abundant crops, the survey data were compiled at the provincial level.

Agroclimatic indexes

The climate data collected during the growing season were the third data source used for modelling crop yields. The station-based daily temperature and precipitation data provided by Environment

Canada and other partner institutions were used to generate the climate-based predictors (Chipanshi et. al. 2015).

Average values of the indexes at all stations within the cropland extent of a specific CAR were used to represent the mean agroclimate of that CAR. If a CAR lacked input climate data, stations from neighbouring CARs were used.

To form a manageable array of potential crop yield predictors, AAFC aggregated the daily agroclimatic indexes into monthly sums and means for the months of May to August. Their standard deviations (Std) over the month were also calculated and included in the modelling methodology (Newlands et al. 2014; Chipanshi et al. 2015). The Std value shows how the daily index varies over the one-month period. The larger the Std, the higher the variability of the parameter in that month.

Data selection

For abundant crops, CAR level crop yield estimates from the July and November Farm Surveys from 1987 to present were used as input variables for the models while yield estimates from the September Farm Survey and the November Farm Survey were used to verify the accuracy of the yield model results. For less abundant crops, the survey data were compiled at the provincial level.

The model was selected by first reviewing the existing models, then by assessing the models available in SAS. Modelling was done at the smallest geographic level for which historical survey data were available. Only the five main crop-producing provinces (Quebec, Ontario, Manitoba, Saskatchewan and Alberta) were modelled.

After comparing results with other models, including a step-wise non robust model and a least-angle robust model, Statistics Canada made the decision to adopt a SAS LASSO robust model. See Statistics Canada (2015)[24] for more details.

Quality issues

The November Farm Survey estimates are considered the most accurate estimate of yield for a given year, due to the fact that the data are collected after the majority of harvesting is completed and the sample size is the largest of all six of the survey occasions. The results of the September Farm Survey can be considered a preliminary estimate of the November results. Therefore, the goal of the modelled yield is not to replicate the results of the September Farm Survey but rather to obtain a sufficiently accurate yield estimate in advance of the November survey results.

The relative difference (presented as a percentage) between the yield estimate of a given method (i.e., September Farm Survey or the yield model) and the November Farm Survey yield estimate was the measure of accuracy. A negative relative difference indicated that the given yield estimate was smaller than the November Farm Survey estimate, while a positive relative difference indicated that the given yield estimate was larger than the November Farm Survey estimate.

$$Relative\ difference = 100 * \frac{Given\ yield\ estimate - November\ Farm\ Survey\ yield\ estimate}{November\ Farm\ Survey\ yield\ estimate}$$

[24] Integrated Crop Yield Modelling Using Remote Sensing, Agroclimatic Data and Survey Data. Retrieved from: http://www23.statcan.gc.ca/imdb-bmdi/document/5225_D1_T9_V1-eng.htm for more details.

Larger relative differences were observed in the model estimates for crops that have a limited amount of historical data available. Estimates derived from models that were constructed with only a limited number of data points were at risk of being statistically unreliable.

Statistics Canada has established three criteria based on the availability of the input data, as well as quality indicators that must be met to ensure the statistical integrity of the estimates and to determine which of the modelled crop yields were of acceptable quality to be published at provincial and national levels. For each year, the yield model estimates for each crop would be evaluated to determine whether their quality is sufficient for publication.

Results

The estimates produced by the SAS LASSO robust model were comparable to those produced by the September survey in terms of relative difference from the November survey estimates for the seven major crops and many of the 12 additional crops published in September. On rare occasions, both the model and the September survey produced extreme relative differences from the November survey estimates, but not necessarily for the same crops/years. These extreme relative differences tended to be larger for the model than for the September survey.

The model produced yield estimates of similar accuracy to the survey based estimates. The modelled estimates were able to be released earlier, resulted in cost savings to Statistics Canada and reduced respondent burden. Since 2016 the farm survey has not been conducted and only the model based estimates are published.

5. Guidelines for NSOs considering the use of EO for official statistics

EO data and big data more broadly represent significant opportunities for complementing and enhancing official statistics. However, there are also challenges in implementing these data sources for statistical purposes. As outlined in this report, it is important for NSOs to identify the algorithmic approach and statistical applications that are most suited to the use of EO data, based on clear organisational benefits, feasibility of methods and likely cost savings. It is also worth considering the range of statistical applications that benefit from EO data is more likely to increase with time as the quality, coverage, frequency and bandwidth resolution of available satellite imagery increases. Given this, it is important for NSOs to critically assess whether using big data generally, and EO data specifically, is appropriate for their statistical purposes.

This chapter provides recommendations to assist NSOs to complete this assessment, however it is not intended to be a one size fits all guide.

5.1 Potential applications of EO data for official statistics

EO data and other big data sources can be applied to improve or replace some NSO processes which produce official statistics. The following applications are suggested by Tam and Clark (2015) by drawing parallels with well-established uses of administrative data for official statistics:

- sample frame or register creation – identifying survey population units and/or providing auxiliary information such as stratification variables;
- partial data substitution for a subgroup of a population – reducing sample size;
- partial data substitution for some required data items – reducing survey instrument length, or enriching the data set without the need for statistical linking;
- imputation of missing data items – substituting for same or similar unit;
- editing – assisting the detection and treatment of anomalies in survey data;
- linking to other data – creating richer data sets and/or longitudinal perspectives;
- data confrontation – ensuring the validity and consistency of survey data; and
- generating new analytical insights – enhancing the measurement and description of economic, social and environmental phenomena. (p. 442).

This is a selection of applications for EO data and other big data sources, and not necessarily an exhaustive list. As NSOs become more experienced in using EO data for official statistics, more applications may emerge.

5.2 Cost-benefit analysis

Conducting a cost-benefit analysis is useful to decide whether to use EO data for statistical applications.

Big data sources, including EO data, should only be used if there is a strong business need, and if it will improve statistical outcomes based on objective cost-benefit criteria.

According to Tam (2015)

Big Data should only be used if it can;

- improve the product offerings of statistical offices e.g. more frequent release of official statistics, more detailed statistics, more statistics for small population groups or areas, or filling an important data gap – business need; or

- improve the cost efficiency in the production of official statistics – business benefit (p.4).

According to Tam and Clarke (2015)

The costs and benefits of using the new data source need to be assessed in terms of factors such as reduction in provider load, sustainability of new source, as well as the accuracy, relevance, consistency, interpretability, and timeliness of those outputs stipulated in Data Quality Frameworks (p.8).

An example of making these assessments is given, using the ABS agricultural pilot project described in Chapter 4.

The full data substitution of survey-based with satellite sensing data for producing agricultural statistics – such as land cover and crop yield – can be assessed as follows:

- **Costs:** What are the likely costs for acquiring, cleaning and preparing the satellite sensing data in a form suitable for further official processing, noting that the computational demands of acquiring, transferring, processing, integrating and analysing large imagery data sets are presently unknown, but are likely to decline over time? What are the costs for the development of a statistical methodology to transform the satellite sensing data into crop yields; and the development of a statistical system to process and dissemination satellite sensing data? What are the costs of obtaining ground reference information (e.g. ABS ground reference data covering ~1k locations? LUCAS survey covering all over Europe ~ 270k locations)? What are the equivalent costs for direct data collections, and how they compare with one another?
- **Reduction in provider load:** How much reduction in provider load would result if direct data collection is replaced by satellite sensing data? How important is it to have this reduction, based on existing provider experience, and prevailing Government policy on reduction of regulatory "red tape"? What is the current degree of cooperation from the farmers and how likely is this degree change for the better, or worse, in the future? What are the data otherwise obtained e.g. by farmers obtained electronically such as yield?
- **Sustainability of the statistical outputs:** Is the data source available to official statisticians for the regular production of official statistics? What is the likelihood that the data source will continue into the future and maintain the current level of quality?
- **Accuracy, relevance, consistency, interpretability, and timeliness:** How does the new source of data compare with the current source, against the criteria outlined in Data Quality Frameworks (referred to in Chapter 2)? Whilst optical satellite sensing provides accurate measurements of "reflectance" – measures of the amount of light reflected from earth back to the satellite sensors - there are several other issues.
- **Availability of knowledge for processing of EO data as well as data scientists?**

Are these issues/accuracies bigger, or smaller, than those due to missing data from direct data collections? In addition, transforming reflectance into crop production statistics require scientific or statistical modelling, an endeavour not commonly adopted by NSOs and may raise interpretability issues. On the other hand, the statistical accuracy of prediction estimates made from these models can be quantified as well as data quality issues in producing these estimates.

As satellite sensing data are available on average at any given interval (from 15 minutes over daily to monthly), they clearly have a distinct advantage over annual or sub-annual direct data collections in terms of the frequency in the availability of crop yield statistics (Tam and Clarke, 2015, p.8).

This section has described the questions ABS posed and answered to produce its pilot project using EO data for crop identification, and is an example of how other NSOs can approach the decision of whether to implement EO data into their statistical outputs.

5.3 Validity of statistical inference

If it is determined using EO data will meet a business need or create efficiency, it should also be considered whether using EO data will be statistically valid. According to Tam and Clarke (2015) "the proposition that bigger datasets are somehow closer to the "truth" is a not accepted by statisticians, since the objective "truth" is very much dependent on how representative a particular Big Data source is of the underlying population and the nature of the statistical inference drawn from such data" (p.437).

Under coverage can be an issue for EO data sources because although the datasets are often large they don't necessarily capture the target population the NSO wants to make inferences about. For example, if a dataset contained crop yield EO data for Tasmania, this would not be valid to make inferences about the whole of Australia. According to Tam and Clark (2015) in some cases big data sources "might need to be supplemented with survey data to obtain coverage of un-represented segments of the population. In other cases, it may be useful to publish statistics that describe sub-populations." (p.442).

5.4 Selecting an appropriate EO data set

When determining whether EO data is appropriate for specific statistical purposes, a key question is whether the required data or information products can be generated from EO at all. The decision-tree in Figure 33 will help to decide whether it is appropriate and possible to use EO data products.

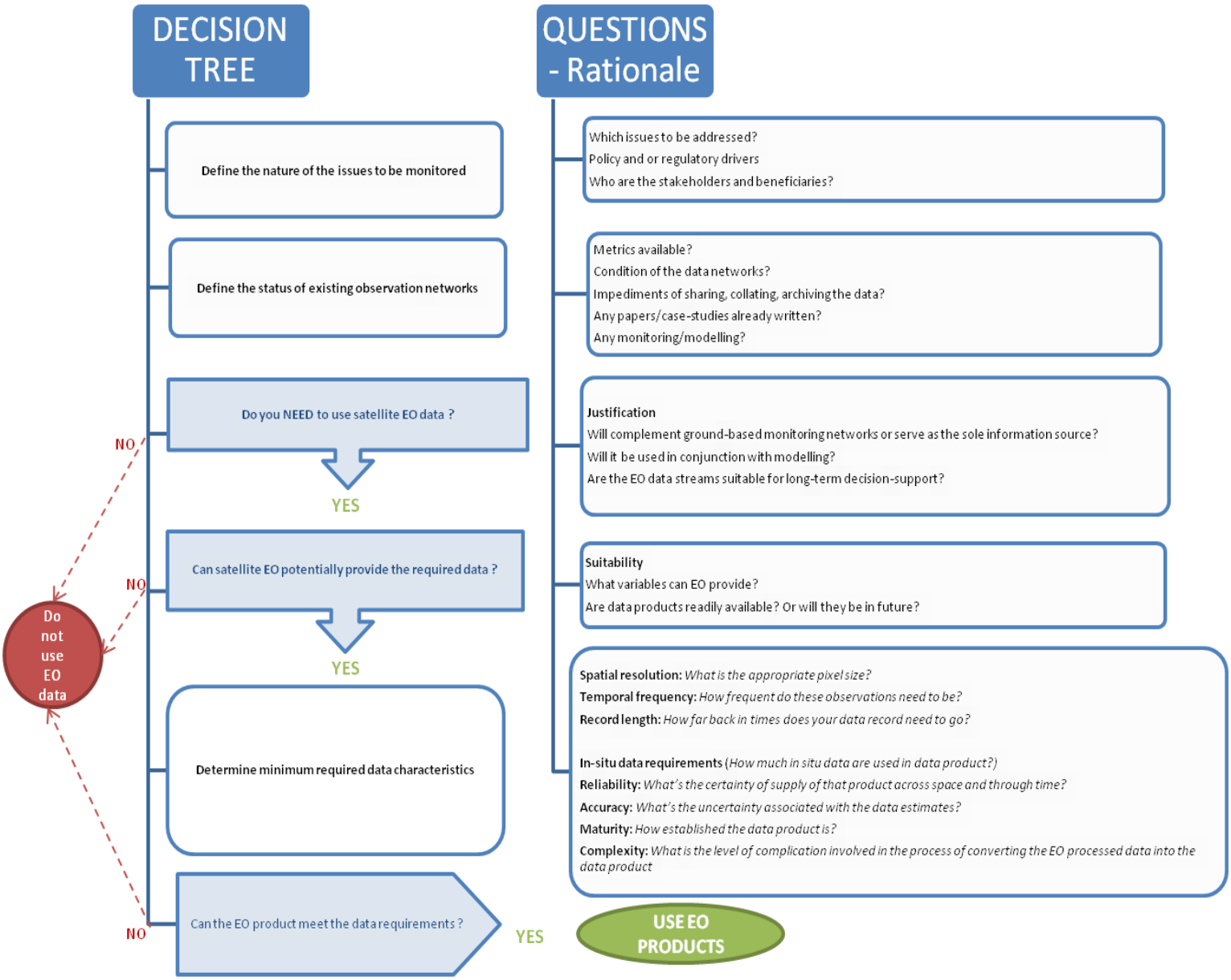


Figure 33: CSIRO Decision Tree on usage of EO data for NSOs

Case studies of implementation of EO data for statistical purposes would be useful in order to further assist with making decisions for the business case about methodological feasibility and costs of acquiring, preparing and pre-processing this data. Such case studies could then help inform decisions for future applications.

5.4.1 Minimum data requirements for EO

To determine minimum EO data requirements, the following questions need to be raised and answered before deciding to use EO data:

Justification	Do you need to use EO? Is there a better alternative source?
Suitability	Can EO provide the required data products?
Spatial resolution	What is the appropriate size of pixel?
Temporal frequency	What is the required frequency of these EO data acquisitions?
Record length	How far back in time does your data record need to go?
Reliability	Do you need guaranteed continuation of data supply into the future?
Accuracy	What degree of accuracy is needed in the information product?
Maturity	Do you want to use only information products that are well documented and are commonly used?
Complexity	What data management, processing and analysis capacity is available?

Figure 34: Requirements for the use of EO

Besides these traditional EO requirements, other criteria need to be considered.

5.4.2 Data sources: access and ownership

Once an NSO has determined that EO data is appropriate to meet their statistical output requirements, sources need to be identified and accessed. Chapter 2 outlined a variety of available sources, including some freely available and privately owned resources.

A key risk for NSOs incorporating EO data into their statistical process is they "have little control or mandate with respect to big data held by private entities, nor is there an assurance that the company and its data will exist into the future. If access is denied in the future, or the data production is terminated, then there is a significant risk to data continuity and time-series datasets, especially if existing systems have been replaced by the new big data solution." (Kitchin, 2015). In the literature, it is generally thought there is currently a general lack of legislation and a framework for NSOs regarding data ownership and access in the big data and EO space.

This is a consideration for NSOs beginning to work with EO data for the first time and an on-going basis. Thought should be given to how the statistical process and outputs would be affected if access to the EO source was no longer possible or if the data source content changed. One example is the sudden

loss of contact with the over 10 years in operation ENVISAT satellite with 9 instruments on board. Another example is that of the two MODIS sensors (Terra and Aqua) that were intended as research instruments but where so successful (and outlived their life expectancy two to three fold) that they generated a significant operational output. With the advent of the Copernicus Sentinel long-term operational satellite missions funded by the European Community and operated by ESA and EUMETSAT there is now an opportunity to invest in methods to use this sophisticated EO data for at least the next 15 years.

5.5 Assessing quality

Data quality depends not only on its own features but also if it conforms to the relevant uses and meets business requirements (Cai & Zhu, 2015). Quality is therefore a multidimensional concept which not only includes the accuracy of statistics, but also stretches to include other aspects such as; relevance, timeliness, accuracy, coherence, interpretability and accessibility. Therefore, the quality assessment should include these aspects.

Commonly, the products obtained using remote sensing must have an accuracy assessment indicator, which indicates the degree to which the data correctly describe the phenomenon they were designed to measure. The accuracy assessment might require a comparison of the results with another independent (but also prone to errors) source of information such as: ground reference data, administrative registers, etc.

According to the GEOSS data quality guidelines (2013), data providers should "address the multiple dimensions of quality. The purpose is not to judge or rank data resources, but to describe the characteristics needed to be known in order for the user to decide whether he/she should use them" (p.1).

These characteristics include (see Table 1 in Chapter 2):

- Coverage, including both spatial and temporal dimensions;
- Consistency, including long-term consistency;
- Uncertainties estimated and documented, including both spatial and temporal dimensions;
- Attribution of error sources (frequency and cause of missing values);
- Validation information, i.e. how the data was assessed for uncertainties by comparison with
- alternative measurements;
- Latency from time of observation;
- Resolution, including both spatial and temporal dimensions;
- Usability, in the sense of being in form and content convenient to use for the specific purpose;
- Simplicity, such that the data and the underlying data model are not unnecessarily complicated or difficult to understand or manipulate (GEOSS, 2013, p.2);

5.6 Dissemination of outputs

The dissemination strategy implemented by the NSO should facilitate access, interpretability and reuse of the data. These factors help to strengthen the use of the information.

Some aspects that could be considered when disseminating results based on EO data are;

- Estimates based on statistical models and other approaches, outlined in Chapter 3 and the supplementary material, should give an associated measure of the statistical accuracy of the estimate, using defensible methods that are clearly documented.

- The methodology behind the statistical model, inherent assumptions and their likely implications, the quality of the EO data and processes undertaken for preparing the data, as seen in Chapter 2, should be fully documented in a user guide.
- Data visualisation: Commonly, products associated with EO data processing have a spatial component (maps, images, geographical layers). The use of geographic viewers allows the query of this information.
- Interpretability: With the aim to promote the usefulness of the information, it is recommended to provide metadata, which describe the main characteristics of the image used (capture date, spatial resolution, sensor), procedures, measures of accuracy and others aspects considered relevant.
- Timeliness: In order to reduce the "time-to-market" of statistical products the delay between the reference period (to which the data pertain) and the date at which the data become available should be the minimum.
- Non –proprietary format: If the products are available for download, it is recommended to publish in a non-proprietary format.
- Legal aspects: It should be guaranteed that the information published fulfil legal aspects established in the country.

5.7 Other considerations and issues

In addition to the issues outlined previously in this chapter, the following should also be considered if an NSO chooses to work with EO data.

- Technological improvements and advancements, such as more sophisticated sensors, will lead to new EO data sources over time. NSOs should regularly review and update their data sources for statistical outputs as better quality sources become available.
- Identification of a specific project or group of projects that can be addressed in a reasonable time. Under this approach, the NSO aims for manageable outcomes, which are likely to gain support from senior management.
- Estimation of the resources that can be deployed. Issues such as budget, hardware, storage devices, software and information policies are determining factors.
- An objective evaluation of knowledge and skills available at the organisation is a key factor. According to the Australian Government Big Data Working Group (2015) "A significant constraint on realising value from big data will be a shortage of talent, particularly of people with deep expertise in statistics and machine learning, and the managers and analysts who know how to operate companies by using insights from big data." (p.12). Decisions on training and development of collaborators improve the sustainability of the initiatives and their success. As was mentioned in Chapter 2, there are more approaches to using EO data than the pure statistical approach and in the long term these more physics-based approaches (including model data assimilation) may be more amenable to automation and thus reduced costs. The question then becomes how NSOs interact with those expert organisations that have the right capabilities.
- When statistical data and information are geo-referenced or spatially enabled, new or further development of skills are required. Skills in spatial thinking and analysis must be improved or be acquired in order to answer questions like sample size and distribution, statistical and geographical coverage, geographic levels, data capture and dissemination and data confidentiality, among others.
- Active participation in forums like the UN GWG on Big Data makes the transition to utilising big data sources and EO data easier. Access to practices, methods, trends and permanent

discussion are very important tools to keep the EO based projects 'alive'. Partnering or collaborating with the two international organisations that are harnessing and coordinating EO data such as GEO and CEOS is recommended.

