ABSTRACT

Title of Document:	A GENERALIZED APPROACH TO WHEAT YIELD FORECASTING USING EARTH OBSERVATIONS: DATA CONSIDERATIONS, APPLICATION, AND RELEVANCE.
	Inbal Becker-Reshef, Doctor of Philosophy, 2012
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Abstract

In recent years there has been a dramatic increase in the demand for timely, comprehensive global agricultural intelligence. The issue of food security has rapidly risen to the top of government agendas around the world as the recent lack of food

access led to unprecedented food prices, hunger, poverty, and civil conflict. Timely information on global crop production is indispensable for combating the growing stress on the world's crop production, for stabilizing food prices, developing effective agricultural policies, and for coordinating responses to regional food shortages.

Earth Observations (EO) data offer a practical means for generating such information as they provide global, timely, cost-effective, and synoptic information on crop condition and distribution. Their utility for crop production forecasting has long been recognized and demonstrated across a wide range of scales and geographic regions. Nevertheless it is widely acknowledged that EO data could be better utilized within the operational monitoring systems and thus there is a critical need for research focused on developing practical robust methods for agricultural monitoring. Within this context this dissertation focused on advancing EO-based methods for crop yield forecasting and on demonstrating the potential relevance for adopting EO-based crop forecasts for providing timely reliable agricultural intelligence. This thesis made contributions to this field by developing and testing a robust EO-based method for wheat production forecasting at state to national scales using available and easily accessible data. The model was developed in Kansas (KS) using coarse resolution normalized difference vegetation index (NDVI) time series data in conjunction with out-of-season wheat masks and was directly applied in Ukraine to assess its transferability. The model estimated yields within 7% in KS and 10% in Ukraine of final estimates 6 weeks prior to harvest. The relevance of adopting such methods to provide timely reliable information to crop commodity markets is demonstrated through a 2010 case study.

A GENERALIZED APPROACH TO WHEAT YIELD FORECASTING USING EARTH OBSERVATIONS: DATA CONSIDERATIONS, APPLICATION AND RELEVANCE

By

Inbal Becker-Reshef

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2012

Advisory Committee:

Professor Christopher Justice, Chair
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Professor Bruce James

Foreword

Chapters 1-3 are comprised of co-authored publications for which I am the lead author. I was responsible for the writing, literature review, developing and executing the methods, data collection, and for the analysis featured in this dissertation. The results and findings presented in this dissertation are the outcome of my work.

Dedication

To my parents
Shoshana & Daniel

siblings
Ma'ayan, David, Yakir & Edith

and to my partner
Guido

Acknowledgements

There are numerous people I am grateful to for their support throughout the course of my PhD. First and foremost, I would like to thank Dr. Chris Justice and Dr. Eric Vermote. It has been a privilege to be mentored and supported by such thoughtful, dedicated and knowledgeable advisors. I sincerely appreciate their commitment to my success and growth as a researcher. They have made my PhD experience productive, stimulating and meaningful and have provided me with unmatched opportunities and learning experiences that allowed me to grow tremendously, professionally and personally. Thank you.

I extend many thanks to the members of my dissertation committee, Dr. Samuel Goward, Dr. Compton Tucker, Dr. Brad Doorn, and Dr. Bruce James for their time, guidance, interest and confidence in my abilities throughout the course of my PhD. They have been a great source of insight, collaboration, and motivation.

Mark Lindeman, from USDA FAS has contributed immensely to my PhD work. I thank him for sharing his enthusiasm, tremendous knowledge and expertise in agricultural monitoring, in particular on the topic of wheat, and for providing me the opportunity to accompany him on two USDA crop travel trips to Ukraine and Russia. His experience and inputs were invaluable in developing the yield model and ensuring it is useful – which was my ambition at the outset of my PhD. Dyakuyu!

I would also like to thank my colleagues fellow graduate students and friends and at UMD Department of Geographical Sciences that I have had the pleasure of working with and alongside in particular: Lydia Prentiss, Jack O’banon, Karen Schleeweis, Giuseppe Molinario, Janet Nackoney, Alyssa Whitcraft, and LeeAnn King. They have been a great source of support, problem solving, and encouragement. I am particularly indebted to Mark Sullivan who developed the GLAM system and has provided me with constant support and friendship. I would also like to acknowledge Dr. Matthew Hansen for bringing me on to the GLAM project and for many insightful discussions along the way.

This research was made possible in large part by the NASA Applied Science Program. I am grateful to Brad Doorn and Lawrence Friedl for their dedication and commitment to maintaining support for our agriculture program. I would also like to gratefully acknowledge support from the NSF IIASA YSSP fellowship I received and extend many thanks to the IIASA Ecosystems Services and Management group, in particular, Steffen, Linda See and Marjin for their interest and many helpful comments.

Lastly I extend tremendous gratitude to my friends, family and to my partner Guido Pupillo who have been an indispensable source of love and encouragement. Their patience and support is so very appreciated. Thank you.

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Chapter 1: Introduction[1]

1.1 Background and Context

1.1.1 Current context

The issue of food security has rapidly risen to the top of government agendas around the world as the recent lack of food access has led to unprecedented food prices, hunger, poverty, and civil conflict. With one in seven people estimated to suffer from hunger and malnutrition, global food production is facing immense challenges from an ever-growing global population, an increasing demand for animal products (particularly in India and China), increased production of biofuels, land degradation, volatile grain markets, limited arable land and water resources, and extreme weather events in particular, severe droughts and floods (Godfray et al. 2010, Foley et al. 2011). With a warming world and a changing climate, these problems will remain major issues for governments in this century (GEO-Agriculture-CoP 2011).

Tools for monitoring and reliably forecasting production are essential for anticipating market imbalances, stabilizing markets and enhancing policy responses (AMIS 2011). As such, following the 'Global Food Price Crisis' in 2008, when the cost of food reached record highs and global food stocks reached near record lows, the World Summit on Food Security called for increased international cooperation and collaboration amongst governments and international agencies to improve the quality of national agricultural statistics, production forecasting and early warning

[1] Some of the material presented in this chapter was previously published in: Becker-Reshef, I., Justice, C., Sullivan, M., Vermote, E., Tucker, C., Anyamba, A., Small, J., Pak, E., Masuoka, E., Schmaltz, J., Hansen, M., Pittman, K., Birkett, C., Williams, D., Reynolds, C., & Doorn, B. (2010). Monitoring Global Croplands with Coarse Resolution Earth Observations: The Global Agriculture Monitoring (GLAM) Project. *Remote Sensing, 2*, 1589-1609

systems for food insecurity (FAO 2009). Subsequently, in June of 2011 the G-20 ministers adopted an action plan on food price volatility and agriculture (G20 2011), and in October of 2011 UN Food and Agriculture Organization (FAO) issued a report (FAO 2011a) titled ‘the State of World Food Insecurity’ which calls for better information systems that provide accurate, consistent, transparent and timely agricultural market data and analysis. This report highlights the need for better use of remotely sensed data, geographic information systems and for improved production forecast models that are able to translate crop growth, meteorological and remote sensing data into yield and production.

