Beyond Crop Production Estimates: Integrated climate, biophysical and remote sensing approaches

"If you can look into the seeds of time, and say which grain will grow and which will not, speak then unto me. " William Shakespeare

A Potgieter et. al.







DATA **#** Application





Global food supply and demand (food security)



- Challenge production nearly DOUBLE by 2050,
- Yield growth of most crops is declining,
- Demand for maize, rice and wheat is increasing and
- Population increased by 40% by 2050
- International markets fail the poor.
- Thus, knowledge of How Much, Where and When is produced will become

Predicting Plant Growth



Crop life cycle duration is closely associated with temperature

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Example 1: USA maize yields David Lobell, *Stanford University, USA*



A scalable crop yield mapper (SCYM)



Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

A scalable satellite-based crop yield mapper

David B. Lobell^{a,*}, David Thau^b, Christopher Seifert^a, Eric Engle^b, Bertis Little^c

APSIM crop simulations of leaf area index (LAI) and yield

Convert LAI to satellite measure

Train regressions, which relate yield to vegetation index and weather, for various image timings



Apply regressions to Landsat in Google Earth Engine ant Science





SCYM Estimate (t/ha)



Example 2: GEOGLAM Inbal Rashef Becker,

Maryland University, USA

Group on Earth Observations Global Agricultural Monitoring (GEOGLAM) & Agricultural Market Information System (AMIS)

Model enhanced using Growing Degree Days (GDD) to improve timeliness Extended to China and all of US China Example: Forecast within 6% of final yields 2-3 months prior to harvest





Example 3: Canada Nathaniel Newlands, *Agriculture and Agri-Food Canada (AAFC)*

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The Integrated Canadian Crop Yield Forecaster (ICCYF) tool Spring Wheat Daily Climate Data Weekly NDVI By Pixels By Station The ICCYF CAR Boundar Paramete Мар Extent map integrates climate, Versatile Soil Moistur GIS Processin Budaet Model (VSMB satellite remote Veekly NDVI By Daily Agroclimatic CAR Indices By Stations sensing derived CAR Crop Land Boundary Extent man storical Yield Data Integration data by CAR MAPE (% vegetation indices, GIS and R Proces < 10 Daily Agroclimat soil and crop Indices By CAR 10 information through 15 -Model Building Parameter Distribution **Barley** 20 -Predictor Selectic rior Distribution Gene (RLARS) a physical processnputs With > 30 Posterior Distributi Rohust Cross Validat Generator (MCMC) lear Real based soil water Time Innuts Nithout Yield Updated Predic Yield Model By CAR distribution budget model and Estimated Unavailable Innuts Data Generati (Random Forests Forecasted Yield Probability B statistical algorithms References: Newlands et al., 2014. Front. Environ. Sci. 2,17. doi : 10.3389/fenv Kouadio el al., 2014. Remote Sens. 6:10193-10214 • Chipanshi et al., 2015. Agri. For. Meteor. 206:137-150



Example 4: Production estimates for major crops in Australia A Potgieter, *University of Queensland Australia*



Regional scale commodity forecasting framework



Near-real time Integrated Crop & Agricultural Monitoring System (iCAMS)



Innovative - Science - Integration - Application

Spatial within season forecast



Legend (%):

Lowest on record

Area Estimates: Reconstructing of time series





(Verhoef et al 1996; Potgieter et al. 2007, 2010, 2011)



Ground truthing - Crowd sourcing



http://www.paddockwatch.com.au

Specific & Total Crop Area & Production







Where to from here

- Framework high efficacy in predicting point and regional crop yield, through integration of satellite imagery and crop simulation models
- Aligns with UN SDG 2 (food security) & SDG 13 (climate change & impacts)
- Issues for further discussion:
 - Scalability (State, Nation Continental, Global)?
 - Automation to enable implementation?
- Increase Lead time further (linking with Global General circulation models)