5.8 Further Recommendations for practitioners working with their first satellite imagery/earth observations data.

Build capability through collaboration with international and national agencies.

Beginning to work with EO data for the first time can be challenging, so NSOs should learn from the knowledge and experience of other agencies. As they become more experienced with EO themselves, NSOs should share this knowledge with other organisations in their network, building the capability of stakeholders globally over time. Partnerships between data providers, NSOs, private industry and academia are important to progress the use of EO data for official statistics. In cases where a NSO does not have experience with topics such as geodetic reference systems, map projections, raster and vector formats, etc., the data landscape can be challenging. An initial step to overcome the situation is to strengthen ties with the national mapping agency of the country.

Intensive courses

A tried and successful method to train NSO experts could be to create intensive courses of one to three weeks to boost the EO required knowledge to the right level for successful implementation of this data for statistical purposes.

Take advantage of open source information online

Nowadays, a lot of help is available in websites, blogs, videos, user forums and free courses. This information sharing can provide a great advantage and, it could be said that the most of the practical issues can be dealt with these tools.

Identify skills required by the organisation

As experience is gained in working with EO data, NSOs can identify internal skill gaps where people with higher or different qualifications are needed. For example, organisational capacity building programs could include education in data science, spatial data infrastructures, remote sensing, spatial data analysis and computer science, among others. If an NSO doesn't have the necessary skills internally, it could also consider whether outsourcing some tasks to other organisations with the relevant expertise or forming multidisciplinary teams across agencies.

Engage with the public to improve perceptions of privacy

When introducing the use of big data such as EO, it is important to engage with the public to ensure their trust in the NSO and its statistical outputs is not negatively impacted. There can be concerns in the community that by using and combining big data sources for official statistics their privacy will be compromised. For NSOs "it is critical that these concerns be addressed through practices such as being transparent about what and how Big Data sources are used" (Strujis, Braaksma and Daas, 2014). EO data is one of the most acceptable forms of Big Data as it is commonly used through Google Earth and the weather forecasts (based on assimilating physics based models with in-situ data and earth observation data by meteorological satellites) including rain radars.

Consider ethical principles and current privacy legislation

As legislation has not currently been updated to comprehensively address cases involving Big Data and privacy concerns, legal obligations of NSOs are not always clear. Preventing "the disclosure of the identity of individuals is an imperative, but this is difficult to guarantee when dealing with Big Data" (Strujis, Braaksma and Daas, 2014). NSOs have their own policies and mandates regarding the privacy and protection of information they collect and showing reasonable care has been taken to protect the identity of individuals and considering ethical standards can serve as a guide. As legislation and guidelines are updated, NSOs should update their policies to reflect this. This aspect applies mainly to the use of very high (sub metre) resolution satellite data.

Consider using Analysis Ready Data (ARD)

The processing required to transform raw EO data to be analysis ready can be time consuming and costly. For NSOs new to the practice and lacking the required skills, the costs of this process could be prohibitive. If this is the case, NSOs should assess whether acquiring ARD would be more cost effective, either by initially seeking ARD or outsourcing the processing of the raw data. For further reading on ARD for statistical purposes refer to section 2.7 of this report.

Disseminate analysis of results and algorithms

By disseminating results of analysis of EO data, NSOs can help other organisations develop their skills working with EO by providing examples, receive feedback and advice from peers and provide value to the public through statistical outputs produced with lower provider burden.

As further exploration is done on the use of earth observations for statistical purposes, if stakeholders continue to share their learnings and experiences with others through global channels, such as the UN GWG on Big Data and UN GGIM, work in this field will continue to evolve and benefit the global community through applications such as measuring populations and monitoring SDGs. Reproducibility of the results by sharing workflow/scripts enhances these considerably.

6. Conclusion

The use of EO data for official statistics represents opportunities and challenges for NSOs. This report has provided information to guide practitioners through the process of critically assessing their business need for EO data, consideration of sources, methodological approaches, examples of case studies and guidelines to consult when making decisions about the use of EO data for statistical purposes.

The use of EO data should be implemented when there is a clear business benefit, and this needs to be assessed on a case by case basis. Given this variability for when and how it is appropriate to use EO data, going forward sharing information, expertise and lessons learned between governments, private businesses and the research community will be essential.

To this end, the initiatives of the UNSD Global Working Group on Big Data and its task teams, UN GGIM, CEOS and GEO will continue to provide a valuable international network of professionals sharing knowledge and progressing the potential of using big data sources, such as EO, for statistical and policy applications. A highly visible application will be the measuring, monitoring and reporting on progress of the 2030 Agenda for Sustainable Development SDGs.

As use of EO data becomes more prevalent and techniques for using these sources are finessed, further applications may become apparent and expand into fields that are not currently anticipated. Throughout this process of expansion, open communication and knowledge sharing will continue to be important, particularly for the benefit of practitioners new to implementing EO data sources into their organisation.

Appendix. Overview of Statistical and Machine Learning Approaches

While statisticians are familiar with standard statistical models, they may not be as familiar with machine learning methods. The purpose of this Appendix is to describe a range of machine learning models that have been used in the analysis of EO data, point to examples of their use in this context, and provide references for further reading. The methods are categorised according to the four types of analytic aims detailed in Chapter 3, namely classification, clustering, regression and dimension reduction. They are also categorised according to whether the focus is an analysis at a single period of time (static data) or over time (dynamic data).

A.1 Methods for analysis of static data

Classification methods

Logistic and multinomial regression are part of the family of generalised linear models (glm). Other examples of generalised linear models that can be used for classification are Poisson regression (e.g., for count data) and negative binomial regression (e.g., for more rare spatial outcomes). Logistic regression is used when the output (response) variable is categorical with two levels (vegetation/not vegetation, high/low, present/absent). Multinomial logistic regression is used when the response variable has more than two levels (trees/grass/bare ground/crop/water, high/medium/low).

If there is a large number of input variables or some variables are potentially redundant, regularisation methods can be employed to reduce or eliminate the effect of variables that do not contribute substantially to the analysis. Common methods include ridge and LASSO regularisation and more general elastic net regularisation. Other methods for variable selection include the familiar forward, backward and stepwise regression approaches, known as forward feature construction and backward feature elimination in the machine learning literature (Silipo, 2015). However, these approaches are quite time consuming and computationally expensive, and are practically only applicable to a data set with an already relatively low number of input variables.

An example of the use of logistic regression with EO data is given by Bavaghar (2015). The author employs the method to estimate the location and extent of deforestation based on variables such as slope and distance to roads and residential areas, and highlights in particular the ability to quantify the uncertainty in predictions as a strength of the approach. An overall 75% correct classification rate was obtained, with an estimate of 12% deforestation of the total study site over the 27 years from 1967 to 1994.

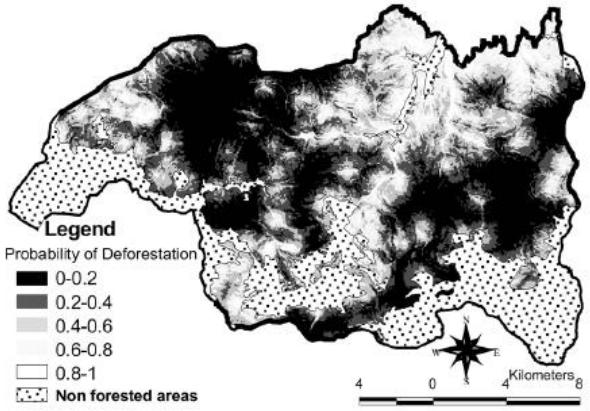


Figure 35: Probability of deforestation obtained using a logistic regression analysis of EO data. Bhavaghar (2015)

Gaussian maximum likelihood classification is one of the most widely used supervised classification techniques with satellite imagery data (Richards, 2013). The goal is to classify observations into groups, where observations in each group are considered to have a Gaussian distribution. More flexible alternatives based on semi-parametric kernel estimation are also available. Maximum Likelihood is also argued to be equivalent to linear or quadratic discriminant analysis (Hogland *et al.*, 2013).

Neural networks are popular classification methods. Neural networks can also be used for regression (see below). When represented graphically a neural network is arranged in a number of layers. The first layer is the input layer representing each of the predictor variables. This is followed by one or more layers of hidden nodes which each represent an activation function acting on a weighted input of the previous layers' outputs. Finally, the output layer may be a single layer in the case of regression or in the case of classification will consist of a node for each possible output category. Due to the dense connectivity of the nodes in a neural network, the final function can represent complex relationships among the input variables, and between the input and output variables.

Neural networks are typically 'trained' or quantified via a back propagation algorithm, which is similar to gradient descent, and iteratively adjusts the weights of the graph after seeing each new data point. This updating of the weights moves the neural network toward some local minima in the parameter space in relation to the training accuracy. Effectively training neural networks generally requires a relatively large training data set.

Deep learning refers to the development of new algorithms to overcome the challenges associated with training neural networks, which have many hidden layers. In particular the 'vanishing gradient' issue which refers to the limitation of traditional back propagation in updating the weights of earlier layers in deep networks.

Neural networks have been used for the analysis of EO data for almost two decades; see studies by Chen et al. (1995), Paola and Schowengerdt (1995), Atkinson and Tatnall (1997), Paola and Schowengerdt (1997) and Foody and coauthors (1995, 1997, 2001), Kavzoglu and Mather (2003), Mertens et al. (2004), Verbeke et al. (2004), Erbek et al. (2004), Kussul et al. (2006) and Kavzoglu and Reis (2008). More recent examples of classification using NN of EO data are given by Srivastava et al. (2012), Shao and Lunetta (2012) and Wang et al. (2015).

For example, neural network techniques have been used to discriminate differences in reflectance between wheat and grass weeds by López-Granados et al. (2008). The authors used a preliminary computation of the most relevant principal components to considerably improve the correct classification rate to between 90% and 100%.

Classification trees are a supervised classification technique that represents class memberships as "leaves" and input variables are "nodes". Branches are formed from these nodes based on splitting the values of the input variables to best group the data.

A classification tree is a member of the family of decision tree methods, which include regression trees, boosted trees, bagged trees, and so on. Classification trees are similar to regression trees (see below), the difference lying in the distribution of the response (categorical or continuous). Classification and regression trees (CART) are constructed using a recursive partitioning approach whereby variables are chosen at each step that best split the data into homogeneous classes. The criteria for choosing the variables and deciding the splits is typically a measure of subset homogeneity such as the Gini index or entropy or, in the case of regression trees, variance reduction.

The main advantage of classification trees in particular, and decision trees in general, is that they are simple and easy to understand. Due to their computational simplicity they can be applied to large amounts of data. However, decision trees can suffer from over-fitting and often require pruning, which in essence is a model selection problem. Furthermore, there is no guarantee of finding the globally optimum tree. Popular extensions to decision trees, designed to address these issues of bias and variance, include boosting (constructing a sequence of trees, each one built from the misclassified observations of the previous tree) and bagging (constructing a set of trees based on random samples of the data). A random forest (RF) is a set of 'shallow' trees constructed from many random samples.

Classification trees have been used to analyse EO data for over 15 years. For example, Lawrence and Wright (2001) employed this method to classify land cover in the Yellowstone ecosystem in the USA, based on Landsat TM imagery. The remote sensing input variables were extracted from two TM scenes covering the region, and included bands 1-7 for each data as well as brightness, greenness and wetness. Elevation, slope and aspect were extracted from a Digital Elevation Map (DEM), and 30-100 reference sample sites were coded from aerial photos. A 'rule based classification' was derived from the classification tree analysis; an extract of this scheme is shown below.

1. Tasseled Cap brightness difference < 22.5
  1.1. Elevation < 1682 m
    1.1.1. June TM band 6 < 139.5
      1.1.1.1. June TM band 4 < 111, THEN Natural vegetation
      1.1.1.2. June TM band 4 > 111, THEN Natural vegetation
    1.1.2. June TM band 6 > 139.5
      1.1.2.1. June TM band 2 < 32.5, THEN Agriculture
      1.1.2.2. June TM band 2 > 32.5, THEN Agriculture
  1.2. Elevation > 1682 m
    1.2.1. June TM band 6 < 116.5, THEN Natural vegetation
    1.2.2. June TM band 6 > 116.5, THEN Natural vegetation
2. Tasseled Cap brightness difference > 22.5
  2.1. Elevation < 1754 m
    2.1.1. Tasseled Cap greenness difference < 1
      2.1.1.1. June TM band 4 < 116.5
        2.1.1.1.1. Tasseled Cap wetness difference < -5.5
          2.1.1.1.1.1. August TM band 5 < 138.5

Figure 36: Extract of a rule-based decision framework constructed using a classification tree based on EO data. Lawrence and Wright (2001).

More recent references to decision trees and remote sensing include Sharma et al. (2013), Al-Obeidat et al. (2015), Chasmer et al. (2014), Otukei and Blaschke (2010) and Peña-Barragán et al. (2011). As discussed in the Case Study in Chapter 4 of this report, Schmidt et al. (2016) compared a number of methods for classifying crop/no crop in Australia, using Landsat imagery, and found that random forests provided the best accuracy and robustness.

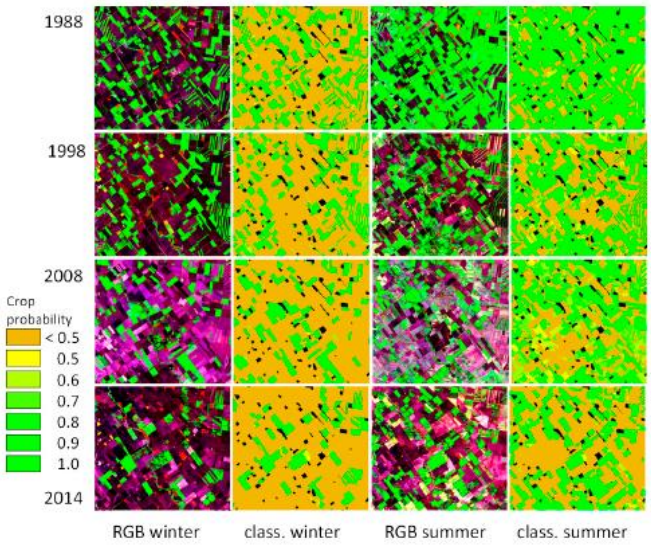


Figure 37: Crop/No Crop classification determined from Random Forest analysis of Landsat imagery. Schmidt et al. (2016)

Support vector machines (SVM) are a class of non-parametric supervised classification techniques. In their simplest form, 2-class SVMs are linear binary classifiers. The term "support vector" refers to the points lying on the separation margin between the data groups or classes.

Linear separability is often not achievable (to a desired level of misclassification accuracy) in practical data applications, so various techniques have been proposed to overcome this limitation. One of the most common is to use kernels to map data to a higher dimensional space in the hope that in this space the data become separable (or at least separable to a reasonable level of misclassification). There are many potential kernel functions available, though the most common in the crop classification literature appear to be the radial basis function and polynomial kernels. The SVM algorithm then constructs a (linear) hyperplane in this higher dimensional space to optimally separate the groups, and then maps this hyperplane back onto the original space. The result for an image, for example, is a curve that allocates observations to classes depending on which side of the line they lie.

An excellent reference for the use of SVMs for remote sensing is Mountrakis *et al.* (2011). Some other papers that examine the use of SVMs for analysis of EO data include Szuster (2011) for land use and land cover classification in tropical coastal zones; Mathur and Foody (2008) for crop classification; Huang et al. (2002a) for land cover classification; Melgani and Bruzzone (2004) for remotely sensed data; and Shao and Lunetta (2012) for land classification.

Some of these papers compared various approaches with SVMs. For example, in the paper by Shao and Lunetta (202), although the CART models were preferred for speed and ease of use, SVMs and NNs were preferred for classification accuracy.

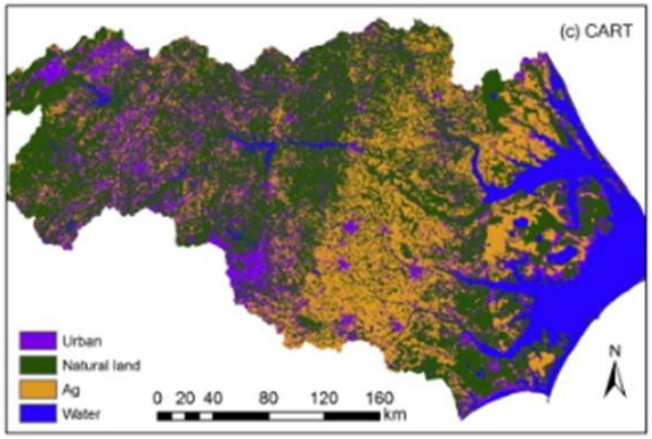


Figure 38: Land classification map created from a CART analysis of EO data. Shao and Lunetta (2012)

Nearest neighbour methods (k-nn) have been used over half a century (Fix and Hodges Jr, 1951). They are a well-known and popular nonparametric classification technique due to their relative simplicity. In their simplest form an object is classified according to a majority vote of its k nearest neighbours. That is, an object's class is assigned to it by the most common class among its k nearest neighbours, where *k* is generally a small positive integer.

Contributions of neighbours to an object's class can be weighted (for example by the inverse of their distance to the object). Extensions of the method to allow "doubt" options are known as (k, l) rules: these rules take a vote among the classes of the k nearest neighbours but do not allocate the majority class to the object unless it receives l or more votes (otherwise the class is declared "in doubt").

Classification using the k-nn rule can be very dependent on the distance used to determine an object's nearest neighbours, as well as the choice of k. In addition, k-nn is known as a "lazy learner": it does not learn from training data, rather it simply uses the training set to undertake classification of new objects. Because of this the method can be very dependent on local data structures, and there can be memory overheads to store adequate training data, making it slow. However, data editing can ameliorate these issues somewhat by taking advantage of the idea that in many cases only a small subset of the training data is necessary to approximate very well the k-nn decision boundary. Many data editing algorithms exist: see Ripley (1996) for some examples.

Some early examples of work in the remote sensing literature using k-nn approaches include Hardin and Thomson (1992), Hardin (1994), Franco-Lopez et al. (2001), Ohmann and Gregory (2002), Collins et al. (2004), Haapanen et al. (2004), Zhu and Basir (2005), Triepke et al. (2008) and Blanzieri and Melgani (2008).

For example, McRoberts et al. (2007) employed k-nn methodology for forest inventory mapping and estimation. The EO data comprised Landsat imagery for 3 dates in 1999-2001 corresponding to early, peak and late vegetation green-up. The imagery was used to derive 12 satellite image-based predictor variables, NDVI and the TC transformations (brightness, greenness, wetness). These predictor variables were then used to estimate four forest attributes: proportion forest area (PFA), volume (m^3 /ha) (VOL), basal area (m^2 /ha) (BA), and stem density (tree count/ha) (D). Multiple pixels were aggregated to obtain estimates (mean, variance) for an area of interest (AOI). The authors found that some of the advantages of the k-nn approach were small area estimation, multivariate estimation, and both point estimation and uncertainty.

Although nearest neighbour methods are conceptually appealing and computationally fast, they are not always the best model for EO data. For example, ver Hoef and Temesgen (2013) compared k-nn and spatial linear models for forestry applications and found that the spatial model was preferred. However, their accuracy and predictive capability can be improved by combining them with other models. For example, Blanzieri and Melgani (2008) preferred a combination of k-nn and SVM methods for classification of remote sensing images.

Intra-or sub-pixel classification approaches can be used to address the issue of so-called "mixed" pixels: pixels that display characteristics of more than one group. Mixed pixels are mainly a concern in coarse (eg MODIS) or moderate (eg Landsat) resolution remotely sensed data. In the context of crop identification, mixed pixels may contain, for example, field boundaries.

The two most common approaches in the remote sensing literature to the mixed pixel classification problem are Spectral Mixture Analysis (SMA) and soft, or fuzzy, classifiers. There is an enormous amount of literature on both of these methods. Fuzzy classifiers and their variants are described in a recent book by Mather and Tso (2016), along with many other methods for classification for remotely sensed data. Details of SMA and its comparative advantages and disadvantages for analysis of remotely sensed data are discussed in the book by Thenkabail (2015, p.229). The method is available in many software packages, for example the Wiki Landscape Toolbox: (http://wiki.landscapetoolbox.org/doku.php/remote_sensing_methods:spectral_mixture_analysis).