As reflected by these reports and action plans, it is widely acknowledged that timely, traceable, transparent, reliable crop production forecasts and estimates have a critical role to play in: regulating markets and anticipating market imbalances; developing national and international agricultural policies; and in effectively mitigating food shortages.

Satellite Earth observations (EO) such as surface reflectance, temperature, and microwave measurements provide the only practical, cost effective means for obtaining timely, objective global information on crop extent, condition and growth. As such, it is explicitly recognized that capabilities afforded by EO data should be better utilized, further developed, and serve as an integral component of the existing operational agricultural monitoring systems (Becker-Reshef et al. 2009a, FAO 2011a). At same time there is a critical need to ensure continuity of the current earth observing systems and to address the inadequacies of the current systems, such as the lack of high quality, accessible, fine (i.e. 0.5m – 20m) and moderate (20m-60m) spatial resolution data with revisit frequency higher than 14-16 days during the growing season, particularly over complex agricultural landscapes (Justice and Becker-Reshef 2007).

Research and development over the past several decades in the field of agricultural remote sensing has led to considerable capacity for crop monitoring within the current regional/global operational monitoring systems including the US Department of Agriculture Foreign Agricultural Service (USDA FAS), the European Commission Joint Research Center (JRC) Monitoring Agricultural Resources Unit (MARS), the UN Food and Agriculture Organization (FAO) Global Information Early Warning System (GIEWS), and the Chinese Academy of Sciences (CAS) China CropWatch System(Becker-Reshef et al. 2009b). These systems are relied upon nationally and internationally to provide crop forecasts as the growing season progresses. Nevertheless many challenges exist for making the best use of the currently available, remotely sensed data within such systems, and there is a critical need for applied research to enhance the capability of such systems around the world (GEO-Agriculture 2012).

1.1.2 Foundation for Satellite Based Agricultural Monitoring

The National Aeronautics and Space Administration (NASA) and the US Department of Agriculture (USDA) have been collaborating to monitor global agriculture from space since the 1970s. Preliminary research and development on satellite monitoring of vegetation and agriculture specifically, started with the Earth Resources Technology Satellites (Landsat system) in the early 1970's (Cohen and Goward 2004, Goward et al. 2011). Key events, including unanticipated severe wheat shortages due to Russian crop failures, drew attention to the importance of timely and accurate prediction of world food supplies. Subsequently, in 1974, the USDA, NASA and National Oceanic and Atmospheric Administration (NOAA) initiated the Large Area Crop Inventory Experiment (LACIE) (Macdonald and Hall 1980). The goal of this experiment was to improve domestic and international crop forecasting methods (Pinter et al. 2003). Early work by USDA and NASA researchers in the late sixties and seventies on relating crop plants to their optical properties (Knipling 1970, Leamer, Weber and Wiegand 1975, Allen and Richardson 1968, Tucker 1979) provided the theoretical basis for monitoring crop growth using remotely sensed information (Hatfield et al. 2008, Pinter et al. 2003). Based on the success of the LACIE experiment that demonstrated satellite imagery could be used operationally to forecast wheat yields in the US and USSR (Bauer 1979), the Agriculture and Resource Inventory Surveys Through Aerospace Remote Sensing (AgRISTARS) program was initiated in the early 1980's jointly by NASA, USDA, NOAA and the US Department of State. Through the research conducted in these NASA-USDA joint programs, the considerable potential of remotely sensed information for monitoring and management of agricultural lands was identified.

One of the most recent efforts that NASA and the USDA Foreign Agricultural Service (FAS) have initiated is the Global Agricultural Monitoring (GLAM) Project focused on applying data from NASA's flagship Earth Observing System (EOS) instrument, the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the Terra satellite, to feed the FAS Decision Support System (DSS) needs. Despite the fact that the research in this field has been active for several decades, it still has not translated into a feasible operational EO-based system for global crop production forecasting. New sensor technologies and continued advancements of quality, temporal and spatial resolution of EO data, offer opportunities for enhancement and continued development of methods for agricultural monitoring.

1.1.3 Current State: USDA FAS Global Agricultural Monitoring.

The Foreign Agricultural Service (FAS) of the US Department of Agriculture (USDA) is a world leader in agricultural monitoring and is currently the only agency internationally providing timely global crop estimates. The FAS works to improve foreign market access for US products, build new markets, improve the competitive position of US agriculture in the global marketplace, and provide food aid and technical assistance to foreign countries (USDA 2007). The mission of the FAS Office of Global Analysis (OGA)/International Production Assessment Division (IPAD) is to produce the most objective and accurate assessment of the global agricultural production outlook and the conditions affecting food security in the world. (USDA 2007).

FAS crop analysts provide estimates of global production in support of the World Agricultural Outlook Board (WAOB) which coordinates reviews and approves the monthly World Agricultural Supply and Demand Estimates (WASDE) report by the 11th day of each month, using a convergence of evidence approach (Vogel and Bange 1999). These production estimates are the official USDA statistics and play a vital role within the global agricultural market as they are utilized in a variety of ways including: principal federal economic indicators, crop condition and early warning alerts, agricultural monitoring and food security, foreign aid assessments for food import needs, disaster monitoring and relief efforts related to food aid, commercial market trends and analysis, and trade policy and exporter assistance.

The crop analyst production estimates are derived by synthesizing information from a wide array of sources, including attaché reports, local reports, field surveys, climate data, and exploiting a variety of tools including RS-based data visualization and analysis. Nevertheless, it is the remotely sensed earth observations that enable crop monitoring to be comprehensive, unbiased, timely owing to their cost-effectiveness, and synoptic and global coverage. Satellite data have played an important role in the FAS DSS system since the mid-1970's, providing timely, synoptic information on crop distribution and condition (Reynolds 2001). FAS is one of the largest users of remotely sensed data in the federal government utilizing a combination of Landsat, Advanced Wide Field Sensor (AWiFS), Deimos, Advanced Very High Resolution Radiometer (AVHRR), Système Pour l'Observation de la Terre (SPOT) and MODIS data for operational monitoring of agriculture worldwide.