An example of intra-pixel classification is given by Zhang et al. (2015a), who propose a stratified temporal spectral mixture analysis (STSMA) for cropland area estimation using MODIS time-series data.

Bayesian networks (BN) are also being used more frequently with EO data for classification. A BN aims to develop a set of relationships between the input variables and the output variable (response) using the conditional dependence of each attribute on each other attribute. The resulting model can be displayed graphically, with input variables as nodes and dependencies between the variables as directed arrows that link the nodes. Each node is quantified conditional on the nodes that affect it, so that the resultant model is a sequence of conditional probabilities leading to the overall probability of the response. The network can inform about the relative importance of variables in influencing the response, effects on the response due to changes in input variables given all of the other variables in the model, and optimal values of the input variables leading to the best response. BNs have been used in the analysis of EO data for over a decade. For example, Stassapoulou *et al.* (1998) applied a BN to GIS data and demonstrated an additional advantage of easily combining multiple data sources in a complex modelling framework. A more recent example is given by Mello *et al.* (2013) who employed BNs for soybean crop detection using remotely sensed data, highlighting the ability to include expert information in the model to improve classification.

Clustering methods

k-means is one of the most common clustering approaches used in machine learning. The algorithm assumes the data is drawn from K different clusters and assigns each unlabelled point to the closest group centre, which are recalculated until no changes occur.

k-means can be used for a range of purposes. For example, it is often employed as a dimension reduction technique for analysis of EO data: a value of k is chosen, which is large but much smaller than the original number of pixels, and the resultant clusters are then used for further classification, regression

or other analysis. Alternatively, the clusters obtained from a k-means analysis can be inspected to gain insight into important factors that differentiate between the groups, or for post-hoc classification. For example, Usman (2013) used a k-means approach to classify high resolution satellite imagery data into classes which were then determined to farmland, bare land and built up areas.

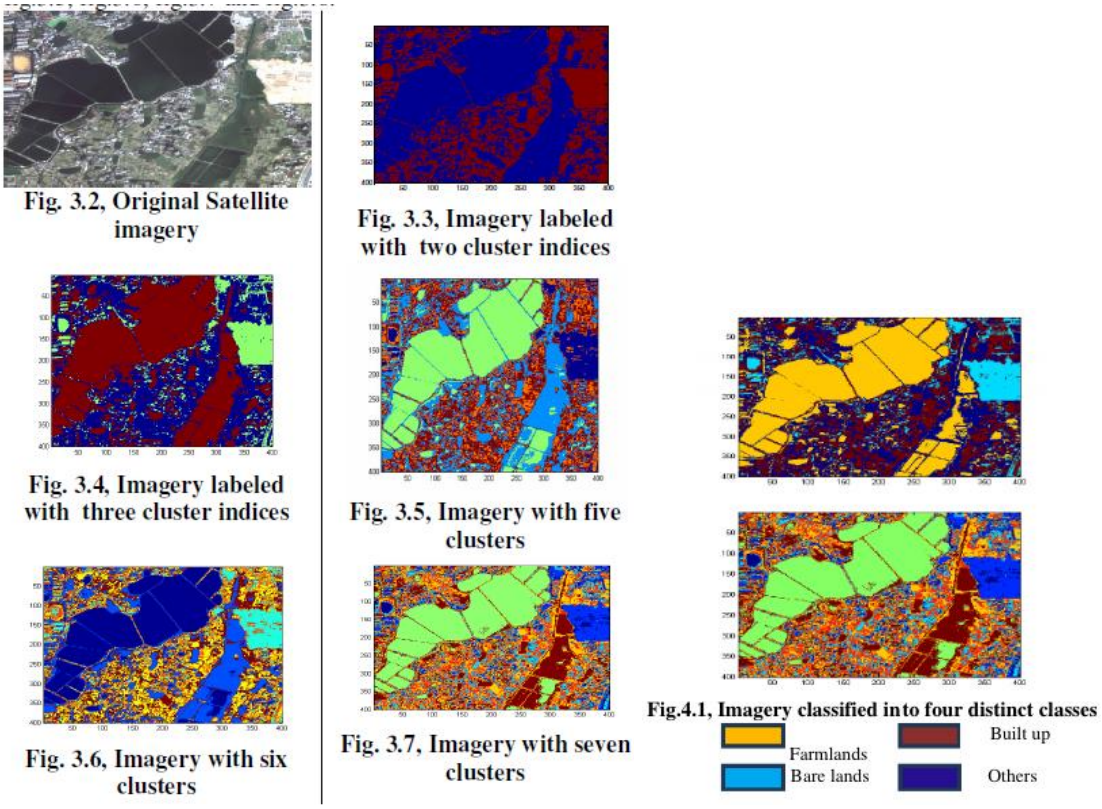


Figure 39: Example of k-means clustering of satellite data with different values of k. Clusters are classified into landuse types. Usman (2013).

Agglomerative clustering and its variants (e.g., hierarchical agglomerative clustering) is also a very popular approach for clustering. The algorithms starts with each point as its own cluster and iteratively merges the closest clusters until a stopping rule is reached.

Mixture models are a popular method for clustering in both the statistical (empirical) and machine learning communities. These models are also known as soft, or fuzzy classifiers.

Mixture models are based on the premise that observed data arise from various sources, or groups. Each group is assumed to have a particular distribution; for example in a Gaussian mixture model the observations in a group may be normally distributed with a group-specific mean and variance. The mixture model is then a weighted sum of these distributions, where the weights correspond to the proportion of observations in the population that belong to that group; this can also be interpreted as the probability that an observation belongs to that particular group. Thus in a 'soft classification', observations are allocated to more than one group with a certain probability; this is in contrast to 'hard classifiers' such as kNN or k-means (see section on machine learning methods below) in which the observation is allocated to only one group.

In a mixture model, the number of groups, the weights, and the parameters of the distributions that describe the groups (e.g. the means and variances of the components of a Gaussian mixture model) may

be known or unknown. The analysis then attempts to estimate the unknown components of the model, and thus unscramble the data into its constituent groups. These are then interpreted as the clusters.

Other examples of the use of mixture models for analysis of EO data include de Melo et al. (2003) for supervised classification of remote sensing multispectral images in an area of Tapajós River in Brazil., and Walsh (2008), who combine secondary forest estimates derived from EO data and a household survey to characterize causes and consequences of reforestation in an area in the Northern Ecuadorian Amazon.

More recently, Tau et al. (2016) employed a Gaussian Mixture Model to estimate and map urban land cover using remote sensing images with very high resolution. Their conclusion was that "the optimized GMM-based method performs at least comparably or superior to the state-of-the-art classifiers such as support vector machines (SVMs), characterizes man-made land-cover types better than conventional methods, fuses spectral and textural features of VHR image properly, and meanwhile has lower computational complexity."

Regression methods

Linear regression is one of the most common empirical models. Here, the response variable is used in its natural form or it is transformed to be more symmetric, for example through a log transformation if the distribution is very skew. The response is then estimated by a linear combination of predictor variables. These predictors can include the original input variables, polynomials (to describe nonlinear relationships with the response), combinations of variables (to describe interactions).

Linear regression can be used in innovative and extended ways to provide official statistics. For example, Liao (2017) used the technique to determine the impact of energy consumption on surface temperature in urban areas. The focus of the study was on 32 major cities in China. Five steps were employed in this analysis:

1. Obtain data for total nighttime lights and total energy consumption (per province per year).
2. Use EO data to identify urban areas.
3. Estimate total energy consumption in urban areas based on total nighttime lights.
4. Use EO data to develop maps of surface temperature.
5. Relate total energy consumption to surface temperature.
6. Extent of urban areas:

Data sources used in this study included:

- a land cover/use map of China in 2010, generated by visual interpretations of Landsat TM/ETM+ images from the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences, used to identify six land use types: artificial surfaces, cultivated land, forest, grassland, water bodies, and unused land.
- Land surface temperature (LST), obtained from Aqua MODIS 8-day, at spatial resolution of 1 km, for 2008 to 2012, during daytime and nighttime.
- Nighttime light (NTL) images from the National Oceanic and Atmospheric Administration (NOAA) of the National Geophysical Data Center (NGDC) for 2008-2012.
- Total energy consumption for each year from 2008 to 2012, for each province in mainland China from the China Energy Statistical Yearbook, except for Taiwan and Tibet.

A regression model was used to estimate total energy consumption (EC) from sum of nighttime lights (NTL) in each province, as illustrated below.

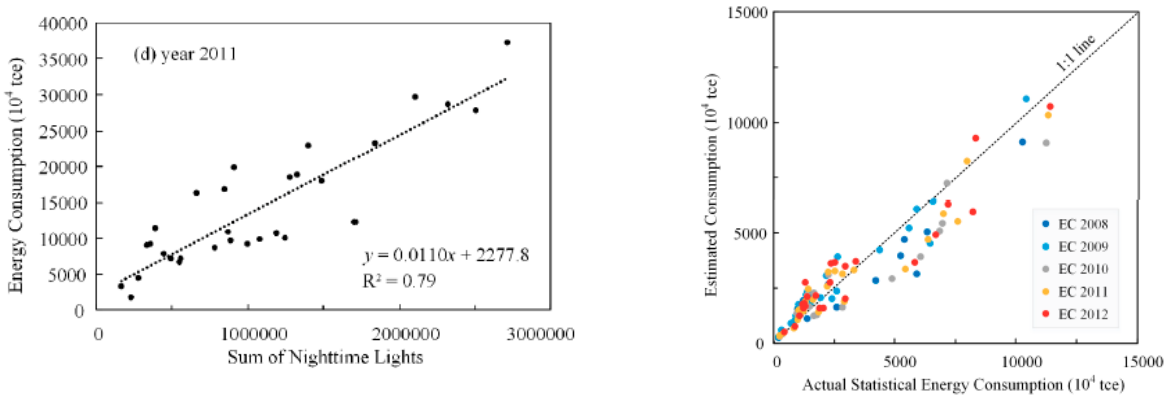


Figure 40: Top left: linear regression analysis to estimate energy consumption from sum of nighttime lights. Top right: comparison of actual and estimated energy consumption. Liao (2017)

The results included estimates of spatial and temporal differences in the correlation between urban-suburban difference in annual mean energy consumption intensity (ΔECI) and SUHI.

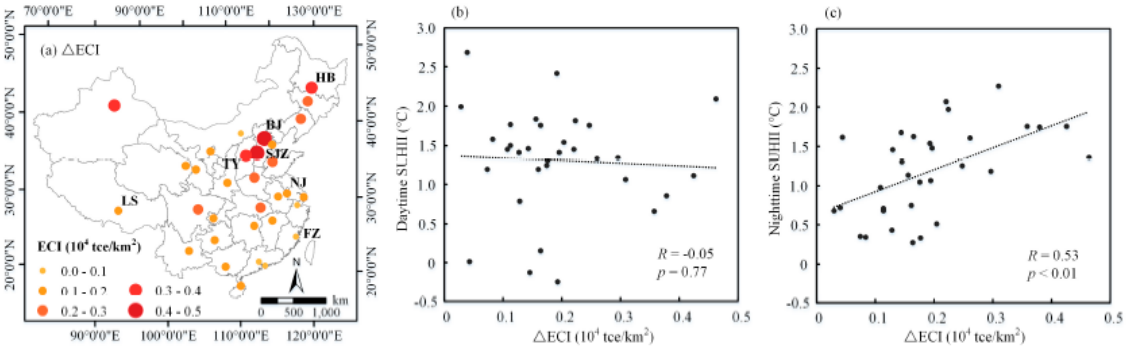


Figure 41: Extracts from Liao (2017) showing a map of differential urban-suburban energy use (left) and linear relationship between this estimate and daytime (middle) and nighttime (right) SUHI.

There are many extensions to linear regression models for analysis of EO data. Three examples are described below.

Generalised linear models (GLMs) can more appropriately incorporate the distribution of the (non-normal) response variable and flexibly link it to the linear function of explanatory (input) variables (e.g. modelling counts as Poisson distributed, with a log link). GLMs can themselves be extended to provide further flexibility, for example as generalised linear mixed models (GLMMs) which describe groupings in the data. Overviews of the use of GLMs for EO data are provided by Morisette and Khorram (1997) and Morisette, Khorram and Mace (1999) in the context of satellite-based change detection.

Spatial models are extensions of regression models that take into account the fact that sites that are geographically close are more likely to be similar than sites that are further away. This spatial autocorrelation can be incorporated in the model to improve predictions. In a similar manner, temporal

patterns, such as daily peaks and troughs, seasonality or longer-varying trends, can be described in a regression model.

Spatio-temporal models incorporate patterns in the image that vary over space, or space and time, respectively. These patterns can be modelled in different ways, for example as temporally varying spatial signatures, or spatially varying patterns at different time periods, or as a full interaction between the three dimensions.

Other extensions include support vector regression (SVR), kernel ridge regression (KRR), random forest regression (RFR) and partial least squares regression (PLSR). These are described by Okujeni and van der Linden (2014) in the context of quantifying urban land cover from HyMap data at 3.6 and 9m spatial resolution. These authors found that SVR and KRR yielded high accuracies for mapping complex urban surface types, i.e. rooftops, pavements, grass- and tree-covered areas.

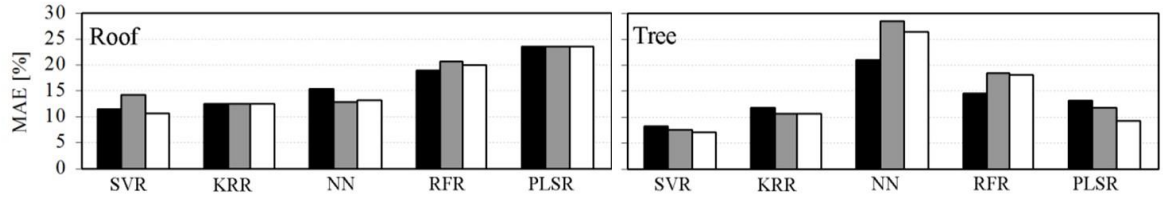


Figure 42: Mean absolute error (MAE%) in object identification (left Roof, right Tree) from various regression analyses of EO data.

Regression trees are a variant on the classification tree methods described in the classification approaches section above, but here the response is continuous and the aim is to minimise the difference in responses within the groups and maximise the difference in average response between the groups. The tree will then predict the expected response for a new object, based on following the branches of the tree to the final (terminal) node and calculating the average value of the responses in that group of objects. The uncertainty of the prediction can also be estimated by the variance of the responses in this group. There are many different kinds of regression trees, including Boosted Regression Trees (BRT) and Random Forests (RF) and gradient boosted machines (GBMs). For example, in GBMs, regression trees are added together, such that each new tree is trained on the errors of the previous trees added together. The sum of these trees is then used to predict the value of new data points.

An excellent introduction and tutorial on boosted regression trees, with implementation in the R statistical software package, is given by Elith, Leathwick and Hastie (2008).

Spectral angle classification is based on the cosine of the angle between pixels' reflectance spectra. It is also known as the $cos\theta$ distance metric in other disciplines. More correctly, spectral angle is a distance or similarity metric which can be used to assess similarity to reference spectra via an appropriate decision rule or criteria. Examples of work using spectral angle approaches in remote sensing applications include Sohn and Rebello (2002), Kuching *et al.* (2007), Petropoulos *et al.* (2010), Yuhas *et al.* (1992), Sohn *et al.* (1999).

Neural networks (NN) are popular regression methods. See the description in the Classification section above. An innovative example of the use of NN for regression analysis with EO data is given by Xie et al. (2016). These authors employ a 'transfer learning' approach, which entails a sequential combination of different analyses (one of which is NN), to map poverty in Uganda, based on nighttime light intensity derived from satellite imagery. The results are illustrated in the figure below.

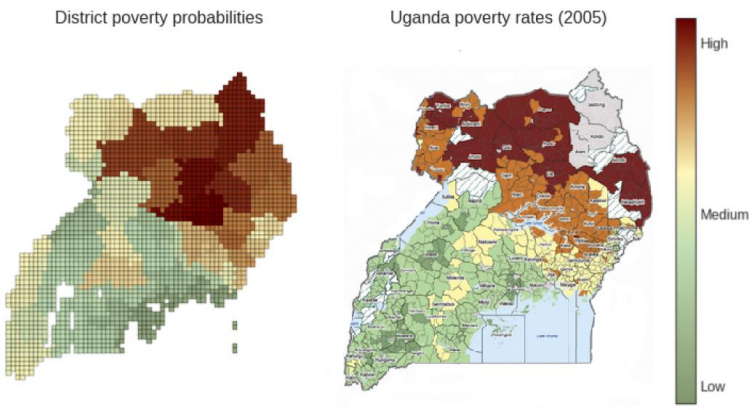


Figure 43: Estimated (left) and reported (right) probabilities of poverty, based in part on a neural network analysis. Xie et al. (2016)

Dimension reduction methods

Principal components analysis (PCA) and its variants such as factor analysis (FA) are popular empirical and machine learning dimension reduction techniques for analysis of EO data. These approaches create linear combinations of the input variables, such that the new combinations (termed components, factors, indices, etc.) encapsulate a large amount of the information or variation in the data. The PCA analysis, for example, generates an independent set of components, each of which has an eigenvalue ('eigen' means 'own' or 'specific') that indicates the proportion of variation explained by the component, and a set of weights attached to each input variable (the eigenvector) that indicates the relative importance of each variable in the component.

PCA methods have been applied to EO data for over a decade. For example, Cablk and Minor (2003) employed four principal components (PCs), derived from the four multi-spectral bands of the high-resolution IKONOS satellite, in a study of South Lake Tahoe, California, in order to determine how impervious cover was represented in each of the four PCs. This is critical for assessing impacts on water quality, wildlife, and fish habitat. In another paper of that time, Call et al. (2003) tested the hypothesis that in-situ spectral signatures, together with water column attenuation measurements, satellite imagery and Geographical Information Systems, can effectively differentiate reef substrates. Principal components analysis of upwelling radiances indicated that wavelengths from 515–580nm are most useful in distinguishing between substrates.

Three more recent examples are as follows. Curzio and Magliulo (2010) assessed the geomorphological effects of soil erosion at the basin scale by integrating Landsat ETM 7+ data and field-surveyed geomorphological data. The authors extracted features using PCA on the original data, and constructed composite images from these which were then used in a classification algorithm. Lawley et al. (2011) applied principal components analysis to 25 years of satellite imagery to identify underlying factors influencing patterns of arid vegetation growth, and regions of similar long-term response. Dominant factors of variation were identified as the spatial distribution of total vegetation growth, seasonality of growth, magnitude of seasonal variability in growth, and regularity of variation in growth. Finally, Estornell et al. (2013), analysed three Landsat images selected from two areas located in the municipalities of Gandia and Vallat, both in the Valencia province (Spain). In the first study area, one Landsat image from 2005 was used. In the second area, two Landsat images were used (from 1994 and 2000) to identify significant changes in land cover. The authors found the second principal component

of the Gandia area image allowed detection of the presence of vegetation. The same component in the Vallat area allowed detection of a forestry area affected by forest fire.

Although PCA is a highly useful and effective method for dimension reduction in satellite image analysis, like any dimension reduction method it does possess a shortcoming: the dominant components (factors) do not contain *all* of the information in the data. Thus the common practice of choosing only the dominant components and using these for further interpretation and analysis can sometimes lead to inaccurate estimation of covariance matrices and may also lead to a loss of spatial information. Other caveats for PCA are that it may not be reliable if only a small number of images are available, and it can be quite time and resource intensive when applied to large image data. Various extensions to PCA have been proposed to overcome some of these issues.

Independent Component Analysis (ICA) is a technique which finds so-called "independent components" of observed data. This data is assumed to be realisations of linear mixtures of unknown latent variables (the independent components) which in turn are assumed to be non-Gaussian and mutually independent. ICA separates a multivariate signal into additive subcomponents.

Independent Component Analysis is related, in a certain sense, to both principal component analysis and factor analysis. However, one of the advantages of ICA over these techniques is that it will often work in situations where the former may fail.

A.2 Summary of methods for static data

The following table summarises some of the techniques discussed above and provides some guidance in the selection of the most appropriate technique under certain situations. It is important to recognise that each technique has its own merits and limitations, and that in any particular application the use of more than one technique may provide greater insight than the use of any one in isolation.

Technique	Parametric?	Computational Load (training speed)	Amount of Parameter Tuning Required	Probabilities of Class Membership?	Spatial and Temporal Dependencies?	Small amount of Training Data?	Tendency To Overfit?
SVM	No	Slow	Significant	No	No	Yes	No
Neural Networks	No	Moderate	Significant	No	No	Maybe	Yes
Decision trees	No	Fast	Low	Yes	No	No	Yes
Boosted Regression Trees	No	Fast	Low	Yes	No	No	Unsure
Multinomial Logistic regression	Yes	Slow	Moderate	Yes	Can be modified	No	No, under user control
K-nn	No	Fast	Low	No	No	No	Yes
SSMs	Yes	Slow	Moderate	Depends	Yes	No	Under user control
INLA-Based	Yes	Faster than equivalent options such as MCMC	Moderate	Depends	Yes	No	Under user control

A.3 Methods for analysis of dynamic data

As described in Chapter 3, there is a variety of heuristic, statistical and machine learning methods for analysing EO data over time.

Comparative approaches

These approaches are popular, as described in Section 3. Fulcher et al (2014) describe how the two approaches outlined in that section can be used for classification. By creating a database of known time series and their classifications, a new time series can be classified by comparing the distance measures between the series in the database. The method proposed by Fulcher et al (2014) learns the properties of a given class of time series and classifies new time series according to these learned properties.

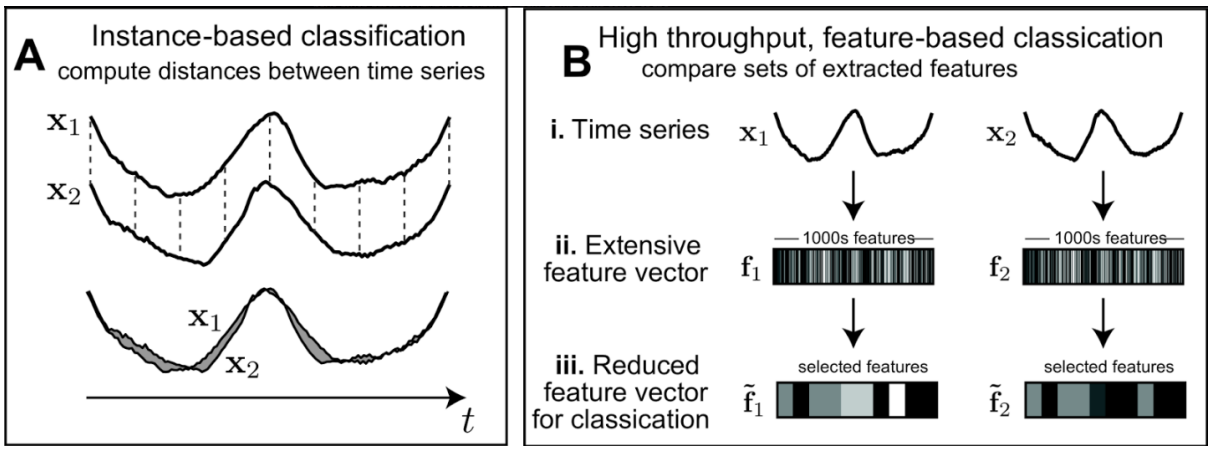


Figure 44: Comparing time series by their structural features

Source: Fulcher et al (2014). What's the difference? Telling apart two sets of signals. Retrieved from: http://systems-signals.blogspot.com.au/

Cubic splines

These models are semi-parametric regression equations which fit a series of (cubic) polynomials to the temporal data (Pollock, 2009); see, for example Reed et al. (1994) for an example of their use in analysis of Normalised Difference Vegetation Index (NDVI) phenological parameters using satellite imagery.

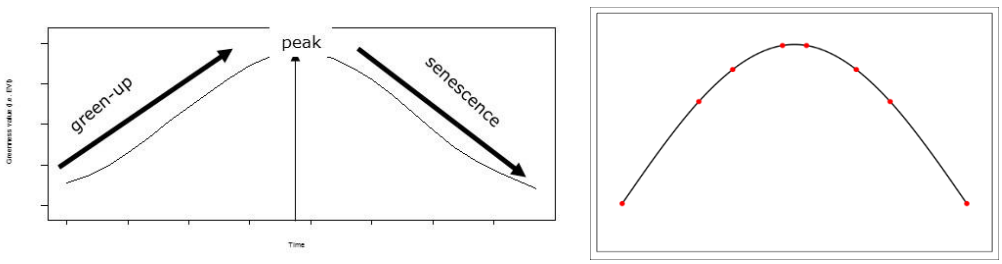


Figure 45: Modelling crop growth (left) using a cubic spline model (right)

Harmonic models

These models fit more structured sinusoidal (shaped like a sine curve) curves to the data. Here, the model parameters are the phase and amplitude. For example, Potgieter and coauthors (2007, 2010,

2011) employ these models for crop estimation using EO data. The Enhanced Vegetation Index (EVI) from 16-day MODIS satellite imagery within the cropping period (i.e. April–November) was investigated to estimate crop area for wheat, barley, chickpea, and total winter cropped area for a case study region in northeast Australia. The authors found significant overall capability to estimate total winter crop area and high accuracy at pixel scale (>98% correct classification) for identifying overall winter cropping. However, discrimination among crops was less accurate.

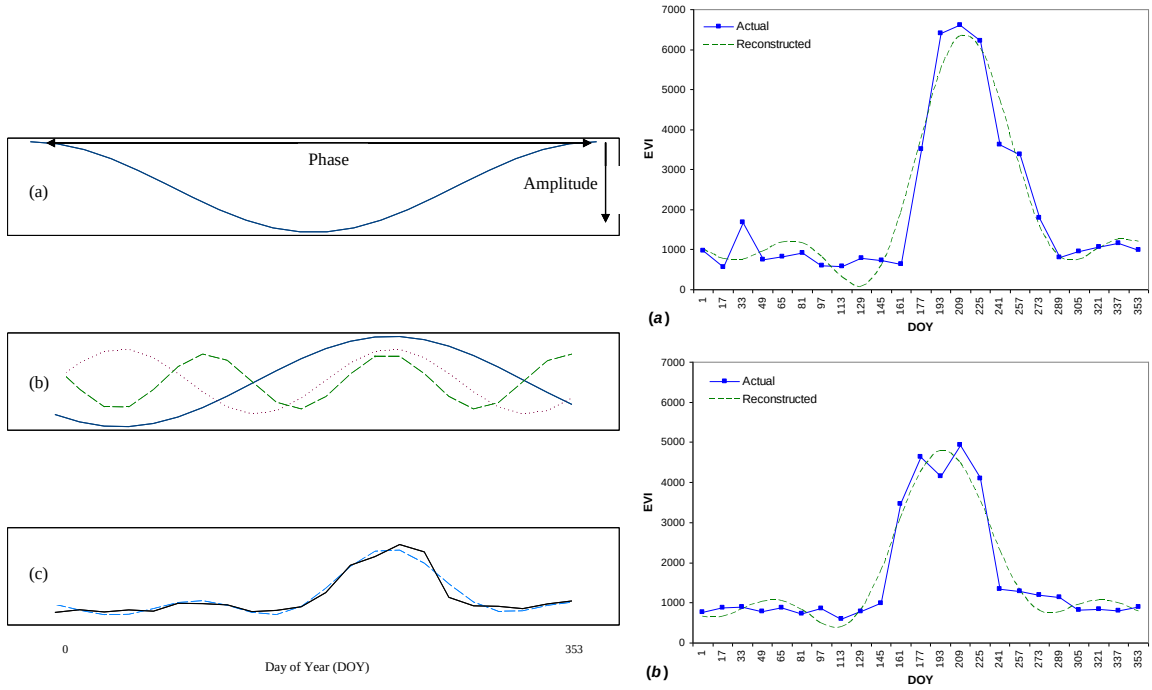


Figure 46: Illustration of harmonic analysis (left) and its application to MODIS imagery of time series of winter crops in 2005 (top right) and 2006 (bottom right). Potgeiter et al. (2007, 2011, 2013)

Spectral decomposition

Just as Principal Components Analysis (PCA) and Independent Components Analysis (ICA) are forms of dimension reduction for static data, spectral decomposition methods such as Fourier transforms can be used as dimension reduction techniques for dynamic data. These methods extract important information from high dimensional space to a smaller dimensional space. The analysis can be an end in itself, or the smaller dimensional space can then be fed to another statistical or machine learning algorithm to form an ensemble approach.

Following on from the example described above, Potgieter *et al*. (2007) utilise spectral decomposition in the form of the Fast Fourier Transform on MODIS time series data, the results of which are then used in a discriminant analysis. A similar approach (spectral decomposition of remotely sensed temporal data being fed to a discriminant analysis supervised classification technique) was undertaken in Potgieter *et al.* (2011). An alternative approach is to fit parametric curves to remotely sensed crop growth data (the previous approaches could be categorised as non-parametric in this sense). Potgieter *et al.* (2013) utilise parametric Gaussian functional curves to reduce data dimensionality, and again classify the resultant curve parameters via discriminant analysis. It is not always clear whether the discriminant analysis assumptions (multivariate normality, for example) are met in these cases.

Functional data analysis (FDA)

FDA is a nonparametric method for describing and classifying curves, in which each sample point in the time series is considered to be a function observed along an underlying continuum (e.g. time). This provides great flexibility in describing the underlying curve.

FDA approaches have been around for over two decades. For example, a FDA method for logistic regression was described by Escabias *et al.* (2005). In this paper, the authors modelled the relationship between the risk of drought and curves of temperatures. A functional logistic regression model was also employed to predict land use based on the temporal evolution of coarse-resolution EO remote sensing data by Cardot *et al.* (2003).

A more recent paper on this topic is by Liu *et al.* (2012) on rotating functional factor analyses to improve estimation of periodic temporal trends in EO data. These authors demonstrated their approach on a six-year time series at 8-day intervals of vegetation index measurements obtained from remote sensing images.

State space models

State space models have been recommended by the Australian Bureau of Statistics (ABS) for the analysis of dynamic EO data. See the paper by Tam and Clark (2015) on "A Statistical Framework for Analysing Big Data" for an exposition of the use of SSMs with reference to official statistics.

State space models are a very common form of spatio-temporal model that can provide a natural setting for analysing time series of EO data, particularly if the process to be modelled can be viewed as one that is spatially evolving through time. Depending on the nature of the data (geostatistical or lattice/areal), various spatial, temporal, and spatio-temporal dependency structures can be incorporated into the model. Cressie and Wikle (2011) devote an entire chapter (Chapter 7) to the various permutations of spatial and temporal dependency models that can be incorporated into what they denote as Dynamic Spatio-Temporal Models (DSTMs), and a further chapter (Chapter 8) to methods of inference for these models.

By far the most common approach to modelling spatio-temporal data is to assume a spatial process evolving through time (e.g. Chen *et al.* (2006), Waller *et al.* (1997), Lagazio *et al.* (2001), Knorr-Held and Besag (1998), Mugglin *et al.* (2002), Jin *et al.* (2005), Jin *et al.* (2005), Norton and Niu (2009), Allcroft and Glaseby (2003), Zhu *et al.* (2005), Zhu *et al.* (2008), Zheng and Zhu (2008), Daniels *et al.* (2006), Ugarte *et al.* (2010)). As noted in Cressie and Wikle (2011), this approach is conceptually reasonable in many applications, and enables the spatio-temporal process to fit within the remit of a dynamic spatial modelling approach, or the state space modelling framework. This approach was investigated by the Australian Bureau of Statistics as a pilot project.
A linear Gaussian state space model takes the general form

$$\begin{aligned} Y_t &= H_t X_t + v_t, & v_t &\sim N_{m_t}(0, R_t) \\ X_t &= M_t X_{t-1} + w_t, & w_t &\sim N_n(0, Q_t)\ , \end{aligned}$$

where, for time $t, t = 1, \cdots, T$, Y_t denotes the m_t-dimensional data vector, X_t denotes the n-dimensional unobserved "state" vector, v_t is the serially independent observation error, and w_t is the serially independent innovation error (Shumway and Stoffer, 2011). It is generally assumed that v_t and w_t are mutually independent. It is also generally assumed that the observation matrix H_t, the state transition

matrix M_t (also known as the evolution or propagator matrix), and the two covariance matrices R_t and Q_t, are known, although this can be relaxed.

Typically the main mechanism for incorporating spatio-temporal dependencies is through the covariance matrices R_t and Q_t. It is common, for example, to view the states X_t as being driven not only by temporal processes but also by spatial ones, thus some form of spatial structure is placed on Q_t. This may take the form of one of the common covariance function structures for geostatistical data or perhaps a sparse, neighbour-based covariance matrix induced by assuming a Markov random field in lattice data. Spatial, temporal, or spatio-temporal structures can also be assumed on the measurement structure.

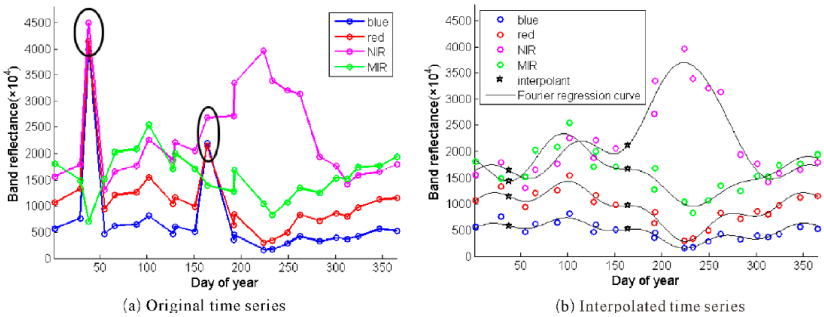
Extensions to these models include non-Gaussian state-space models, non-linear observation equation models, agent-based approaches, generalised additive mixed effects models and multivariate response models. Another important area of research in this context is dimension reduction via spectral decompositions. Such dimension reduction can substantially reduce computational load when fitting these dynamic models to data.

State space models have been employed for crop estimation and prediction for over 15 years. For example, Wendroth et al. (2003) used this approach to predict yield of barley across a landscape. More recently, Schneibel et al. (2017) applied the method to annual Landsat time series data with the aim of detecting dry forest degradation processes in South-Central Angola.

An example of using a Hidden Markov Model to analyse EO data is given by Yuan et al. (2015) in the context of detecting urban encroachment onto farmland in China. Two sources of data were used in this study:

- MODIS data 2001-2010 (large-scale coverage, high temporal resolution [16 day], open) downloaded from the Level 1 and Atmosphere Archive and Distribution System (LAADS) website; this provided four spectral reflectance bands for vegetation and land surface, i.e., band 1 (red: 620–670 nm), band 2 (NIR: 841–875 nm), band 3 (blue: 459–479 nm), band 7 (MIR: 2105–2155 nm)
- ESA Global Land Cover (GlobCover) map for 2009, for model training: farmland, built-up classes.

As a pre-processing step, Functional Analysis (via a Fourier model, see above) was used to create high quality time series of band reflectances. A k-means analysis was also employed to cluster land use, using training data. A sliding window was then used to smooth estimates and a Hidden Markov Model was employed to identify change in classes. The authors obtained 96% correct change detection and 0.04% false alarm.



(a) Original time series (b) Interpolated time series

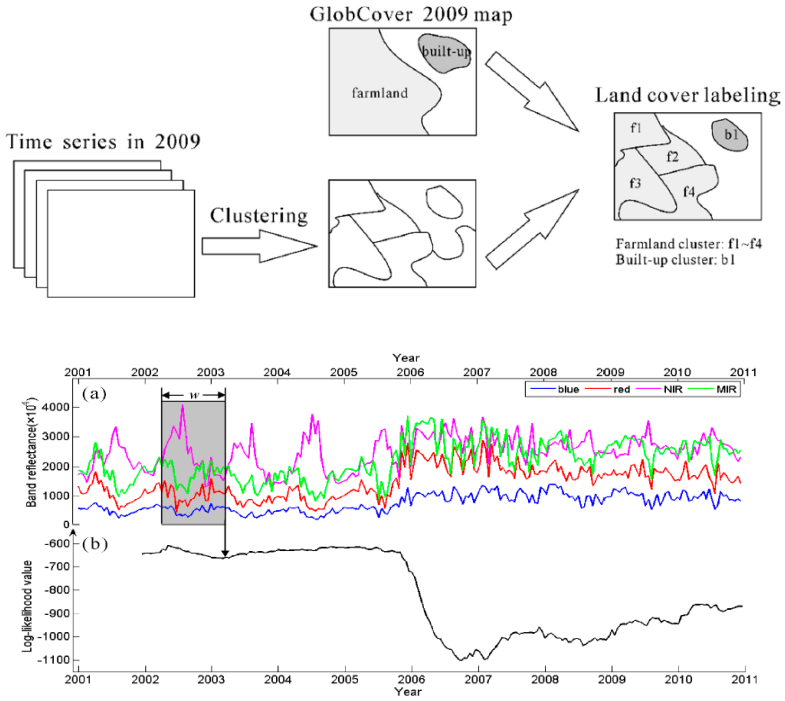


Figure 47: (Top) Functional analysis employed to interpolate EO data time series. (Middle) K-means clustering employed to classify farmland. (Bottom) Hidden Markov model to identify urban encroachment. Yuan et al. (2015)

A.4 Choice between methods

Comparisons between various empirical methods and machine learning approaches have been made for over a decade. Advantages and disadvantages of the different methods depend on the nature of the problem. Some examples of these comparisons are as follows:

- A comparison was made by Hogland *et al.* (2013) between the ML technique and multinomial (a.k.a. polytomous) logistic regression for the analysis of remotely sensed data. Their conclusion was that the logistic regression methods were less restrictive, more flexible and easier to interpret. The authors also referenced papers that show these approaches perform at least as well as other machine learning techniques; see below.
- De Melo *et al.* (2003) compared ML with Gaussian mixture models for supervised classification of remote sensing multispectral images, with a general preference for Gaussian mixture models.
- Shao and Lunetta (2012) compared support vector machines (SVMs) to neural networks and CART (classification and regression trees) on limited training data for Land cover classification using MODIS time series data.
- Otukei and Blaschke (2010) considered land cover change assessment using decision trees, SVMs (with a radial basis kernel function), and the maximum likelihood classifier and concluded that decision trees performed best.
- Szuster et al. (2011) compared maximum likelihood classification and ANNs to SVMs for land use and land cover classification in tropical coastal zones.

- Yang et al. (2011) assessed various supervised classifiers using SPOT 5 imagery (a high resolution satellite), and found that the maximum likelihood and support vector machine techniques performed best of those considered.
- Huang et al. (2002a) investigated SVMs for land cover classification and compared to neural networks, maximum likelihood, and decision trees.
- Melgani and Bruzzone (2004) considered SVMs for remotely sensed data, comparing their use to that of neural networks (radial basis function NNs) and *K*-nearest neighbour (K-NN). They concluded that SVMs are a viable option.
- Yang et al. (2011) assessed various supervised classifiers using SPOT 5 imagery (a high resolution satellite and found that maximum likelihood and SVM techniques peformed best.

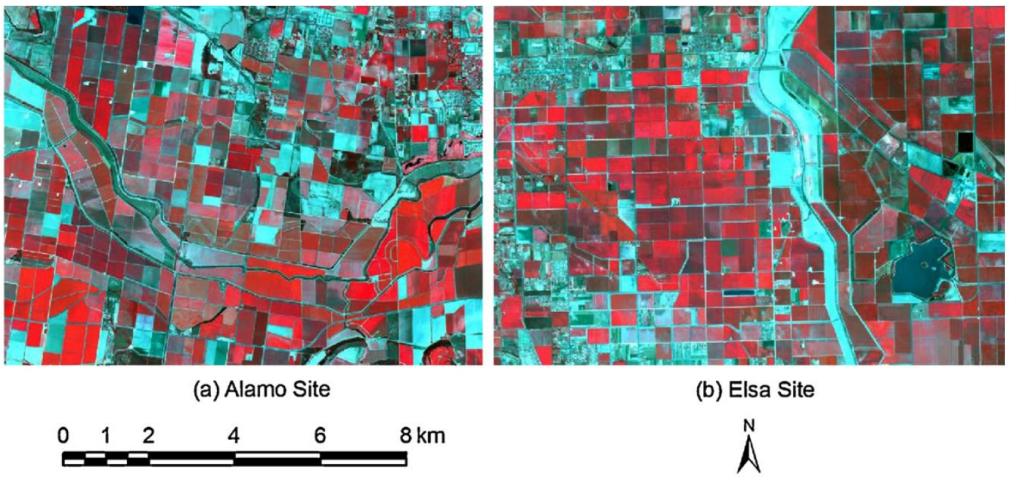


Fig. 1. Color-infrared composites extracted from a 10-m SPOT 5 satellite image for two intensively cropped areas near Alamo and Elsa, Texas.