1.1.4 Programmatic Context: GLAM

The research in this thesis was carried out in large part within the context of the most recent USDA-NASA-UMD collaboration: GLAM initiated in 2002. GLAM is a joint research project between the USDA FAS, the Global Inventory Monitoring and Modeling Studies (GIMMS) group at NASA Goddard Space Flight Center (GSFC), the University of Maryland (UMD) Department of Geographical Sciences. It was initiated in 2002 and is funded jointly by USDA-FAS and the NASA Science Applications Program (Becker-Reshef et al. 2010a). The goal of GLAM is to enhance the agricultural monitoring and the crop-production estimation capabilities of the FAS by using the new generation of NASA satellite observations including from MODIS and the Visible Infrared Imaging Radiometer Suite (VIIRS) instruments. This project built one of the most comprehensive data management systems for remotely-sensed based global agricultural monitoring (USDA-FAS 2009a). It was developed taking advantage of the significant investment made by NASA in instrument characterization and product development by the MODIS Land Science Team, using MODIS data provided in Near Real Time by the Land Atmosphere Near real-time Capability for EOS (LANCE) (Murphy et al. 2011). The philosophy, as shaped by the FAS, was to remove the burden of front-end processing of satellite data from the user and present time-series data in a manageable form, for ease of interrogation by the analyst (Becker-Reshef et al. 2009a).

Currently a suite of 8-day and 16-day composite MODIS time-series Vegetation Indices (Normalized Difference Vegetation Index, (NDVI), and Normalized Difference Water Index, (NDWI)) are custom processed and provided in near real time to USDA crop analysts. The vegetation index (VI) products are generated from the MOD09 Land Surface Reflectance product (Vermote, El Saleous and Justice 2002). The analysts use these data, in combination with crop masks, to track the evolution of crops through the growing season by making inter-annual comparisons. However, at present, these data are rarely integrated into crop forecasting models. Figure 1 provides an example of how the GLAM MODIS DBMS was used to qualitatively track the impact of the 2008–2009 drought on crops in Argentina. This drought had a devastating effect on crops leading to a 30–60 percent reduction in production relative to the previous year (USDA-FAS 2009b).

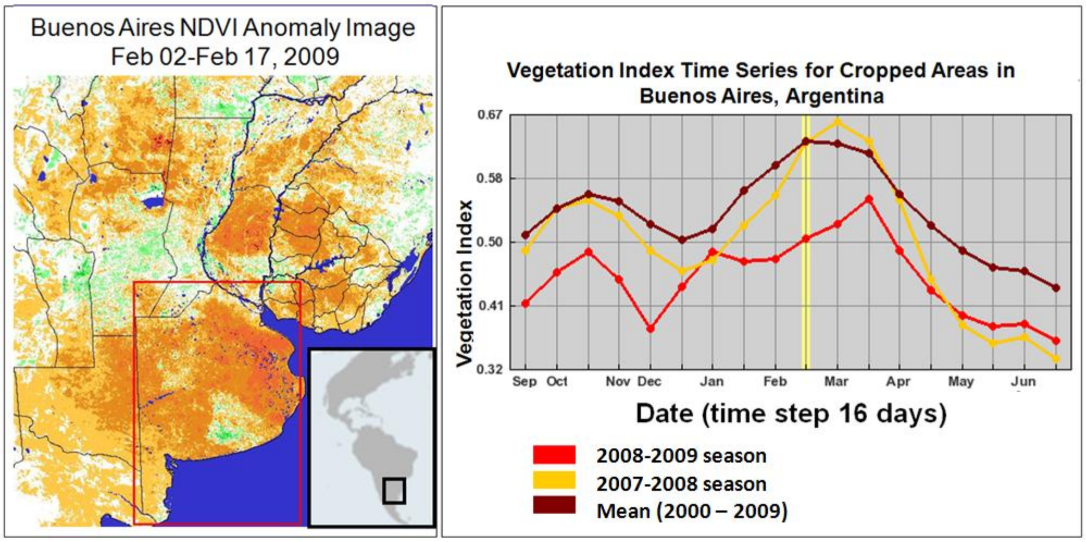


Figure 1.1 NDVI anomaly image (left), February 2nd -17th 2009, showing the impact of the 2009 drought in Argentina. Brown indicates negative anomalies, where NDVI was below the average NDVI for 2000-2008, green indicates higher than average NDVI values. The NDVI time series graph on the right compares the 2009 NDVI temporal profile of croplands in the Buenos Aries district to the mean NDVI profile and to the previous year. (Becker-Reshef et al. 2010a)

1.2 Rationale for this research

1.2.1 Current state (limitations) of crop yield models

Despite several studies on crop production forecasting, crop yield models have seldom progressed to implementation over large areas in an operational domain and are typically applicable primarily in the region for which they were developed. A variety of methods have been developed to estimate crop yields using remotely sensed information. These include biophysical crop-simulation models that retrieve crop growth parameters from remotely sensed data and used as inputs to calibrate and drive the models. The main drawback of such models is that they typically require local calibration and numerous crop specific inputs such as soil characteristics, management practices, agro-meteorological data and planting dates, in order to simulate crop growth and development through the crop cycle (Moriondo, Maselli and Bindi 2007, Dubey et al. 1994). Examples of such crop simulation models and tools include Crop Environment Resource Synthesis (CERES) (Ritchie and Otter 1985), World Food Studies (WOFOST) (Vandiepen et al. 1989), CopSyst (Vanevert and Campbell 1994) Simulateur mulTIdisciplinaire pour les Cultures Standard (STICS) (Brisson et al. 1998), Erosion Productivity Impact Calculator (EPIC) (Williams 1990), Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al. 2003) and Agricultural Production Systems Simulator (APSIM) (Keating et al. 2003). Another class of models are statistical regression-based methods which are the most commonly used remote sensing-based approaches for yield forecasting (Wall, Larocque and Leger 2007). These are based on empirical relationships between historic yields and reflectance-based vegetation indices. They are typically straightforward to implement and do not require numerous inputs. A main drawback of empirically-based approaches is that relationships between yield and reflectance are typically localized and are not easily extendable to other areas (Doraiswamy et al. 2003, Moriondo et al. 2007). Nonetheless, they are often the preferred approach, owing to their limited data requirements and simplicity of implementation. This dissertation is focused on developing an empirical yet transferable yield forecasting approach.