Figure 48: Crop identification using EO data. Yang et al. (2011)

A.5 Combining methods

Instead of choosing a single method, an increasingly popular approach in the machine learning literature is to combine approaches.

An example of the combination of different methods for improved classification is given by Sweeney *et al.* (2015). These authors combined probabilistic modelling, in the form of logistic regression, with traditional remote sensing approaches to obtain maps of small-scale cropland. While the various methods are well established, the authors argued that the novelty of their approach is in the sequence of their application and the way in which they are combined.

An example of the combination of different methods for improved clustering in remotely sensed images is given by Neagoe and Chirila-Berbentea (2016). In this paper, the authors propose a merger of kNN and Gaussian mixture models, whereby the former method is used to identify starting points for the latter method and EM (expectation maximisation) is employed for analysis.

References

ABARES, (2016). Agricultural Commodity Statistics 2016. Australian Bureau of Agricultural and Resource Economics and Sciences, Canberra. Retrieved from www.agriculture.gov.au/abares/publications/display?url=http://143.188.17.20/anrdl/DAFFService/display.php%3Ffid%3Dpb_agcstd9abcc0022016_Sn9Dg.xml

Adams, J. B., Sabol, D. E., Kapos, V., Almeida Filho, R., Roberts, D. A., Smith, M. O. and Gillespie, A. R. (1995). Classification of multispectral images based on fractions of endmembers: Application to land-cover change in the Brazilian Amazon. *Remote sensing of Environment*, 52(2), 137–154.

Allcroft, D. J. and Glaseby, C. A. (2003). A latent Gaussian Markov random field model for spatio-temporal rainfall disaggregation. *Journal of the Royal Statistical Society. Series C: Applied Statistics*, 52(4), 487–498.

Al-Obeidat, F., Al-Taani, A. T., Belacel, N., Feltrin, L. and Banerjee, N. (2015). A Fuzzy Decision Tree for Processing Satellite Images and Landsat Data. *Procedia Computer Science*, 52, 1192–1197.

Anderson, K., Ryan, B., Sonntag, W., Argyro, K., Friedl, L. (2017) Earth observation in service of the 2030 Agenda for Sustainable Development, *Geo-spatial Information Science*, 20:2, 77-96.

Aplin, P. and Atkinson, P. M. (2001). Sub-pixel land cover mapping for per-field classification. *International Journal of Remote Sensing*, 22(14), 2853–2858.

Aplin, P., Atkinson, P. M., Curran, P. J. and Others (1999). Per-field classification of land use using the forthcoming very fine spatial resolution satellite sensors: problems and potential solutions. *Advances in remote sensing and GIS analysis*, pp. 219–239.

Atkinson, P. M. and Tatnall, A. R. L. (1997). Introduction neural networks in remote sensing. *International Journal of remote sensing*, 18(4), 699–709.

Augustin, N. H., Musio, M., von Wilpert, K., Kublin, E., Wood, S. N. and Schumacher, (2009). Modelling spatio temporal forest health monitoring data. *Journal of the American Statistical Association*,104 (487), 899-911.

Baíllo, A., Cuesta-Albertos, J. A. and Cuevas, A. (2011a). Supervised Classification for a Family of Gaussian Functional Models. *Scandinavian Journal of Statistics*, 38, 480– 498.

Baíllo, A., Cuevas, A. and Fraiman, R. (2011b). Classification Methods for Functional Data. In *The Oxford Handbook of Functional Data Analysis*. (Eds F. Ferraty and Y. Romain), pp. 259–297. Oxford: Oxford University Press, UK.

Banerjee, S., Carlin, B. P. and Gelfand, A. E. (2014). *Hierarchical modeling and analysis for spatial data*. Crc Press, second edition.

Banerjee, S., Gelfand, A. E., Finley, A. O. and Sang, H. (2008). Gaussian Predictive Process Models for Large Spatial Data Sets. *Journal of the Royal Statistical Society. Series B (Statistical Methodology)*, 70(4), 825–848.

Bastin, L. (1997). Comparison of fuzzy c-means classification, linear mixture modelling and MLC probabilities as tools for unmixing coarse pixels. *International Journal of Remote Sensing*, 18(17), 3629–3648.

Bateson, C., Asner, G. P., Wessman, C. and Others (2000). Endmember bundles: A new approach to incorporating endmember variability into spectral mixture analysis. *Geo- science and Remote Sensing, IEEE Transactions on*, 38(2), 1083–1094.

Bavaghar, P. (2015) Deforestation modelling using logistic regression and GIS. *Journal of Forest Science* 61, 193-199.

Bédard, F. and Reichert, G. (2013). Integrated Crop Yield and Production Forecasting using Remote Sensing and Agri-Climatic data. Analytical Projects Initiatives final report. Remote Sensing and Geospatial Analysis, Agriculture Division, Statistics Canada

Benediktsson, J. A. and Swain, P. H. (1992). Consensus theoretic classification methods. *IEEE Trans. Syst., Man, Cybern.*, vol. 22, 688–704.

Benediktsson, J. A., Sveinsson, J. R. and Swain, P. H. (1997). Hybrid consensus theoretic classification. *Geoscience and Remote Sensing, IEEE Transactions on*, 35(4), 833–843.

Benz, U. C., Hofmann, P., Willhauck, G., Lingenfelder, I. and Heynen, M. (2004). Multi- resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of photogrammetry and remote sensing*, 58(3), 239–258.

Berliner, L. M., Wikle, C. K. and Cressie, N. (2000). Long-lead prediction of Pacific SSTs via Bayesian dynamic modeling. *Journal of Climate*, 13(22), 3953–3968.

Berliner, L. M., Wikle, C. K. and Milliff, R. F. (1999). Multiresolution wavelet analyses in hierarchical Bayesian turbulence models. In *Bayesian inference in wavelet-based models* (Eds P. Mueller and B. Vidakovic), Chapter 21, pp. 341–359. New York: Springer.

Bernardinelli, L., Clayton, D., Pascutto, C., Montomoli, C., Ghislandi, M. and Songini, M. (1995). Bayesian analysis of space–time variation in disease risk. *Statistics in medicine*, 14(21-22), 2433–2443.

Besag, J. (1974). Spatial interaction and the statistical analysis of lattice systems. *Journal of the Royal Statistical Society. Series B (Methodological)*, 36(2), 192–236.

Bigdeli, B., Samadzadegan, F. and Reinartz, P. (2015). Fusion of hyperspectral and LIDAR data using decision template-based fuzzy multiple classifier system. *International Journal of Applied Earth Observation and Geoinformation*, 38, 309–320.

Billheimer, D., Cardoso, T., Freeman, E., Guttorp, P., Ko, H. W. and Silkey, M. (1997). Natural variability of benthic species composition in the Delaware Bay. *Environmental and Ecological Statistics*, 4(2), 95–115.

Blangiardo, M., Cameletti, M., Baio, G. and Rue, H. H. (2013). Spatial and spatio– temporal models with R--INLA. *Spatial and Spatio–temporal Epidemiology*, 7, 39–55.

Blanzieri, E. and Melgani, F. (2008). Nearest neighbor classification of remote sensing images with the maximal margin principle. *Geoscience and Remote Sensing, IEEE Transactions on*, 46(6), 1804–1811.

Bolin, D. and Lindgren, F. (2013). A comparison between Markov approximations and other methods for large spatial data sets. *Computational Statistics & Data Analysis*, 61, 7–21.

Bradley, J. R., Wikle, C. K. and Holan, S. H. (2016) Bayesian Spatial Change of Support for Count-Valued Survey Data with Application to the American Community Survey. *Journal of the American Statistical Association*, 0(ja), 1–43.

Breiman, L. (1996). Bagging Predictors. *Machine Learning*, 24(2), 123–140.

Breiman, L. (2001) Statistical modeling: the two cultures. *Statistical Science* 16(9), 199-231.

Breiman, L., Friedman, J., Stone, C. J. and Olshen, R. A. (1984). *Classification and Regression Trees.* CRC press.

Briem, G. J., Benediktsson, J. A. and Sveinsson, J. R. (2002). Multiple classifiers applied to multisource remote sensing data. *Geoscience and Remote Sensing, IEEE Transactions on*, 40(10), 2291–2299.

Brynjarsdóttir, J. and Berliner, M. (2014). Dimension–Reduced Modelling of Spatio– Temporal Processes. *Journal of the American Statistical Association*, 109(508), 1647– 1659.

Cablk, M.E. and Minor, T.B. (2003). Detecting and discriminating impervious cover with high-resolution IKONOS data using principal component analysis and morphological operators. *International Journal of Remote Sensing*, 24: 4627–4645.

Çalış, N. and Erol, H. (2012). A new per-field classification method using mixture discriminant analysis. *Journal of Applied Statistics*, 39(10), 2129–2140.

Calder, C. A. (2007). Dynamic factor process convolution models for multivariate space- time data with application to air quality assessment. *Environmental and Ecological Statistics*, 14(3), 229–247.

Call , K.A., Hardy, J.T., and Wallin, D. O. (2003). Coral reef habitat discrimination using multivariate spectral analysis and satellite remote sensing. *International Journal of Remote Sensing*, 24: 2627–2639.

Cao, Q., Guo, Z. and Yang, Y. (2015). An improved back propagation neural network approach to the remote sensing land use and land cover classification. *Computer Science and Applications: Proceedings of the 2014 Asia-Pacific Conference on Computer Science and Applications (CSAC 2014), Shanghai, China, 27-28 December 2014*, 369. CRC Press.

Cardot H, Faivre R, Goulard M (2003) Functional approaches for predicting land use with the temporal evolution of coarse resolution remote sensing data. Journal of Applied Statistics 30: 1185-1199.

Carlin, B. P., Polson, N. G. and Stoffer, D. S. (1992). A Monte Carlo approach to non-normal and nonlinear state-space modelling. *Journal of the American Statistical Association*, 87(418), 493–500.

Carr, J. R. (1999). Classification of digital image texture using variograms. *Advances in remote sensing and GIS analysis*, pp. 135–146.

Cavalli, R.M., Licciardi, G.A., and Chanussot, J. (2013). Detection of Anomalies Produced by Buried Archaeological Structures Using Nonlinear Principal Component Analysis Applied to Airborne

Hyperspectral Image. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 6: 659 – 669.

Chasmer, L., Hopkinson, C., Veness, T., Quinton, W. and Baltzer, J. (2014). A decision- tree classification for low-lying complex land cover types within the zone of discontinuous permafrost. *Remote Sensing of Environment*, 143, 73–84.

Chen, K. S., Tzeng, Y. C., Chen, C. F. and Kao, W. L. (1995). Land-cover classification of multispectral imagery using a dynamic learning neural network. *Photogrammetric Engineering and Remote Sensing*, 61(4), 403–408.

Chen, L., Fuentes, M. and Davis, J. M. (2006). Spatial-temporal statistical modelling and prediction of environmental processes. In *Hierarchical Modelling for the Environmental Sciences: Statistical methods and applications* (Eds J. S. Clark and A. E. Gelfand), chapter 7, pp. 121–144. New York: Oxford University Press.

Chiang, S.-S., Chang, C.-I. and Ginsberg, I. W. (2000). Unsupervised hyperspectral image analysis using independent component analysis. *Geoscience and Remote Sensing Symposium Proceedings. IGARSS 2000. IEEE 2000 International*, volume 7, pp. 3136–3138.

Chipanshi, A., Zhang, Y., Kouadio, L., Newlands, N., Davidson, A., Hill, H., Warren, R., Qian, B., Daneshfar, B., Bedard, F. and Reichert, G. (2015). Evaluation of the Integrated Canadian Crop Yield Forecaster (ICCYF) Model for In-season Prediction of Crop Yield across the Canadian Agricultural Landscape. Agricultural and Forest Meteorology, 206:137-150. DOI: http://dx.doi.org/10.1016/j.agrformet.2015.03.007

Clark, J. S. and Gelfand, A. E. (2006). *Hierarchical Modelling for the Environmental Sciences: Statistical methods and applications*. New York: Oxford University Press, UK.

Clayton, D. G. (1996). Generalized Linear Mixed Models. In *Markov Chain Monte Carlo in Practice* (Eds W. Gilks, S. Richardson and D. Spiegelhalter), 275–301. Chapman & Hall.

Clayton, D. G. and Bernardinelli, L. (1992). Bayesian methods for mapping disease risk. In *Geographical and Environmental Epidemiology: Methods for Small–Area Studies* (Eds P. Elliot, J. Cuzick, D. English and R. Stern), 205–220. UK: Oxford University Press.

Cliff, A. D. and Ord, J. K. (1981). *Spatial processes: models and applications*. London, UK: Pion.

Clinton, N., Yu, L. and Gong, P. (2015). Geographic stacking: Decision fusion to increase global land cover map accuracy. *ISPRS Journal of Photogrammetry and Remote Sensing*, 103, 57–65.

Collins, M. J., Dymond, C. and Johnson, E. A. (2004). Mapping subalpine forest types using networks of nearest neighbour classifiers. *International Journal of Remote Sensing*, 25(9), 1701–1721.

Cowles, M. K. (2003). Efficient model-fitting and model-comparison for high-dimensional Bayesian geostatistical models. *Journal of Statistical Planning and Inference*, 112(1-2), 221–239.

Crammer, K. and Singer, Y. (2002). On the algorithmic implementation of multiclass kernel-based vector machines. *The Journal of Machine Learning Research*, 2, 265– 292.

Cressie, N. A. C. (1993). *Statistics for Spatial Data Revised Edition*. Wiley Series in probablility and mathematical statistics. New York: John Wiley & Sons, Inc.

Cressie, N. and Huang, H.-C. (1999). Classes of nonseparable, spatio-temporal stationary covariance functions. *Journal of the American Statistical Association*, 94(448), 1330– 1339.

Cressie, N. and Verzelen, N. (2008). Conditional-mean least-squares fitting of Gaussian Markov random fields to Gaussian fields. *Computational Statistics and Data Analysis*, 52(5), 2794–2807.

Cressie, N. and Wikle, C. K. (2011). *Statistics for Spatio–Temporal Data*. Wiley.

Cressie, N., Shi, T. and Kang, E. L. (2010a). Fixed Rank Filtering for Spatio-Temporal Data. *Journal of Computational and Graphical Statistics*, 19(3), 724–745.

Cressie, N., Shi, T. and Kang, E. L. (2010b). Fixed rank filtering for spatio–temporal data.

Cuevas, A. (2014). Journal of Statistical Planning and Inference A partial overview of the theory of statistics with functional data. *Journal of Statistical Planning and Inference*, 147, 1–23.

Curzio, S.L. and Magliulo, P. (2010). Soil erosion assessment using geomorphological remote sensing techniques: an example from southern Italy. *Earth Surface Processes and Landforms* 35: 262–271.

Daniels, M. J., Zhou, Z. and Zou, H. (2006). Conditionally Specified Space-Time Models for Multivariate Processes. *Journal of Computational and Graphical Statistics*, 15(1), 157–177.

De Fries, R. S., Hansen, M., Townshend, J. R. G. and Sohlberg, R. (1998). Global land cover classifications at 8 km spatial resolution: the use of training data derived from Landsat imagery in decision tree classifiers. *International Journal of Remote Sensing*, 19(16), 3141–3168.

De Melo, A.C.O, de Moraes, R.M., dos Santos Machado, L. (2003) Gaussian mixture models for supervised classification of remote sensing multispectral images. In Progress in Pattern Recognition, Speech and Image Analysis, Volume 2905 of the series Lecture Notes in Computer Science, pp. 440-447.

De Wit, A. J. W. and Clevers, J. (2004). Efficiency and accuracy of per-field classification for operational crop mapping. *International journal of remote sensing*, 25(20), 4091– 4112.

Dekker, A., Peters, S., Vos, R., Rijkeboer, M. (2013) Remote sensing for inland water quality detection and monitoring: state-of-the-art application in Friesland waters. In van Dijk, A., Bos, G. (Eds) GIS and Remote Sensing Techniques in Land and Water management. CRC Press. Chapter 3.

Delaigle, A. and Hall, P. (2012a). Achieving near perfect classification for functional data. *Journal of the Royal Statistical Society. Series B: Statistical Methodology*, 74(2), 267– 286.

Delaigle, A. and Hall, P. (2012b). Methodology and theory for partial least squares applied to functional data. *Annals of Statistics*, 40(1), 322–352.

Delaigle, A., Hall, P. and Bathia, N. (2012). Componentwise classification and clustering of functional data. *Biometrika*, 99(2), 299–313.

Delsol, L., Ferraty, F. and Martinez-Calvo, A. (2011). Functional Data Analysis: An Interdisciplinary Statistical Topic. In *Statistical Learning and Data Science.* (Eds.

Dennison, P. E. and Roberts, D. A. (2003). Endmember selection for multiple endmember spectral mixture analysis using endmember average RMSE. *Remote Sensing of Environment*, 87(2), 123–135.

Diggle, P. J. and Ribeiro, P. J. J. (2007). *Model–Based Geostatistics*. New York: Springer.

Doucet, A., de Freitas, N. and Gordon, N. (eds) (2001). *Sequential Monte Carlo methods in practice*. New York: Springer Science & Business Media.

Du, P., Xia, J., Zhang, W., Tan, K., Liu, Y. and Liu, S. (2012). Multiple classifier system for remote sensing image classification: A review. *Sensors*, 12(4), 4764–4792.

Elith, J., Leathwick, J.R., Hastie, T. (2008) A working guide to boosted regression trees. *Journal of Animal Ecology* 77, 802-813.

Erbek, F. S., Özkan, C. and Taberner, M. (2004). Comparison of maximum likelihood classification method with supervised artificial neural network algorithms for land use activities. *International Journal of Remote Sensing*, 25(9), 1733–1748.

Erol, H. and Akdeniz, F. (2005). A per-field classification method based on mixture distribution models and an application to Landsat Thematic Mapper data. *International Journal of Remote Sensing*, 26(6), 1229–1244. Evensen, G. (2009) Data assimilation: the ensemble Kalman filter. New York: Springer Science & Business Media, second edition.

Escabias M., Aguilera, A.M., Valderrama, M.J. (2005). Modelling environmental data by functional principal component logistic regression. *Environmetrics* 16: 95-107.

Esch, T., Taubenbock, H., Roth, A., Heldens, W., Felbier, A., Thiel, M., Schmidt, M., Muller, A., Dech, S. (2012). TanDEM-X mission – new perspectives for the inventory and monitoring of global settlement patterns. *Journal of Applied Remote Sensing* 6(1), 061702-1-061702-21.

Estornell, J., Marti-Gavila, J.M. , Sebastia, M. T. and Mengual, J. (2013). Principal component analysis applied to remote sensing. *Modelling in Science Education and Learning*, 6(2): 83–89.

European Commission (2016). MARS bulletins May 2016. Retrieved from https://ec.europa.eu/jrc/en/publication/eur-scientific-and-technical-research-reports/jrc-mars-bulletin-crop-monitoring-europe-may-2016-fairly-good-outlook-despite-unsettled

Fan, J., Han, F. and Liu, H. (2014). Challenges of Big Data analysis. National Science Review (June 2014) 1 (2): 293-314. Retrieved from http://nsr.oxfordjournals.org/content/1/2/293.full.

Febrero-Bande, M. and de la Fuente, M. O. (2012). Statistical Computing in Functional Data Analysis: The RPackage fda.usc. *Journal of Statistical Software*, 51(4), 1–28.

Fernández-Prieto, D. (2002). An iterative approach to partially supervised classification problems. *International Journal of Remote Sensing*, 23(18), 3887–3892.

Ferraty, F. and Romain, Y. (eds) (2011). *The Oxford Handbook of Functional Data Analysis.* Oxford: Oxford University Press, UK.

Ferreira, M. A. R., Holan, S. H. and Bertolde, A. I. (2011). Dynamic multiscale spatiotemporal models for Gaussian areal data. *Journal of the Royal Statistical Society. Series B: Statistical Methodology*, 73(5), 663–688.

Finkenstädt, B., Held, L. and Isham, V. (eds) (2007). *Statistical methods for spatio- temporal systems*. Boca Raton, FL: CRC Press.

Fix, E. and Hodges Jr, J. L. (1951). Discriminatory analysis-nonparametric discrimination: consistency properties. Technical report, DTIC Document.

Food and Agriculture Organisation (FAO) (2016). FAO Cereal Supply and Demand Brief. Retrieved from http://www.fao.org/worldfoodsituation/csdb/en/.

Foody, G. M. (1996a). Approaches for the production and evaluation of fuzzy land cover classifications from remotely-sensed data. *International Journal of Remote Sensing*, 17(7), 1317–1340.

Foody, G. M. (1996b). Fuzzy modelling of vegetation from remotely sensed imagery. *Ecological modelling*, 85(1), 3–12.

Foody, G. M. (1997). Fully fuzzy supervised classification of land cover from remotely sensed imagery with an artificial neural network. *Neural Computing & Applications*, 5(4), 238–247.

Foody, G. M. (1999). Image classification with a neural network: from completely-crisp to fully-fuzzy situations. *Advances in remote sensing and GIS analysis*, pp. 17–37.

Foody, G. M. and Arora, M. K. (1997). An evaluation of some factors affecting the accuracy of classification by an artificial neural network. *International Journal of Remote Sensing*, 18(4), 799–810.

Foody, G. M., Lucas, R. M., Curran, P. J. and Honzak, M. (1997). Non-linear mixture modelling without end-members using an artificial neural network. *International Journal of Remote Sensing*, 18(4), 937–953.

Foody, G. M., McCulloch, M. B. and Yates, W. B. (1995). Classification of remotely sensed data by an artificial neural network: issues related to training data characteristics. *Photogrammetric Engineering and Remote Sensing*, 61(4), 391–401.

Franco-Lopez, H., Ek, A. R. and Bauer, M. E. (2001). Estimation and mapping of forest stand density, volume, and cover type using the k-nearest neighbors method. *Remote sensing of environment*, 77(3), 251–274.

Freund, Y., Schapire, R. E. and Others (1996). Experiments with a new boosting algorithm. In *ICML*, volume 96, pp. 148–156.

Friedl, M. A. and Brodley, C. E. (1997). Decision tree classification of land cover from remotely sensed data. *Remote sensing of environment*, 61(3), 399–409.

Friedman, J., Hastie, T. and Tibshirani, R. (2010) Regularisation Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–22.

Friedman, J., Hastie, T., Tibshirani, R. and Others (2000). Additive logistic regression: a statistical view of boosting (with discussion and a rejoinder by the authors). *The annals of statistics*, 28(2), 337–407.

Frühwirth-Schnatter, S. (2006). *Finite Mixture and Markov Switching Models.* New York: Springer.

Fulcher, B.D., Little, M.A., Jones, N.S. (2013). Highly comparative time-series analysis: the empirical structure of time series and their methods. *Journal of the Royal Society* https://doi.org/10.1098/rsif.2013.0048

Fuentes, M., Chen, L. and Davis, J. M. (2008). A class of nonseparable and nonstationary spatial temporal covariance functions. *Environmetrics*, 19, 487–507.

Gallego, J.C.M., Michaelsen, J., Bossyns, B., Fritz, S. (2008) Best practices for crop area estimation with Remote Sensing. GEOSS Community of Practice Ag 0703a. JRC Scientific and Technical Reports. Retrieved from https://www.earthobservations.org/documents/cop/ag_gams/GEOSS%20best%20practices%20area%20estimation%20final.pdf

Gao, F., Masek, J., Schwaller, M., and Hall, F. (2006). On the blending of the Landsat and MODIS surface reflectance: predict daily Landsat surface reflectance. Remote Sensing, 44(8), 2207-2218

Gao, F., Anderson, M.C., Zhang, X., Yang, Z., Alfieri, J.G., Kustas, W.P., Mueller, R., Johnson, D.M., and J.H. Prueger. (2017). Toward mapping crop progress at field scales using Landsat and MODIS imagery. *Remote Sens. Environ.*, 188, 9–25.

Geib, C., Taubenbock, H. (2013) Remote sensing contributing to assess earthquake risk: from a literature review towards a roadmap. *Natural Hazards* 68 (1), 7-48.

Gelfand, A. E. and Vounatsou, P. (2003). Proper multivariate conditional autoregressive models for spatial data analysis. *Biostatistics*, 4(1), 11–25.

Gelfand, A. E., Diggle, P. J., Fuentes, M. and Guttorp, P. (eds) (2010). *Handbook of Spatial Statistics*. Boca Raton, FL: Chapman & Hall.

Gelfand, A. E., Schmidt, A. M., Banerjee, S. and Sirmans, C. F. (2004). Nonstationary multivariate process modeling through spatially varying coregionalization. *Test*, 13(2), 263–312.

Geneletti, D. and Gorte, B. G. H. (2003). A method for object-oriented land cover classification combining Landsat TM data and aerial photographs. *International Journal of Remote Sensing*, 24(6), 1273–1286.

Gettler-Summa, M., Bottou, L., Goldfarb, B., Murtagh, F., Pardoux, C., and Touati, M. (2011). Statistical Learning and Data Science p. 189–195. Boca Raton, FL: Chapman & Hall.

Ghosh, A., Mishra, N. S. and Ghosh, S. (2011). Fuzzy clustering algorithms for unsupervised change detection in remote sensing images. *Information Sciences*, 181(4), 699–715.

Ghosh, A., Subudhi, B. N. and Bruzzone, L. (2013). Integration of Gibbs Markov random field and Hopfield-type neural networks for unsupervised change detection in remotely sensed multi-temporal images. *Image Processing, IEEE Transactions on*, 22(8), 3087– 3096.

Global Strategy 2017. Handbook on Remote Sensing for Agricultural statistics. Rome, www.gsars.org, 250pp.

Gneiting, T. (2002). Nonseparable , Stationary Covariance Functions for Space-Time Data. *Journal of the American Statistical Association*, 97(458), 590–600.

Goldfarb, B., Murtagh, F., Pardoux, C., and Touati, M., pp. 197–203. Boca Raton, FL: Chapman & Hall.

González - Manteiga, W. and Vieu, P. (2011). Methodological Richness of Functional Data Analysis. In *Statistical Learning and Data Science.*

Gordon, N., Salmond, D. and Smith, A. (1993). Novel approach to nonlinear/non-Gaussian Bayesian state estimation. *IEE Proceedings F Radar and Signal Processing*, 140(2), 107–113.

Grenzdörffer, G. (2001). Requirements and possibilities of remote sensing for precision agriculture - current status and future developments. In: Grenier, G., and Blackmoore S. [ed.] (2001). Proceedings of the Third European Conference on Precision Agriculture, Montpellier June 18th-21st, 1, 211 – 216.

Guerschman, J. P. , Donohue, R. J., Van Niel T. G., Renzullo L. J., Dekker A. G. , Malthus T. J., McVicar T. R. and Van Dijk, A. I. J. M. (2016). Earth observation for water resources management Part II in Earth observation for water resources management: current use and future opportunities for the water sector, (2016) Eds. García, L., Rodríguez, D., Wijnen, M. and Pakulski, I., World Bank, Washington, US. ISBN: 978-1-4648-0475-5; e-ISBN: 978-1-4648-0476-2 ; http://dx.doi.org/10.1596/978-1-4648-0475-5., PDF: https://openknowledge.worldbank.org/bitstream/handle/10986/22952/9781464804755.pdf

Guha, S., Hafen, R., Rounds, J., Xia, J., Li, J., Xi, B. and Cleveland, W. S. (2012). Large complex data: divide and recombine (D & R) with RHIPE. *Stat*, 1, 53–67.

Haapanen, R., Ek, A. R., Bauer, M. E. and Finley, A. O. (2004). Delineation of forest/nonforest land use classes using nearest neighbor methods. *Remote Sensing of Environment*, 89(3), 265–271.

Han, M. and Liu, B. (2015). Ensemble of extreme learning machine for remote sensing image classification. *Neurocomputing*, 149, 65–70.

Hansen, M. C., DeFries, R. S., Townshend, J. R. G. and Sohlberg, R. (2000). Global land cover classification at 1 km spatial resolution using a classification tree approach. *International journal of remote sensing*, 21(6-7), 1331–1364.

Hansen, M., Dubayah, R. and DeFries, R. (1996). Classification trees: an alternative to traditional land cover classifiers. *International journal of remote sensing*, 17(5), 1075– 1081.

Hardin, P. J. (1994). Parametric and nearest-neighbor methods for hybrid classification: a comparison of pixel assignment accuracy. *Photogrammetric Engineering and Remote Sensing*, 60(12), 1439–1448.

Hardin, P. J. and Thomson, C. N. (1992). Fast nearest neighbor classification methods for multispectral imagery. *The Professional Geographer*, 44(2), 191–202.

Hastie, T., Tibshirani, R. and Friedman, J. (2009). The Elements of Statistical Learning Data Mining, Inference and Prediction. New York: Springer, second edition.

Hentze, K., Thonfeld, F. and Menz, G. (2016). Evaluating Crop Area Mapping from MODIS Time-Series as an Assessment Tool for Zimbabwe's "Fast Track Land Reform Programme". *PloS one*, *11*(6).

Hogland, J., Billor, N., Anderson, N. (2013) Comparison of standard maximum likelihood classification and polytomous logistic regression used in remote sensing. *European Journal of Remote Sensing* 46, 623-640.

Hooten, M. B. and Wikle, C. K. (2008). A hierarchical Bayesian non-linear spatio- temporal model for the spread of invasive species with application to the Eurasian Collared-Dove. *Environmental and Ecological Statistics*, 15(1), 59–70.

Hooten, M. B. and Wikle, C. K. (2010). Statistical Agent-Based Models for Discrete Spatio-Temporal Systems. *Journal of the American Statistical Association*, 105(October 2014), 236–248.

Hooten, M. B., Wikle, C. K., Dorazio, R. M. and Royle, J. A. (2007). Hierarchical spatio-temporal matrix models for characterizing invasions. *Biometrics*, 63(2), 558–567.

Hoque, Phinn, S. et al. (2016) Assessing tropical cyclone impacts using object-based moderate spatial resolution image analysis: a case study in Bangladesh. International Journal of Remote Sensing, 37 22: 5320-5343.

Hoque, Phinn, S. et al. (2017): Modelling tropical cyclone risks for present and future climate change scenarios using geospatial techniques. International Journal of Digital Earth, 1-18.

Horváth, L. and Kokoszka, P. (2012). *Inference for Functional Data with Applications*. New York: Springer.

Huang, C., Davis, L. S. and Townshend, J. R. G. (2002). An assessment of support vector machines for land cover classification. *International Journal of Remote Sensing*, 23(4), 725–749.

Huang, G., Huang, G. B., Song, S. and You, K. (2015). Trends in extreme learning machines: A review. *Neural Networks*, 61, 32–48.

Huang, X. and Zhang, L. (2013). An SVM ensemble approach combining spectral, structural, and semantic features for the classification of high-resolution remotely sensed imagery. *Geoscience and Remote Sensing, IEEE Transactions on*, 51(1), 257–272.

Irwin, M. E., Cressie, N. and Johannesson, G. (2002). Spatial-temporal nonlinear filtering based on hierarchical statistical models. *Test*, 11(2), 249–302.

Walter, V. (2003). Object-based classification of remote sensing data for change detection. *ISPRS Journal of photogrammetry and remote sensing*, 58(3), 225–238.

Jackson, Q., Landgrebe, D. and Others (2002). Adaptive Bayesian contextual classification based on Markov random fields. *Geoscience and Remote Sensing, IEEE Transactions on*, 40(11), 2454–2463.

Jacques, J. and Preda, C. (2014). Functional data clustering: a survey. *Advances in Data Analysis and Classification*, 8(3), 231–255.

Jin, X., Banerjee, S. and Carlin, B. P. (2007). Order-Free Co-Regionalized Areal Data Mod- els with Application to Multiple-Disease Mapping. *Journal of the Royal Statistical Society. Series B (Statistical Methodology)*, 69(5), 817–838.

Jin, X., Carlin, B. P. and Banerjee, S. (2005). Generalized Hierarchical Multivariate CAR Models for Areal Data. *Biometrics*, 61(4), 950–961.

Julea, A., Méger, N., Bolon, P., Rigotti, C., Doin, M.P., Lasserre, C., Trouvé, E. and Lazarescu, V.N. (2011). Unsupervised spatiotemporal mining of satellite image time series using grouped frequent sequential patterns. *IEEE Transactions on Geoscience and Remote Sensing*, *49*(4),1417-1430.

Julea, A., Méger, N., Rigotti, C., Trouvé, E., Jolivet, R. and Bolon, P. (2012). Efficient Spatio-temporal Mining of Satellite Image Time Series for Agricultural Monitoring. *Trans. MLDM*, *5*(1), 23-44.

Katzfuss, M. and Cressie, N. (2011). Spatio–Temporal Smoothing and EM Estimation for Massive Remote–Sensing Data Sets. *Journal of Time Series Analysis*, 32(4), 430–446.

Katzfuss, M. and Cressie, N. (2012). Bayesian hierarchical spatio–temporal smoothing for very large datasets. *Environmetrics*, 23(1), 94–107.

Katzfuss, M., Stroud, J. R. and Wikle, C. K. (2016). Understanding the ensemble Kalman filter. *The American Statistician*.

Kavzoglu, T. and Mather, P. M. (2003). The use of backpropagating artificial neural networks in land cover classification. *International Journal of Remote Sensing*, 24(23), 4907–4938.

Kavzoglu, T. and Reis, S. (2008). Performance analysis of maximum likelihood and artificial neural network classifiers for training sets with mixed pixels. *GIScience & Remote Sensing*, 45(3), 330–342.

Kim, H., Sun, D. and Tsutakawa, R. K. (2001). A Bivariate Bayes Method for Improving the Estimates of Mortality Rates with a Twofold Conditional Autoregressive Model. *Journal of the American Statistical Association*, 96(456), 1506–1521.

Kittler, J., Hatef, M., Duin, R. P. W. and Matas, J. (1998). On combining classifiers. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 20(3), 226–239.

Kneip, A. and Sarda, P. (2011). Factor Models and Variable Selection in High-Dimensional Regression Analysis. *The Annals of Statistics*, 39(5), 2410–2447.

Knorr-Held, L. (2000). Bayesian modelling of inseparable space-time variation in disease risk. *Statistics in medicine*, 19(17-18), 2555–2567.

Knorr-Held, L. and Besag, J. (1998). Modelling risk from a disease in time and space. *Statistics in medicine*, 17(18), 2045–2060.

Knorr-Held, L. and Rue, H. (2002). On Block Updating in Markov Random Field Models for Disease Mapping. *Scandinavian Journal of Statistics*, 29(4), 597–614.

Kong, Z. and Cai, Z. (2007). Advances of Research in Fuzzy Integral for Classifiers' fusion. *Software Engineering, Artificial Intelligence, Networking, and Parallel/Distributed Computing, 2007. SNPD 2007. Eighth ACIS International Conference on*, volume 2, pp. 809–814.

Kuching, S., Shafri, H. Z. M., Suhaili, A. and Mansor, S. (2007). The Performance of Maximum Likelihood, Spectral Angle Mapper, Neural Network and Decision Tree Classifiers in Hyperspectral Image Analysis. *Journal of Computer Science*, 3(6), 419–423.

Kuhn, H. (1955). The Hungarian Method for the Assignment Problem. *Naval Research Logistics Quarterly*, 2(1-2), 83–97.

Kussul, N., Skakun, S. and Kussul, O. (2006). Comparative analysis of neural networks and statistical approaches to remote sensing image classification. *International Journal of Computing*, 5(2), 93–99.

Lagazio, C., Dreassi, E. and Biggeri, A. (2001). A hierarchical Bayesian model for space time variation of disease risk. *Statistical Modelling*, 1(01), 17–29.Lam, L. (2000). Classifier combinations: implementations and theoretical issues. In *Mul- tiple classifier systems*, pp. 77–86. Springer.

Lange, T., Mosler, K. and Mozharovskyi, P. (2014). Fast nonparametric classification based on data depth. *Statistical Papers*, 55(1), 49–69.

Latifovic, R., Trishchenko, A. P., Chen J., Park W.B., Khlopenkov, K. V., Fernandes, R., Pouliot, D., Ungureanu, C., Luo, Y., Wang, S., Davidson, A., Cihlar, J., (2005). Generating historical AVHRR 1 km baseline satellite data records over Canada suitable for climate change studies. Canadian Journal of Remote Sensing,31(5), 324-346.

Lawley, E.F., Lewis, M.M., and B. Ostendorf. (2011). Environmental zonation across the Australian arid region based on long-term vegetation dynamics. *Journal of Arid Environments*, 75: 576–585.

Lawrence, R.L. and Wright, A. (2001) Rule-based classification systems using Classification and Regression Tree (CART) analysis. *Photogrammetric Engineering and Remote Sensing*, 67, 1137-1142.

Lawson, A. B. (2013). *Bayesian disease mapping: hierarchical modeling in spatial epidemiology*. CRC press, second edition.

Le, N. D. and Zidek, J. V. (2006). *Statistical analysis of environmental space-time processes*. Springer Science & Business Media.

Lee, T.-W. and Lewicki, M. S. (2002). Unsupervised image classification, segmentation, and enhancement using ICA mixture models. *Image Processing, IEEE Transactions on*, 11(3), 270–279.

Lee, T.-W., Lewicki, M. S. and Sejnowski, T. J. (2000). ICA mixture models for unsupervised classification of non-Gaussian classes and automatic context switching in blind signal separation. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 22(10), 1078–1089.

Lee, Y., Lin, Y. and Wahba, G. (2001). Multicategory support vector machines. In *Proceedings of the 33rd Symposium on the Interface*. Costa Mesa, CACiteseer, TECHNICAL REPORT NO. 1043.

Lee, Y., Lin, Y. and Wahba, G. (2004). Multicategory support vector machines: Theory and application to the classification of microarray data and satellite radiance data. *Journal of the American Statistical Association*, 99(465), 67–81.

Lewis, A., Lymburner, L., Purss, M.B.J., Brooke, B., Evans, B., Dekker, A.G., Irons, J.R., Minchin, S., Mueller, N., Oliver, S., Roberts, D., Ryan, B., Thankappan, M., Woodcock, R. & Wyborn (2016),

Rapid, high-resolution detection of environmental change over continental scales from satellite data - the Earth Observation Data Cube Rapid, high-resolu **; I**nternational Journal of Digital Earth 9 (1), INTERNATIONAL 9 106-111**.** 0 **DOI:** 10.1080/17538947.2015.1111952.

Li, C.H., Kuo, B.C., Lin, C.T. and Huang, C.S. (2012a). A spatial–contextual support vector machine for remotely sensed image classification. *Geoscience and Remote Sensing, IEEE Transactions on*, 50(3), 784–799.

Li, J., Marpu, P. R., Plaza, A., Bioucas-Dias, J. M. and Benediktsson, J. A. (2012b). A New Multiple Classifier System for Semi-supervised Analysis of Hyperspectral Images. In *ICPRAM (1)*, pp. 406–411.

Li, X., Liu, X. and Yu, L. (2014). Aggregative model-based classifier ensemble for improving land use/cover classification of Landsat TM Images. *International Journal of Remote Sensing*, 35(4), 1481–1495.

Liao (2017) The Impact of Energy Consumption on the Surface Urban Heat Island in China's 32 Major Cities. *Remote Sensing* 9, 250.

Lindgren, F. and Rue, H. (2015). Bayesian Spatial Modelling with R-INLA. *Journal of Statistical Software*, 63(19), 1-25.

Lindgren, F., Rue, H. and Lindström, J. (2011). An explicit link between Gaussian fields and Gaussian Markov random fields : the stochastic partial differential equation approach [with Discussion]. *Journal of the Royal Statistical Society Series B: Methodology*, 73(4), 423–498.

Liu, C., Ray, S., Hooker, G., Friedl, M. (2012) Functional factor analysis for periodic remote sensing data. *The Annals of Applied Statistics* 6(2), 601-624.

Lloyd, C. D. (2010). *Local models for spatial analysis*. CRC Press, second edition.