Most countries and agricultural agencies, including the USDA National Agricultural Statistics Service (NASS) rely primarily on traditional methods for generating crop statistics. These include multiple frame-based sample surveys from farm operators, and objective yield surveys where ground measurements of crop yields are collected from randomly selected fields (Allen, Hanuscak and Graig 2002). A primary challenge for better integration of EO-based monitoring into the existing operational monitoring systems is limited investments in the research and development necessary to realize the operational potential of the US civilian space assets.

This research builds on the extensive body of research that has been carried out over the past several decades on crop yield forecasting, utilizing advances in remotely sensed capabilities and products to develop an operationally viable, robust approach for assessing yields prior to harvest at national scales. The focus was on utilizing readily available EO data sets and optimizing the approach according to the spatial and temporal resolution of the available data.

1.2.2 Why Wheat?

This dissertation is focused specifically on wheat yield forecasting for several reasons. Wheat cultivation is one of the primary agricultural land uses worldwide with the highest planted area among food crops. Wheat is the most important cereal crop traded on international markets (Wittwer 1995, FAO 2003). Wheat shortfalls due to severe droughts in the principal export countries were major factors in the recent global grain price surges in 2008 and 2010 (FAO 2011a) and contributed to the low global wheat stocks in 2008 (Trostle 2008). In 2008 global wheat stocks reached a thirty-year low, and the U.S. wheat stocks fell to their lowest levels since the late 1940's which was a significant factor leading to the 2008 food price crisis (Vocke 2008). In addition, wheat is the major commodity provided as food aid. Consequently wheat shortages not only impact wheat and wheat-product prices, but also have dire implications for ensuring food security in developing countries (WFP 2009, Mitchell and Mielke 2005). Timely and accurate forecasts of wheat production prior to harvest at regional, national and international scales for both developing and at-risk countries are crucial. Such estimates can help to improve food accessibility risk management, as well as play an important role in stabilizing global markets and informing policy and decision making (AMIS 2011, GEO-Agriculture 2012, FAO 2010, OECD et al. 2011).

1.3 Thesis Objectives

The overall focus of this dissertation is to advance EO-based crop yield forecasting and demonstrate the relevance for adopting such methods for providing timely reliable agricultural intelligence. This dissertation has three primary research objectives addressing three challenges as outlined below:

1. **Challenge:** Crop-type mask availability
    - **Objective:** Determine the appropriate spatial and temporal resolution for crop yield forecasting using easily accessible data

2. **Challenge:** Model transferability
    - **Objective:** Develop a robust EO-based model for winter wheat yield forecasting at state to national scales that is empirical yet portable between wheat growing locations

3. **Challenge:** Demonstration of Relevance
    - **Objective:** Demonstrate the potential benefit of EO-based crop forecasts for informing crop commodity markets by exploring the relationship between USDA wheat production forecasts and global wheat price variability using 2010 as a demonstration case study

1.4 Structure of the Thesis

This dissertation consists of five chapters (Figure 1.1). Chapters 1, 2, and 3 were originally written in self-contained journal publication formats and have been condensed in the dissertation to avoid redundancy and to improve the flow.

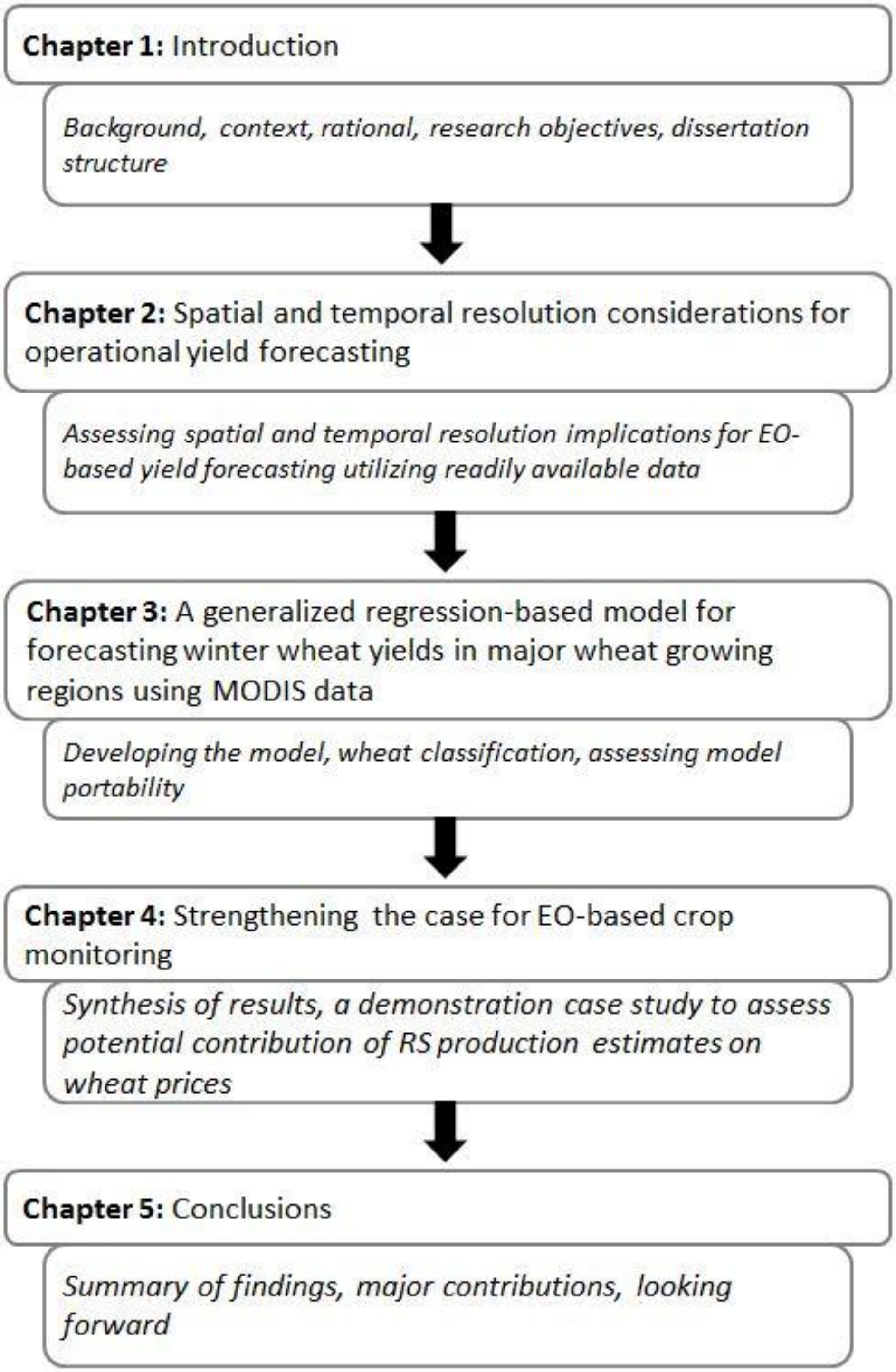


Figure 1.2 Structure of this dissertation.