Lopatin, J., Dolos, K., Hernandez, H.J., Gelleguillos, M., Fasshacht, F.E. (2016). Comparing Generalized Linear Models and random forest to model vascular plant species richness using LiDAR data in a natural forest in central Chile. *Remote Sensing of the Environment* 173, 200-2010.

López-Granados, F., Peña-Barragán, J.M., Jurado-Expósito, M., Francisco- Fernández, M., Cao, R., Alonso-Betanzos, A., and Fontenla-Romero, O. (2008). Multispectral classification of grass weeds and wheat (Triticum durum) using linear and nonparametric functional discriminant analysis and neural networks. *Weed Research*, 48, 28–37.

Löw, F., Michel, U., Dech, S. and Conrad, C. (2013). Impact of feature selection on the accuracy and spatial uncertainty of per-field crop classification using support vector machines. *ISPRS Journal of Photogrammetry and Remote Sensing*, 85, 102–119.

Löw, F., Schorcht, G., Michel, U., Dech, S. and Conrad, C. (2012). Per-field crop classification in irrigated agricultural regions in middle Asia using random forest and support vector machine ensemble. In *SPIE Remote Sensing*, (8538). International Society for Optics and Photonics.

Lu, D. and Weng, Q. (2007). A survey of image classification methods and techniques for improving classification performance. *International Journal of Remote Sensing*, 28(5), 823–870.

Lu, D., Batistella, M., Moran, E. and Mausel, P. (2004). Application of spectral mixture analysis to Amazonian land-use and land-cover classification. *International Journal of Remote Sensing*, 25(23), 5345–5358.

Lu, D., Moran, E. and Batistella, M. (2003). Linear mixture model applied to Amazonian vegetation classification. *Remote sensing of environment*, 87(4), 456–469.

M. K., Plant, R. E. and Six, J. (2011). Object-based crop identification using multiple vegetation indices, textural features and crop phenology. *Remote Sensing of Environment*, 115(6), 1301–1316.

MacNab, Y. C. and Dean, C. B. (2001). Autoregressive spatial smoothing and temporal spline smoothing for mapping rates. *Biometrics*, 57(3), 949–956.

Marchesi, S. and Bruzzone, L. (2009). ICA and kernel ICA for change detection in multi- spectral remote sensing images. In *Geoscience and Remote Sensing Symposium, 2009 IEEE International, IGARSS 2009*, volume 2, pp. II-980. IEEE.

Marley, J., Defina, R., Traeger, K., Elazar, D., Amarasinghe, A., Biggs, G., and Tam. S-M. 2016. Investigative Pilot Report (unpublished).

Martino, S., Aas, K., Lindqvist, O., Neef, L. R. and Rue, H. (2011). Estimating stochastic volatility models using integrated nested Laplace approximations. *The European Journal of Finance*, 17(7), 487–503.

Martins, T. G., Simpson, D., Lindgren, F. and Rue, H. (2013). Bayesian computing with INLA: New features. *Computational Statistics and Data Analysis*, 67, 68–83.

Maselli, F., Rodolfi, A. and Conese, C. (1996). Fuzzy classification of spatially degraded Thematic Mapper data for the estimation of sub-pixel components. *International Journal of Remote Sensing*, 17(3), 537–551.

Mather, P., Tso, B. (2016) Classification Methods for Remotely Sensed Data, Second Edition. CRC Press.

Mathur, A. and Foody, G. M. (2008). Crop classification by support vector machine with intelligently selected training data for an operational application. *International Journal of Remote Sensing*, 29(8), 2227–2240.

McIver, D. K. and Friedl, M. A. (2002). Using prior probabilities in decision-tree classification of remotely sensed data. *Remote Sensing of Environment*, 81(2), 253–261.

McRoberts et al. (2007) Estimating areal means and variances of forest attributes using the k-Nearest Neighbors technique and satellite imagery. *Remote Sensing of the Environment* 111.

Melgani, F. and Bruzzone, L. (2004). Classification of hyperspectral remote sensing images with support vector machines. *IEEE Transactions on Geoscience and Remote Sensing*, 42(8), 1778–1790.

Mello, M.P., Risso, J., Atzberger, C., Aplin, P., Pebesma, E., Vieira, C.A.O., Rudorff, B.F.T. (2013) Bayesian networks for raster data (BayNeRD): plausible reasoning from observations. *Remote Sensing* 5(11), 5999-6025.

Mertens, K. C., Verbeke, L. P. C., Westra, T. and De Wulf, R. R. (2004). Sub-pixel mapping and sub-pixel sharpening using neural network predicted wavelet coefficients. *Remote Sensing of Environment*, 91(2), 225–236.

Mishra, N. S., Ghosh, S. and Ghosh, A. (2012). Fuzzy clustering algorithms incorporating local information for change detection in remotely sensed images. *Applied Soft Computing*, 12(8), 2683–2692.

Moreno-Seco, F., Inesta, J. M., De León, P. J. P. and Micó, L. (2006). Comparison of classifier fusion methods for classification in pattern recognition tasks. *Structural, Syntactic, and Statistical Pattern Recognition*, pp. 705–713. Springer.

Morisette, J.T., Khorram, S. (1997) An introduction to using generalized linear models to enhance satellite-based change detection. Geoscience and Remote Sensing. IGARSS '97. Remote Sensing – A Scientific Vision for Sustainable Development. 1997 IEEE International.
DOI: 10.1109/IGARSS.1997.609064

Morisette, J.T., Khorram, S. and Mace, T. (1999) Land-cover change detection enhanced by generalized linear models. *International Journal of Remote Sensing* 20(14), 2703-2721.

Moser, G. and Serpico, S. B. (2013). Combining support vector machines and markov random fields in an integrated framework for contextual image classification. *Geoscience and Remote Sensing, IEEE Transactions on*, 51(5), 2734–2752.

Moser, G., Serpico, S. B. and Benediktsson, J. A. (2013). Land-cover mapping by Markov modeling of spatial–contextual information in very-high-resolution remote sensing im- ages. *Proceedings of the IEEE*, 101(3), 631–651.

Mountrakis, G., Im, J. and Ogole, C. (2011). Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66(3), 247–259.

Muff, S., Riebler, A. and Held, L. (2015). Bayesian analysis of measurement error models using integrated nested Laplace approximations. *Journal of the Royal Statistical Society Series C: Applied Statistics*, pp. 231–252.

Mugglin, A. S., Cressie, N. and Gemmell, I. (2002). Hierarchical statistical modelling of influenza epidemic dynamics in space and time. *Statistics in medicine*, 21(18), 2703– 21.

Nakamura, R., Osaku, D., Levada, A., Cappabianco, F., Falcão, A. and Papa, J. (2013). OPF-MRF: Optimum-path forest and markov random fields for contextual-based image classification. In *Computer Analysis of Images and Patterns*, pp. 233–240. Springer.

Neagoe, V.-E., Chirila-Berbentea, V. (2016) Improved Gaussian mixture model with expectation-maximization for clustering of remote sensing imagery. Geoscience and Remote Sensing Symposium (IGARSS), 2016 IEEE International, DOI: 10.1109/IGARSS.2016.7729792

Newlands, N.K., Zamar, D.S., Kouadio, L.A., Zhang, Y., Chipanshi, A., Potgieter, A., Toure, S. and Hill, H.S. (2014). An integrated, probabilistic model for improved seasonal forecasting of agricultural crop yield under environmental uncertainty. *Frontiers in Environmental Science*, *2*, 17.

Norton, J. D. and Niu, X.-F. (2009). Intrinsically Autoregressive Spatiotemporal Models With Application to Aggregated Birth Outcomes. *Journal of the American Statistical Association*, 104(486), 638–649.

Ohmann, J. L. and Gregory, M. J. (2002). Predictive mapping of forest composition and structure with direct gradient analysis and nearest-neighbor imputation in coastal Oregon, USA. *Canadian Journal of Forest Research*, 32(4), 725–741.

Okujeni, A.O. and van der Linden, S. (2014) A Comparison of Advanced Regression Algorithms for Quantifying Urban Land Cover. *Remote Sensing* 6, 6324-6346.

Olofsson, P., Foody, G.M., Herold, M., Stehman, S.V., Woodcock, C.E. and Wulder, M.A. (2014). Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment*, *148*, 42-57.

Otukei, J. R. and Blaschke, T. (2010). Land cover change assessment using decision trees, support vector machines and maximum likelihood classification algorithms. *International Journal of Applied Earth Observation and Geoinformation*, 12(SUPPL. 1), 27– 31.

Pal, M. and Mather, P. M. (2003). An assessment of the effectiveness of decision tree methods for land cover classification. *Remote Sensing of Environment*, 86(4), 554–565.

Pal, M. and Mather, P. M. (2005). Support vector machines for classification in remote sensing. *International Journal of Remote Sensing*, 26(5), 1007–1011.

Paola, J. D. and Schowengerdt, R. A. (1995). A review and analysis of backpropagation neural networks for classification of remotely-sensed multi-spectral imagery. *International Journal of remote sensing*, 16(16), 3033–3058.

Paola, J. D. and Schowengerdt, R. A. (1997). The effect of neural-network structure on a multispectral land-use/land-cover classification. *Photogrammetric Engineering and Remote Sensing*, 63(5), 535–544.

Pedley, M. I. and Curran, P. J. (1991). Per-field classification: an example using SPOT HRV imagery. *Remote Sensing*, 12(11), 2181–2192.

Pena et al. (2016) Object based image classification of summer crops with machine learning methods. *Remote Sensing* 6, 5019.

Peña-Barragán, J. M., Ngugi, M. K., Plant, R. E., Six, J., PeÃa-BarragÃn, J. M., Ngugi, Penaloza, M. A. and Welch, R. M. (1996). Feature selection for classification of polar regions using a fuzzy expert system. *Remote Sensing of Environment*, 58(1), 81–100.

Petropoulos, G. P., Vadrevu, K. P., Xanthopoulos, G., Karantounias, G. and Scholze, M. (2010). A comparison of spectral angle mapper and artificial neural network classifiers combined with Landsat TM imagery analysis for obtaining burnt area mapping. *Sensors*, 10(3), 1967–1985.

Pettitt, A. N., Weir, I. S. and Hart, A. G. (2002). A conditional autoregressive Gaussian process for irregularly spaced multivariate data with application to modelling large sets of binary data. *Statistics and Computing*, 12(4), 353–367.

Phinn, S.R., Dekker, A.G., Brando, V.E., and Roelfsema, C.M. (2005). Mapping water quality and substrate cover in optically complex coastal and reef waters: an integrated approach, *Marine Pollution Bulletin*, 51,(1–4),459-469. Retrieved from: http://www.sciencedirect.com/science/article/pii/S0025326X04003583

Pitt, Michael, K. and Shephard, N. (1999). Filtering via simulation: Auxiliary particle filters. *Journal of the American Statistical Association*, 94(446), 590–599.

Planet. (2016). About Planet. Retrieved from https://www.planet.com/about/

Platt, R. V. and Rapoza, L. (2008). An Evaluation of an Object-Oriented Paradigm for Land Use/Land Cover Classification. *The Professional Geographer*, 60(1), 87–100.

Pollock, D. (2009). Trends in economic time series. Retrieved from: http://www.le.ac.uk/users/dsgp1/COURSES/TSERIES/1TRENDS.PDF

Potgieter, A., Apan, A., Dunn, P., and Hammer, G. (2007). Estimating crop area using seasonal time series of Enhanced Vegetation Index from MODIS satellite imagery. *Crop and Pasture Science*, 58(4), 316-325.

Potgieter, A., Apan, A., Hammer, G. and Dunn, P. (2011). Estimating winter crop area across seasons and regions using time-sequential MODIS imagery. *International journal of remote sensing*, *32*(15), 4281-4310.

Potgieter, A.B., Lawson, K. and Huete, A.R. (2013). Determining crop acreage estimates for specific winter crops using shape attributes from sequential MODIS imagery. *International Journal of Applied Earth Observation and Geoinformation*, *23*, 254-263.

Preda, C., Saporta, G. and Lévéder, C. (2007). PLS classification of functional data. *Computational Statistics*, 22(2), 223–235.

PRIMS. (2016). Retrieved from http://philippinericeinfo.ph

Pringle, M., Schmidt, M. and Tindall, D. (2018): Multi season, multi sensor time series modelling based on geostatistical concepts - to predict broad groups of crops. Submitted to Remote Sensing of Environment.

Qiu, F. (2008). Neuro-fuzzy based analysis of hyperspectral imagery. *Photogrammetric Engineering & Remote Sensing*, 74(10), 1235–1247.

Qi, Y. and J. Zhang. (2009). (2D) PCALDA: An efficient approach for face recognition. *Applied Mathematics and Computation*, 213: 1–7.

R Development Core Team (2011). R: A Language and Environment for Statistical Computing. Vienna, Austria : the R Foundation for Statistical Computing. ISBN: 3-900051-07-0. Retrieved from http://www.R-project.org/.

Rahman, A. F. R. and Fairhurst, M. C. (2003). Multiple classifier decision combination strategies for character recognition: A review. *Document Analysis and Recognition*, 5(4), 166–194.

Ramsay, J. O. and Silverman, B. W. (2005). *Functional Data Analysis*. New York: Springer, second edition.

Ranawana, R. and Palade, V. (2006). Multi-classifier systems: Review and a roadmap for developers. *Int. J. Hybrid Intell. Syst.*, 3(1), 35–61.

Rani, S., and Sikka, G. (2012). Recent techniques of clustering of time series data: a survey. *International Journal of Computer Applications* 52(15), 1-9.

Reed, B.C., Brown, J.F., VanderZee, D. et al. (1994) Measuring phenological variability from satellite imagery. *Journal of Vegetation Science* 5(5), Applications of Remote Sensing and Geographic Information Systems in Vegetation Science, pp. 703-714.

Richards, J. (2013) *Remote Sensing Digital Image Analysis*, Springer, Berlin
Scannapieco, M., Virgillito, A., and D. Zardetto. 2013. *Placing Big Data in Official Statistics: A Big Challenge?* Accessed: https://ec.europa.eu/eurostat/cros/system/files/NTTS2013fullPaper_214.pdf

Richardson, S., Abellan, J. J. and Best, N. (2006). Bayesian spatio-temporal analysis of joint patterns of male and female lung cancer risks in Yorkshire (UK). *Statistical Methods in Medical Research*, 15(4), 385–407.

Riebler, A., Held, L. and Rue, H. (2012). Estimation and Extrapolation of Time Trends in Registry Data – Borrowing Strength from Related Populations. *The Annals of Applied Statistics*, 6(1), 304–333.

Ripley, B. D. (1977). Modelling Spatial Patterns. *Journal of the Royal Statistical Society. Series B (Methodological)*, 39(2), 172–212.

Ripley, B. D. (1988). *Statistical Inference for Spatial Processes*. Cambridge University Press.

Ripley, B. D. (1994). Neural networks and related methods for classification. *Journal of the Royal Statistical Society. Series B (Methodological)*, pp. 409–456.

Ripley, B. D. (1996). *Pattern recognition and neural networks*. Cambridge university press.

Roos, M. and Held, L. (2011). Sensitivity analysis in Bayesian generalized linear mixed models for binary data. *Bayesian Analysis*, 6(2), 259–278.

Roy, M., Ghosh, S. and Ghosh, A. (2014). A novel approach for change detection of remotely sensed images using semi-supervised multiple classifier system. *Information Sciences*, 269, 35–47.

Royle, J. A. and Berliner, L. M. (1999). A Hierarchical Approach to Multivariate Spatial Modeling and Prediction. *Journal of Agricultural, Biological, and Environmental Statistics*, 4(1), 29–56.

Rue, H. and Held, L. (2005). *Gaussian Markov random fields: theory and applications*. CRC Press.

Rue, H., Martino, S. and Chopin, N. (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *Journal of the Royal Statistical Society, Series B*, 71(2), 319–392.

Ruiz-Cárdenas, R., Krainski, E. T. and Rue, H. (2012). Direct fitting of dynamic models using integrated nested Laplace approximations - INLA. *Computational Statistics and Data Analysis*, 56(6), 1808–1828.

Sahu, S. K. and Mardia, K. V. (2005). Recent Trends in Modeling Spatio-Temporal Data.

Sain, S. R. and Cressie, N. (2007). A spatial model for multivariate lattice data. *Journal of Econometrics*, 140(1), 226–259.

Sain, S. R., Furrer, R. and Cressie, N. (2011). A spatial analysis of multivariate output from regional climate models. *Annals of Applied Statistics*, 5(1), 150–175.

Sakamoto, T., Wardlow, B.D., Gitelson, A.A., Verma, S.B., Suyker, A.E., and Arkebauer, T.J. (2010). A two-step filtering approach for detecting maize and soybean phenology with time-series MODIS data. *Remote Sens. Environ*., 114, 2146–2159.

Sakamoto, T., Wardlow, B.D., and Gitelson, A.A. (2011) Detecting spatiotemporal changes of corn developmental stages in the US Corn Belt using MODIS WDRVI data. *IEEE Trans. Geosci. Remote Sens*., 49, 1926–1936.

Samat, A., Du, P., Baig, M. H. A., Chakravarty, S. and Cheng, L. (2014). Ensemble learning with multiple classifiers and polarimetric features for polarized SAR image classification. *Photogrammetric Engineering & Remote Sensing*, 80(3), 239–251.

Scannapieco, M., Virgillito, A., and Zardetto,D. (2013). *Placing Big Data in Official Statistics: A Big Challenge?* Accessed: https://ec.europa.eu/eurostat/cros/system/files/NTTS2013fullPaper_214.pdf

Schmidt, M., Pringle, M., Rakhesh, D., Denham, R. and D. Tindall. 2016. A Framework for Large-Area Mapping of Past and Present Cropping Activity Using Seasonal Landsat Images and Time Series Metrics. Retrieved from http://www.mdpi.com/2072-4292/8/4/312.

Schneibel et al. (2017) Using Annual Landsat Time Series for the Detection of Dry Forest Degradation Processes in South-Central Angola. *Remote Sensing* 9, 905.

Schrödle, B. and Held, L. (2011a). A primer on disease mapping and ecological regression using INLA. *Computational Statistics*, 26(2), 241–258.

Schrödle, B. and Held, L. (2011b). Spatio-temporal disease mapping using INLA. *Environmetrics*, 22(6), 725–734.

Schrödle, B., Held, L. and Rue, H. (2012). Assessing the Impact of a Movement Network on the Spatiotemporal Spread of Infectious Diseases. *Biometrics*, 68(3), 736–744.

Sengupta, A. and Cressie, N. (2013). Hierarchical Statistical Modeling of Big Spatial Datasets Using the Exponential Family of Distributions. *Spatial Statistics*, 4, 14–44.

Sengupta, A., Cressie, N., Frey, R. and Kahn, B. (2013). Statistical modelling of MODIS cloud data using the spatial random effects model. *National Institute for Applied Statistics Research Australia*, 3111-3123.

Shaddick, G. and Wakefield, J. (2002). Modelling multivariate pollutant data at multiple sites. *Journal of the Royal Statistical Society. Series C: Applied Statistics*, 51(3), 351– 372.

Shah, C. A., Arora, M. K. and Varshney, P. K. (2004). Unsupervised classification of hyperspectral data: an ICA mixture model based approach. *International Journal of Remote Sensing*, 25(2), 481–487.

Shah, C. A., Varshney, P. K. and Arora, M. K. (2007) ICA mixture model algorithm for unsupervised classification of remote sensing imagery. *International Journal of Remote Sensing*, 28(8), 1711–1731.

Shah, C., Arora, M. K., Robila, S., Varshney, P. K. and Others (2002). ICA mixture model based unsupervised classification of hyperspectral imagery. In *Applied Imagery Pattern Recognition Workshop, 2002. Proceedings. 31st*, pp. 29–35. IEEE.

Shah, V. P., Younan, N. H., Durbha, S. S. and King, R. L. (2010). Feature identification via a combined ICA–wavelet method for image information mining. *Geoscience and Remote Sensing Letters, IEEE*, 7(1), 18–22.

Shalan, M. A., Arora, M. K. and Ghosh, S. K. (2003). An evaluation of fuzzy classifications from IRS 1C LISS III imagery: a case study. *International Journal of Remote Sensing*, 24(15), 3179–3186.

Shao, Y. and Lunetta, R. S. (2012). Comparison of support vector machine, neural net- work, and CART algorithms for the land-cover classification using limited training data points. *ISPRS Journal of Photogrammetry and Remote Sensing*, 70, 78–87.