Chapter 2: Spatial and temporal resolution considerations for crop yield forecasting at state to national scales in the absence of seasonal crop type masks[2]

2.1 Introduction

2.1.1 Context

Within-season spatial information on crop-type distribution are fundamental for up-to-date crop condition monitoring and yield forecasting over large agricultural areas. Yet the availability of such data is often limited and the temporal and spatial scales of the data available for this task are rarely at the required scales (Curnel et al. 2011, Justice and Becker-Reshef 2007). Within this context this study focused on developing a practical approach to wheat yield forecasting at national/sub-national scales in the absence of up-to-date (i.e. within the current growing season) crop-type information.

The approach developed in this study was based on spatially aggregating a single, crop-specific mask from a recent (within 6 years) preceding growing season assuming that the total area of wheat planted varies little in successive years. Preceding season masks are more likely to be available than within season masks and are easier to produce once the growing season is complete, as crop phenology (i.e. crop temporal profiles) can be used to differentiate crop types (Kastens et al. 2005). The approach proposed in this chapter can have significant implications for operational monitoring at national scales, as a single, recent, crop-specific mask from a preceding season can

[2] The material presented in this chapter was submitted for publication and is currently in revision. The paper was submitted to IEEE Geoscience and Remote Sensing Letters as: Becker-Reshef I., Vermote E., Justice C. Spatial Aggregation of Crop Type Masks for Enhanced Monitoring of Winter Wheat Yield.

be used in combination with coarse resolution EO NDVI time series for yield forecasting over multiple years.

2.1.2 Crop Type Maps for Yield Forecasting

Stratifying a region into cropland and, more specifically, crop type---a process commonly termed masking---is an important step in developing EO-based yield forecasting models (Kastens et al. 2005). Such masks enable the isolation of the remotely sensed (RS) crop-specific signal throughout the growing season, reducing the noise on the signal from other land cover or crop types. A variety of cropland masking methods used for isolating the crop signal for the purpose of yield forecasting have been documented in the literature. For example, Maselli et al. (2000) used NDVI thresholds to isolate the crop pixels of interest in the Sahelian region. Genovese et al. (2001) showed that using the cropland class from a medium resolution land cover classification improved coarse resolution yield forecasting accuracies. Similarly, Rojas (2007) in a study on corn yield in Kenya and Funk and Budde (2009) in a study on NDVI-based crop production anomaly estimates in Zimbabwe, used cropland masks to improve the accuracies of their yield forecasts. One of the difficulties in monitoring and forecasting crop yields using RS imagery is the availability of timely and annual crop masks for identification of the crop under investigation. Often, a general cropland mask is used to distinguish cropped areas from other land use types, rather than a crop-type specific mask (REF, Rasmussen 1997, Genovese et al. 2001). A general cropland mask can be used to isolate a general cropland signal but does not provide a crop-specific signal. There are significant differences in the spectral response between crops through the growing season (Wardlow, Egbert and Kastens 2007, Odenweller and Johnson 1984, Johnson 2010). Due to the widespread practice of crop rotation, the use of a crop-specific mask requires that a season-specific mask be produced for developing the statistical relationship. Moreover, in order to forecast yields during the growing season, the crop-specific mask is required prior to the end of the growing season, which can present a significant logistical challenge (Kastens et al. 2005) and therefore this critical information is seldom available during the growing season. Even in the case of the USA where the USDA NASS, a world leader in operational crop type mapping and monitoring, produces annual crop type maps, this information is only publically released after the end of the growing season.

To address this challenge this study sought:

- to investigate a practical approach to yield forecasting over large regions (i.e. state and national levels) using available EO data and that can be implemented in cases where within-season crop type masks are not readily available
- to assess the associated accuracy tradeoffs relative to an 'optimal' case where within season crop type masks are available.

2.2 Data and Study Site

2.2.1 Study Site

The State of Kansas was chosen as the study site for this research, as it is the primary wheat growing state in the U.S. Reliable annual winter wheat classifications are available from the USDA NASS Kansas Cropland Data Layer (CDL) (Mueller, Boryan and Seffrin 2009). On average, between 2000 and 2010, Kansas produced over one fifth of the total U.S. wheat production.

In Kansas, at the state and county levels, winter-wheat planted-area generally remains relatively constant between consecutive years. According to the USDA National Agricultural Statistics Service (NASS) statistics the standard deviation of wheat planted area in KS between 2000 and 2011 was 6% (NASS 2012b). Due to the widespread practice of crop rotations (figure 2.1), the location of planted wheat fields alternates from one year to the next within the majority of counties in the state, although the total planted area remains relatively constant. As such, a static wheat mask (derived from a single growing season) at a moderate resolution would not be sufficient for capturing the wheat signal over multiple growing seasons for the purpose of yield forecasting where crop rotation is common practice.

This study relied on two types of available data: i) Crop type maps from the USDA NASS CDL for five years, 2006 through 2011, and ii) NASA MODIS 250m 8-day and 16-day NDVI composites. These datasets are summarized below.

2.2.2 The USDA NASS Cropland Data Layer (CDL)

The CDL is a crop-specific, rasterized, geo-referenced land-cover map produced by NASS. (Mueller et al. 2009, NASS 2012a). NASS is the agency responsible for administering the USDA's U.S. program for collecting and publishing agricultural statistics at the national, state and county levels. The CDL is produced annually for the main agricultural growing states within the United States and is released to the public domain after the release of official county crop estimates. The KS NASS CDL layers used in this study were produced by NASS using medium resolution (30 to 56 meter) imagery from the Indian IRS AWiFS data, Landsat 5, Landsat 7, the NASS June Agricultural Survey (JAS), and Farm Service Agency (FSA) Common Land

Unit for ground truth and training data. The major crop types within the CDL generally have a classification accuracy ranging between 85% and 95% (NASS 2010). In this study, winter wheat binary masks were extracted from the Kansas 2006, 2007, 2008, 2009, 2010 and 2011 CDLs and aggregated to a range of increasingly coarser spatial resolutions in order to investigate the relationship between crop rotation and spatial scale and the feasibility of using spatially aggregated crop masks to forecast yields when seasonal crop type masks are not available.