Sharma, R., Ghosh, A. and Joshi, P. K. (2013). Decision tree approach for classification of remotely sensed satellite data using open source support. *Journal of Earth System Science*, 122(5), 1237–1247.

Shekhar, S., Schrater, P. R., Vatsavai, R. R., Wu, W. and Chawla, S. (2002). Spatial contextual classification and prediction models for mining geospatial data. *Multimedia, IEEE Transactions on*, 4(2), 174–188.

Shumway, R. H. and Stoffer, D. S. (2011). *Time series analysis and its applications: with R examples*. New York: Springer Science & Business Media, third edition.

Sigrist, F., Künsch, H. R. and Stahel, W. A. (2015). Stochastic partial differential equation based modelling of large space-time data sets. *Journal of the Royal Statistical Society. Series B: Statistical Methodology*, 77(1), 3–33.

Singh, K. K., Nigam, M. J., Pal, K. and Mehrotra, A. (2014). A fuzzy kohonen local information C-means clustering for remote sensing imagery. *IETE Technical Review*, 31(1), 75–81.

Silipo, R. (2015). Seven Techniques for Data Dimensionality Reduction. Accessed: https://www.knime.org/blog/seven-techniques-for-data-dimensionality-reduction

Sohn, Y. and Rebello, N. S. (2002). Supervised and unsupervised spectral angle classifiers. *Photogrammetric Engineering and Remote Sensing*, 68(12), 1271–1280.

Sohn, Y., Moran, E. and Gurri, F. (1999). Deforestation in North-Central Yucatan (1985- 1995)-Mapping secondary succession of forest and agricultural land use in Sotuta using the cosine of the angle concept. *Photogrammetric engineering and remote sensing*, 65, 947–958.

Somers, B., Asner, G. P., Tits, L. and Coppin, P. (2011). Endmember variability in spectral mixture analysis: A review. *Remote Sensing of Environment*, 115(7), 1603–1616.

Srivastava, P. K., Han, D., Rico-Ramirez, M. A., Bray, M. and Islam, T. (2012). Selection of classification techniques for land use/land cover change investigation. *Advances in Space Research*, 50(9), 1250–1265.

Stassapoulou, A., Petrou, M., Kittler, J. (1998) Application of a Bayesian network in a GIS based decision making system. *International Journal of Geographic Information Science*, 12, 23-46.

Statistics Canada (2015). Integrated Crop Yield Modelling Using Remote Sensing, Agroclimatic Data and Survey Data. Retrieved from: http://www23.statcan.gc.ca/imdb-bmdi/document/5225_D1_T9_V1-eng.htm

Steele, Pål Roe Sundsøy, Carla Pezzulo, Victor A. Alegana, Tomas J. Bird, Joshua Blumenstock, Johannes Bjelland, Kenth Engø-Monsen, Yves-Alexandre de Montjoye, Asif M. Iqbal, Khandakar N. Hadiuzzaman, Xin Lu, Erik Wetter, Andrew J. Tatem, Linus Bengtsson

Steele, J.E. Sundsoy, P.R., Pezzulo, C. *et al.* (2017) Mapping poverty using mobile phone and satellite data. *Journal of the Royal Society Interface*. Published online 1 February 2017. DOI: 10.1098/rsif.2016.0690

Strickland, C. M., Simpson, D. P., Turner, I. W., Denham, R. and Mengersen, K. L. (2011). Fast Bayesian analysis of spatial dynamic factor models for multitemporal remotely sensed imagery. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 60(1), 109–124.

Stroud, J. R., Müller, P. and Sansó, B. (2001). Dynamic models for spatiotemporal data. *Journal of the Royal Statistical Society. Series B (Methodological)*, 63, 673–689.

Stroud, J. R., Stein, M. L., Lesht, B. M., Schwab, D. J. and Beletsky, D. (2010). An ensemble Kalman filter and smoother for satellite data assimilation. *Journal of the American Statistical Association*, 105(491), 978–990.

Struijs, P., Braaksma, B. and Daas, P.J.H. (2014). Official statistics and Big Data. Big Data and Society. electronic version last access 13072016 http://bds.sagepub.com/content/1/1/2053951714538417.article-info

Suliman, A. and Zhang, Y. (2015). A Review on Back-Propagation Neural Networks in the Application of Remote Sensing Image Classification. *Journal of Earth Science and Engineering*, 5, 52–65.

Sweeney, S., Ruseva, T., Estes, L., Evans, T. (2015) Mapping cropland in smallholder-dominated savannas: integrating remote sensing techniques and probabilistic modelling. *Remote Sensing* 7, 15295-15317.

Szuster, B. W., Chen, Q. and Borger, M. (2011). A comparison of classification techniques to support land cover and land use analysis in tropical coastal zones. *Applied Geography*, 31(2), 525–532.

Tam, S-M. (1987). Analysis of a repeated survey using a dynamic linear model. *International Statistical Review*, 55, 63-73.

Tam, S-M. (2015). A Statistical Framework for Analysing Big Data. *Survey Statistician*, 72, 36-51

Tam, S.-M. and Clarke, F. (2015). Big Data, Statistical Inference and Official Statistics. International Statistical Review, 83(3), 436-448.

Tau, J. et al. (2016) A study of a Gaussian mixture model for urban land-cover mapping based on VHR remote sensing imagery. *International Journal of Remote Sensing* 37.

Taubenbock, H. Esch, T., Felbier, A., Wisener, M., Roth, A., Dech, S. (2012) Monitoring urbanization in mega cities from space. *Remote Sensing of the Environment* 117, 162-176.

Taubenbock, H. Esch, T., Felbier, A., Wisener, M., Roth, A., Dech, S. (2012) Monitoring urbanization in mega cities from space. *Remote Sensing of the Environment* 117, 162-176.

Thenkabail, P.S. (2015) Remotely Sensed Data Characterization, Classification, and Accuracies. (Ed). CRC Press.

Therneau, T., Atkinson, B. and Ripley, B. D. (2015). rpart: Recursive Partitioning and Regression Trees.

Tierney, L. and Kadane, J. B. (1986). Accurate Approximations for Posterior Moments and Marginal Densities. *Journal of the American Statistical Association*, 81(393), 82–86.

Tompkins, S., Mustard, J. F., Pieters, C. M. and Forsyth, D. W. (1997). Optimization of endmembers for spectral mixture analysis. *Remote Sensing of Environment*, 59(3), 472–489.

Triepke, F. J., Brewer, C. K., Leavell, D. M. and Novak, S. J. (2008). Mapping forest alliances and associations using fuzzy systems and nearest neighbor classifiers. *Remote Sensing of Environment*, 112(3), 1037–1050.

Tripathy, R., Chaudhary, K.N., Nigam, R., Manjunath, K.R., Chauhan, P., Ray, S.S., Parihar, J.S. (2014). Operational semi-physical spectral-spatial wheat yield model development. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XL-8, 2014 ISPRS Technical Commission VIII Symposium, 09 – 12 December 2014, Hyderabad, India

Tso, B. and Olsen, R. C. (2005). A contextual classification scheme based on MRF model with improved parameter estimation and multiscale fuzzy line process. *Remote Sensing of Environment*, 97(1), 127–136.

Ugarte, M. D., Goicoa, T. and Militino, A. F. (2010). Spatio-temporal modeling of mortality risks using penalized splines. *Environmetrics*, 21, 270–289.

United Nations Economic Commission for Europe (UNECE), (2013). Generic Statistical Business Process Model – GSBPM - (Version 5.0, December 2013). Retrieved from http://www1.unece.org/stat/platform/display/GSBPM/GSBPM+v5.0

United Nations Economic Commission for Europe (UNECE). (2015). Forty-sixth session, Report of the Global Working Group on Big data for official statistics, E/CN.3/2015/4. Retrieved from http://unstats.un.org/unsd/statcom/doc15/2015-4-BigData.pdf

United States Department of Agriculture (USDA) (2016). May report. Retrieved from http://www.usda.gov/oce/commodity/wasde/.

Usman, B. (2013). Satellite Imagery Land Cover Classification using K-Means Clustering Algorithm: Computer Vision for Environmental Information Extraction. *Elixir Journal of Computer Science and Engineering* 18671-18675.

Vapnik, V. (1979). Estimation of Dependencies Based on Data.

Verbeke, L. P. C., Vancoillie, F. M. B. and De Wulf, R. R. (2004). Reusing back- propagation artificial neural networks for land cover classification in tropical savannahs. *International Journal of Remote Sensing*, 25(14), 2747–2771.

Ver Hoef, J.M, Temesgen, H. (2013) A Comparison of the Spatial Linear Model to Nearest Neighbor (k-NN) Methods for Forestry Applications. PLoS ONE 8(3) //doi.org/10.1371/journal.pone.0059129

Wackernagel, H. (2003). *Multivariate geostatistics: an introduction with applications*. Berlin: Springer Science & Business Media, third edition.

Wall, M. M. (2004). A close look at the spatial structure implied by the CAR and SAR models. *Journal of Statistical Planning and Inference*, 121(2), 311–324.

Waller, L., Carlin, B. P., Xia, H. and Gelfand, A. E. (1997) Hierarchical Spatio-Temporal Mapping of Disease Rates. *Journal of the American Statistical Association*, 92(438), 607–617.

Walsh, S. (2008) Integration of Hyperion Satellite Data and A Household Social Survey to Characterize the Causes and Consequences of Reforestation Patterns in the Northern Ecuadorian Amazon. *Photogrammetric Engineering and Remote Sensing 74.*

Walter, V. (2004). Object-based classification of remote sensing data for change detection.

Wang, F. (1990). Fuzzy supervised classification of remote sensing images. *Geoscience and Remote Sensing, IEEE Transactions On*, 28(2), 194–201.

Wang, Q., Shi, W., Atkinson, P. M. and Li, Z. (2015). Land Cover Change Detection at Subpixel Resolution With a Hopfield Neural Network. *Selected Topics in Applied Earth Observations and Remote Sensing, IEEE Journal of*, 8(3), 1339–1352.

Warmerdam, F., Kiselev, A., Morissette, D., Butler, H., Shih, K., Neteler, M., Reimer, S., Amici, A., Villeneuve, S., Byrne, M. and Krawczyk, D. (2016). GDAL - Geospatial Data Abstraction Library.

Wendroth et al. (2003). Predicting yield of barley across a landscape: A state-space modeling approach. *Journal of Hydrology*, 272, 250-263.

Wettle, M., Hatmann, K., Heege, T., and A. Mittal. (2013). Satellite derived bathymetry using physics-based algorithms and multispectral satellite imagery, *Asian Association on Remote Sensing.* Accessed: http://www.a-a-r-s.org/acrs/administrator/components/com_jresearch/files/publications/SC02-0919_Full_Paper_ACRS2013_Wettle-et-al_online.pdf

Whiteside, T. and Ahmad, W. (2005). A comparison of object-oriented and pixel-based classification methods for mapping land cover in northern Australia. In *Proceedings of SSC2005 Spatial intelligence, innovation and praxis: The national biennial Conference of the Spatial Sciences Institute*, 1225–1231.

Whittle, P. (1954). On Stationary Processes in the Plane. *Biometrika*, 41(3/4), 434–449.

Wikle, C. K. (2002) A kernel-based spectral model for non-Gaussian spatio-temporal processes. *Statistical Modelling*, 2(4), 299–314.

Wikle, C. K. (2010) Low rank representations as models for spatial processes. In *Hand- book of Spatial Statistics* (Eds A. E. Gelfand, P. J. Diggle, M. Fuentes and P. Guttorp), 89–106. Boca Raton, FL: Chapman & Hall.

Woźniak, M. M., Graña, M. and Corchado, E. (2014). A survey of multiple classifier systems as hybrid systems. *Information Fusion*, 16(1), 3–17.

Wu, W. and Gao, G. (2012). Remote Sensing Image Classification with Multiple Classifiers Based on Support Vector Machines. In *Computational Intelligence and Design (ISCID), 2012 Fifth International Symposium on*, volume 1, pp. 188–191.

Wyborne, L. (2013). High Performance Computing. AusGeo News March 2013 Issue 109. Accessed http://www.ga.gov.au/ausgeonews/ausgeonews201303/computing.jsp.

Xu, K., Wikle, C. K. and Fox, N. I. (2005). A Kernel-Based Spatio-Temporal Dynamical Model for Nowcasting Weather Radar Reflectivities. *Journal of the American Statistical Association*, 100(472), 1133–1144.

Xu, L., Krzyżak, A. and Suen, C. Y. (1992). Methods of combining multiple classifiers and their applications to handwriting recognition. *Systems, man and cybernetics, IEEE transactions on*, 22(3), 418–435.

Yang, C., Everitt, J. H. and Murden, D. (2011). Evaluating high resolution SPOT 5 satellite imagery for crop identification. *Computers and Electronics in Agriculture*, 75(2), 347– 354.

Yang, X., Blower, JD., Bastin, L., Lush, V., Zabala, A., Masó, J., Cornford, D., Díaz, P., Lumsden, J. (2013). An integrated view of data quality in Earth observation. Phil Trans R Soc A 371: 20120072.http://dx.doi.org/10.1098/rsta.2012.0072.

Yang, C., Everitt, J. H. and Murden, D. (2011). Evaluating high resolution SPOT 5 satellite imagery for crop identification. *Computers and Electronics in Agriculture*, 75(2), 347– 354.

Yang, J., Zhang, D., Frangi, A. F. and Yang, J.Y. (2004). Two-dimensional PCA: A new approach to appearance-based face representation and recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 26: 131–137.

Ye, J., Janardan, R., and Q. Li (2005). Two-dimensional linear discriminant analysis, *in* L. K. Saul, Y. Weiss & L. Bottou (eds), *Advances in Neural Information Processing Systems 17*, MIT Press, Cambridge, MA, 1569–1576.

Yeom, J-M., and Kim, H-O. (2015) Comparison of NDVIs from GOCI and MODIS Data towards Improved Assessment of Crop Temporal Dynamics in the Case of Paddy Rice. Remote sensing (7), 11326 – 11343.

Yuan et al. (2015) Continuous Change Detection and Classification Using Hidden Markov Model: A Case Study for Monitoring Urban Encroachment onto Farmland in Beijing. *Remote Sensing* 7, 15318-15339.

Yuhas, R. H., Goetz, A. F. H. and Boardman, J. W. (1992). Discrimination among semi- arid landscape endmembers using the spectral angle mapper (SAM) algorithm. In *Summaries of the third annual JPL airborne geoscience workshop,* volume 1, pp. 147–149. Pasadena, CA: JPL Publication.

Zhang, D.Q. and Zhou, Z.H. (2005). 2D PCA: Two-directional two-dimensional PCA for efficient face representation and recognition, Neurocomputing, 2005, 69: 224–231.

Zhang, C. and Xie, Z. (2014). Data fusion and classifier ensemble techniques for vegetation mapping in the coastal Everglades. *Geocarto International*, 29(3), 228–243.

Zhang, J. and Foody, G. M. (2001). Fully-fuzzy supervised classification of sub-urban land cover from remotely sensed imagery: statistical and artificial neural network approaches. *International journal of remote sensing*, 22(4), 615–628.

Zhang, J., Wei, F., Sun, P., Pan, Y., Yuan, Z. and Yun, Y. (2015a). A Stratified Temporal Spectral Mixture Analysis Model for Mapping Cropland Distribution through MODIS Time-Series Data. *Journal of Agricultural Science*, 7(8), 95–110.

Zhang, X. and Chen, C. H. (2002). New independent component analysis method using higher order statistics with application to remote sensing images. *Optical Engineering*, 41(7), 1717–1728.

Zhang, Y., Yang, H. L., Prasad, S., Pasolli, E., Jung, J. and Crawford, M. (2015b). Ensemble multiple kernel active learning for classification of multisource remote sensing data. *Selected Topics in Applied Earth Observations and Remote Sensing, IEEE Journal of,* 8(2), 845–858.

Zhao, H., Yuen, P.C., and Kwok, J.T. (2006). A novel incremental principal component analysis and its application for face recognition. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics),* 36: 873 – 886.

Zheng, Y. and Zhu, J. (2008). Markov chain Monte Carlo for a Spatial-Temporal Autologistic Regression Model. *Journal of Computational and Graphical Statistics*, 17(1), 123–137.

Zhu, H. and Basir, O. (2005). An adaptive fuzzy evidential nearest neighbor formulation for classifying remote sensing images. *Geoscience and Remote Sensing, IEEE Trans- actions on*, 43(8), 1874–1889.

Zhu, J., Huang, H. and Wu, J. (2005). Modeling Spatial-Temporal Binary Data Using Markov Random Fields. *Journal of Agricultural, Biological, and Environmental Statis- tics*, 10(2), 212–225.

Zhu, J., Rasmussen, J. G., Moller, J., Aukema, B. H. and Raffa, K. F. (2008). Spatial- Temporal Modeling of Forest Gaps Generated by Colonization From Below- and Above-Ground Bark Beetle Species. *Journal of the American Statistical Association,* 103(481), 162–177.

1. List of acronyms

9.1 GENERAL TERMS

DQF (Data Quality Framework)

EO (Earth Observations)

NGOs (Non-Governmental organisations)

NSOs (National Statistics Officers)

9.2 TECHNICAL TERMS (Remote sensing)

ARD (Analysis Ready Data)

GEO (Geostationary) satellites

GSD Ground Sampling Distance

LAI (Leaf Area Index)

LEO (Low Earth polar Orbiting) satellites

LIDAR (Light Detection And Ranging)

MEO (Medium Earth Orbit) satellites

MIR (Mid Infrared) wavelengths

MODIS (MODerate-resolution Imaging Spectroradiometer)

NIR (Nearby Infrared) wavelengths

OLCI (Ocean Land Colour Imager)

RMSE (Root Mean Squared Error), bias, and CC (Correlation Coefficient)

SAR (Synthetic Aperture Radar)

SLAR (Synthetic Aperture Radar Altimeter)

SLSTR (Sea and Land Surface Temperature Radiometer)

SWE (Snow Water Equivalent)

SWIR (Shortwave Infrared) Wavelengths

TIR (Thermal Infrared) wavelengths

VIS (Visible) wavelengths

9.3 ORGANISATIONS/SYSTEMS AND ONLINE RESOURCES

CEOS (Committee on Earth Observation Satellites) http://ceos.org/

CRESDA (Center for Resource Satellite Data and Applications, China) http://www.cresda.com/EN/

CSA (Canadian Space Agency) http://www.asc-csa.gc.ca/eng/

CSIRO (Commonwealth Scientific and Industrial Research Organisation) http://www.csiro.au/

ESA (European Space Agency) http://www.esa.int/ESA

EU (European Union) http://europa.eu/index_en.htm

GA (Geoscience Australia) http://www.ga.gov.au/

GEO (Group on Earth Observations) https://www.earthobservations.org/index.php

GEOGLAM (GEO Global Agriculture Monitoring) https://www.earthobservations.org/geoglam.php

GEOSS (Global Earth Observation System of System) http://www.earthobservations.org/geoss.php

GFOI (Global Forest Observations Initiative) http://www.gfoi.org/

GWG (Global Working Group) on Big Data for Official Statistics http://unstats.un.org/unsd/bigdata/

INPE (Instituto Nacional de Pesquisas Espaciais, the Brasilian National Institute for Space Research) www.inpe.br

JAXA (Japan Aerospace Exploration Agency) http://global.jaxa.jp/

NASA (National Aeronautics and Space Administration) https://www.nasa.gov/

NASA Earth Observation: https://earthdata.nasa.gov/earth-observation-data

OSCAR (Observing Systems Capability Analysis and Review Tool) https://www.wmo-sat.info/oscar/

OSCAR database: http://www.wmo-sat.info/oscar/spacecapabilities

UN GGIM (United Nations Committee of Experts on Global Geospatial Information Management) http://ggim.un.org/

UN SC (Statistical Commission) http://unstats.un.org/unsd/statcom

UN SDSN (Sustainable Development Solutions Network) http://unsdsn.org/

USGS (United States Geological Survey) https://www.usgs.gov/

WMO (World Meteorological Organisation) SDGs (Sustainable Development Goals) http://public.wmo.int/en/resources/bulletin/wmo-supporting-2030-agenda-sustainable-development

NCI (National Computational Infrastructure) http://nci.org.au/

VPAC (Victorian Partnership for Advanced Computing Ltd)