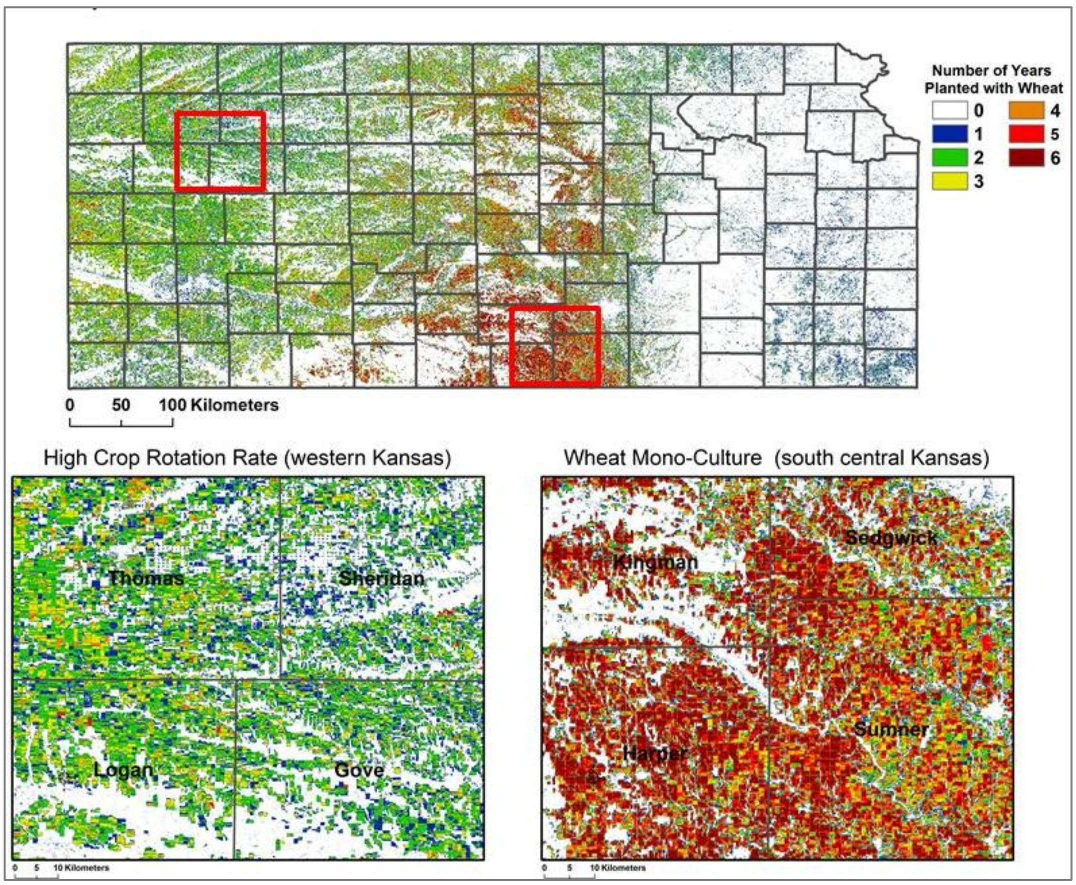


Figure 2.1 Crop rotation rates in Kansas over 6 years: 2006-2011. Low rotation rates are in red (i.e. no rotation where 6 out of 6 years were planted with wheat) and high rotation rates are in blue. Top panel shows the entire state and the lower panels highlight two contrasting areas. Left panel is an area where crop roatation is wide-spread, and the right panel is an area with a wheat mono-culture

2.2.3 Vegetation Index Time Series Data

NDVI was chosen as the remotely sensed input parameter as it has been shown to be strongly correlated during the growing season to crop condition parameters such as vigor, stress, green biomass and photosynthetic capacity (Jackson et al. 1986, Wiegand and Richardson 1990, Patel et al. 2006, Idso et al. 1979b, Tucker 1979, Tucker et al. 1981, Sellers 1985). The NDVI was computed from the MODIS surface reflectance time-series CMG daily product using equation 2.1 (Tucker 1979).

MODIS 250 meter 16-day and 8-day NDVI composite time-series were obtained for the 2006 through 2011 growing seasons from the Global Agricultural Monitoring (GLAM) database (Becker-Reshef et al. 2010a). The 16-day composite dataset is generated as an input to the MODIS Vegetation Continuous Fields (VCF) intermediate surface-reflectance dataset (Carroll et al. 2011) produced by NASA MODIS Advanced Processing System (MODAPS) (Masuoka E. 2011). The 8-day composite data set is derived from the MOD09 Surface Reflectance product (Vermote and Kotchenova 2008). NDVI was computed using the Red (MODIS band 1, 620nm – 670nm) and near infrared (MODIS band 2, 841nm – 876nm) bands:

$$(NIR - RED)/ (NIR + RED) \quad \text{(Tucker 1979).}$$

Equation 2.1

Remotely sensed derived VI's have long been recognized for their value as inputs to crop yield and production forecasting models, as well as for tracking crop growth and development (Pinter et al. 1981, Funk and Budde 2009, Tucker et al. 1980, Hatfield 1983, Maselli et al. 1993, Rasmussen 1992, Quarmby et al. 1993). In particular, it has been shown that crop forecasting models are significantly improved when crop masks are used in conjunction with the VI data, as the crop masks isolate the signal of the crop under investigation (Kastens et al. 2005, Doraiswamy et al. 2004). In this study, CDL-derived binary wheat masks were scaled up to a range of coarser spatial resolutions and used to extract NDVI time-series for wheat pixels.

2.3 Methods

This study was carried out in five main steps: 1) Assessment of temporal resolution suitability of available EO data for yield forecasting; 2) spatial aggregation of the 2006 - 2011 wheat masks to increasingly coarser spatial resolution percent-wheat masks; 3) analysis of inter-annual percent wheat variability over five years at a series of spatial resolutions; 4) extraction of wheat-specific NDVI temporal profiles; 5) yield estimation under two scenarios for crop mask availability.

2.3.1 Temporal Resolution Assessment

Crops grow and develop rapidly during the growing season. Winter wheat is generally planted in autumn and crop emergence and stand establishment typically occurs in late autumn prior to winter. Winter wheat requires a process of vernalization (exposure to low temperatures) in order to flower the following spring (Miller 1999). Vernalization requires exposure to temperatures of 5 to 10 degrees Celsius for a period of six to eight weeks, and the crop must be biologically active for at least four weeks prior to vernalization. In colder climates winter wheat typically enters a state of dormancy during the winter. During winter, vegetative growth slows or ceases and the crop's resistance to cold weather is increased. Once the soil warms up in the spring, winter wheat resumes rapid vegetative growth followed by reproductive development and reaches maturity in early to mid-summer.

Frequent observations are critical for effectively monitoring the crop's development and state. In general, composite data are used in order to eliminate clouds and to obtain high quality observations by selecting the nearest to nadir observations. Both 16-day and 8-day composites are freely available from NASA's MODIS sensor at the 250m resolution. In this study, the seasonal maximum NDVI was used as the primary model input for estimating wheat yields (Becker-Reshef et al. 2010b). The 16-day composites are not maximum NDVI composites, but are rather the best quality observation within the 16 day period. (Best quality not only with respect to cloud and atmosphere perturbation but also with respect to geometry, so the selection favors observations closest to nadir.) Consequently the 16-day time-series data are likely to often miss the seasonal NDVI peak of wheat. As such it was expected that the higher temporal resolution data, i.e. 8-day composites, would be better suited than the 16-day composites, for extracting the seasonal maximum NDVI signal. To assess this, seasonal NDVI profiles of wheat were extracted for all counties in KS at 250m resolution using both the 8-day and 16-day data sets. The results indicate that in Kansas the NDVI seasonal peaks extracted from the 8-days composite were consistently higher than the NDVI peaks extracted from 16-day composites for the period of study (2006-2011). The results for this analysis are shown in figures 2.2 through 2.4. From visual inspection of figure 2.2, an example from Rice County, it appears that the 8-day data is better able to capture the seasonal peak. Therefore this was further explored by extracting the maximum seasonal NDVI of wheat from every county in KS over five growing seasons (figures 2.3 and 2.4). . The Results from this analysis indicate that indeed the 8-day composites are better able to capture the seasonal peaks and are consistently higher than the peaks extracted from the 16-day data. The 8-day MODIS data set was selected for this study.

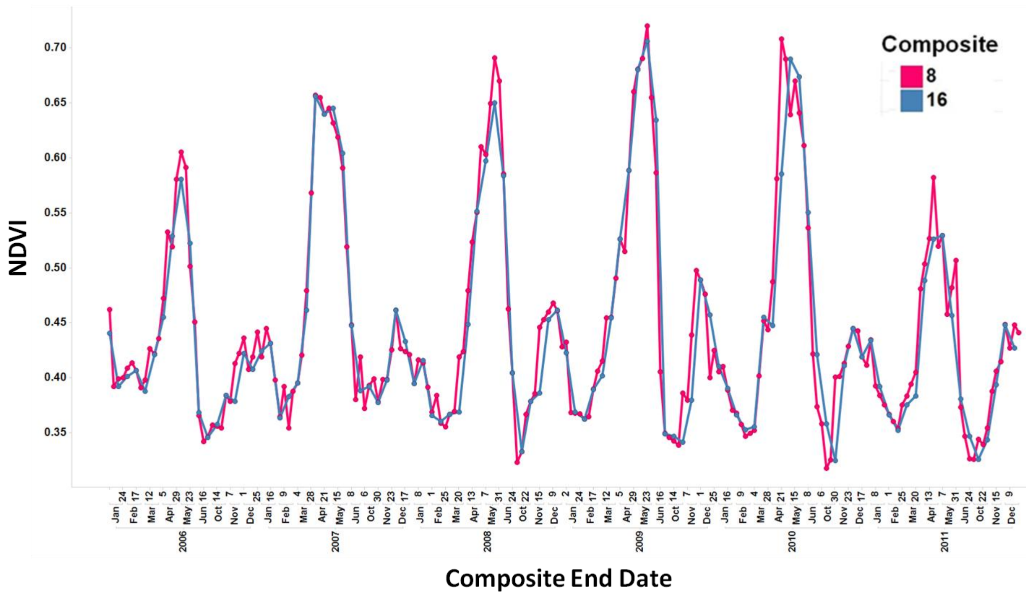


Figure 2.2 Rice County NDVI time series graph (2006-2011) comparing the 16-day (blue) versus 8-day (pink) wheat profiles. The 8-day NDVI seasonal peaks are consistently higher than the corresponding 16-day NDVI seasonal peaks.

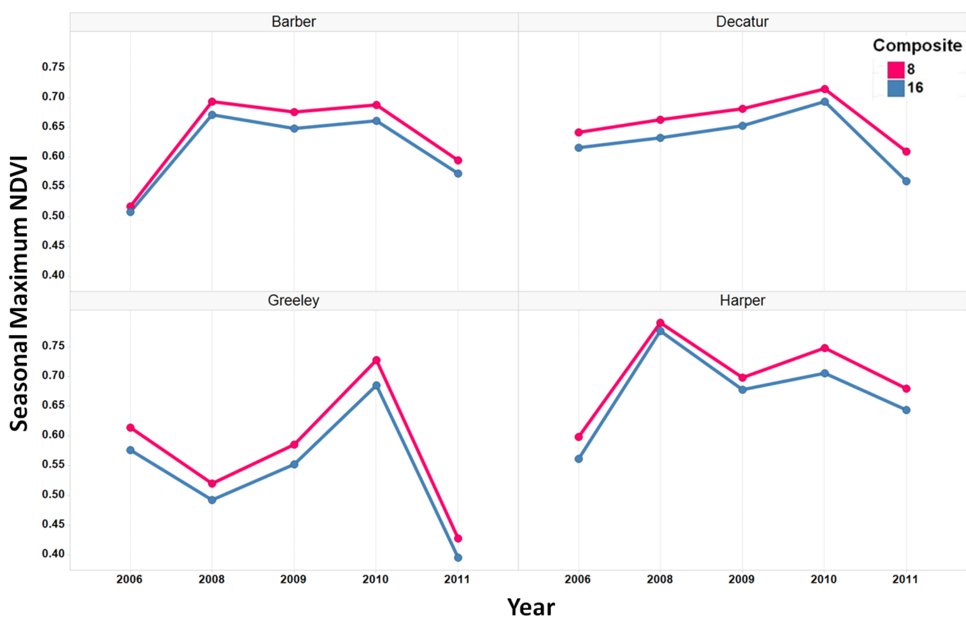


Figure 2. Seasonal maximum NDVI extracted for wheat pixels from 4 counties in KS over 5 growing seasons. The pink indicates the 8-day seasonal maximum NDVI and the blue indicates the 16-day seasonal maximum NDVI for each for the 5 seasons.

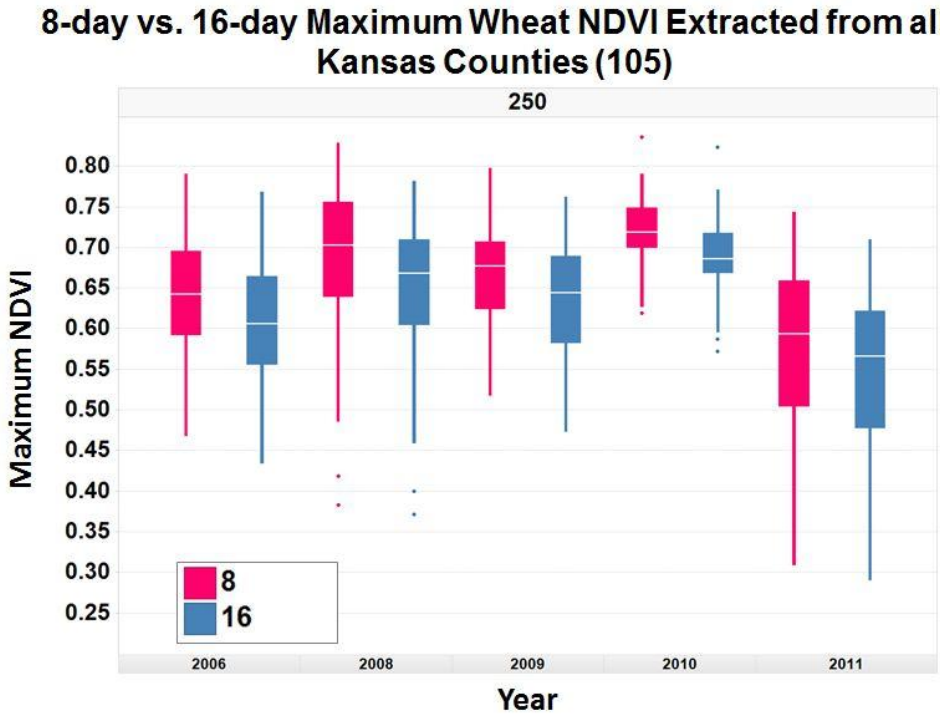


Figure 2.4 Contrasting the 8-day versus 16-day distributions of the wheat seasonal maximum NDVI extracted from all counties in KS

2.3.2 Spatial Aggregation of Wheat Masks

Once the temporal resolution was selected the next step was to extract the winter wheat pixels from the season specific Kansas CDLs (2006-2011) creating six binary wheat masks at the CDL's native 56 meters spatial resolution. Wheat pixels were assumed to be pure pixels and therefore assigned a value of 100% and all other pixels were set to 0%. These masks were then re-projected to match the MODIS NDVI time-series data sinusoidal projection.

Each of the six annual wheat masks was scaled up to a series of fifteen, increasingly coarser resolution percent wheat masks, where pixel values represent the proportion of wheat within each pixel.. The output was 90 wheat masks: 15 masks for each year between 2006 and 2011 at the following spatial resolutions: 250m, 750m, 500m, 1km, 2km, 3km, 4km, 5km 6km, 7km, 8km 9km 10km, 20km, county (on average ~

45km, in this case each county was treated as a single grid cell). At each resolution the per-pixel percent wheat was calculated by averaging the value of the 56 meter binary masks (wheat – 100, not wheat – 0) within the coarser resolution pixel (equation 1). This approach is similar to the spatial aggregation approach commonly described in the literature (Woodcock and Strahler 1987, Morisette et al. 2003, Nelson et al. 2009).

For pixel x at coarse resolution r: $PctW_{x,r} = \frac{nCDLWheat}{N}$

Equation 2.1

Where $PctW_{x,r}$ is the scaled-up percent-wheat value for a given pixel x, at coarse resolution r. N is the number of 56m pixels within pixel x. nCDLWheat is the number of 56m wheat pixels derived from the CDL wheat mask within pixel x (figure 2.5).

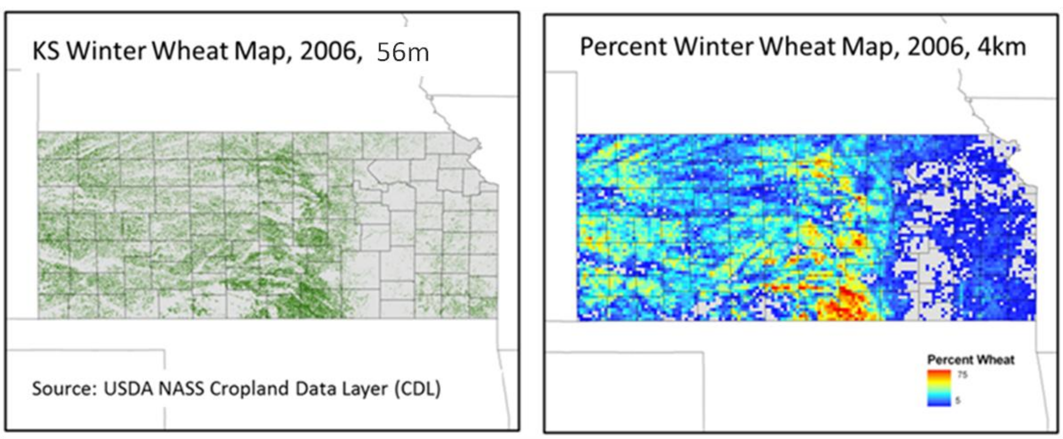


Figure 2.5 Example of the 2006 wheat mask at 56m resolution (left: green shows the wheat pixels) and a corresponding mask aggregated as percent wheat per 4km grid cell (right: color scale represents % wheat).

2.3.3 Analysis of Inter-annual Percent Wheat Variability

At the basis of the developed approach, is the assumption that at certain spatial resolution, the percent wheat within a given pixel remains stable from one year to the next (within a limited number of years), despite crop rotations. In other words the spatial variability of percent wheat between years becomes stable. Implied is that the overall planted area within the region of interest is relatively constant over the specified time frame. In the case of Kansas, the wheat planted area varied by 6% between 2000 and 2011. To assess this assumption in Kansas and determine the spatial resolution at which the per-pixel wheat purity remains constant over a period of 6 growing seasons, the range of the percent wheat values ($RPct_{xr}$) for every pixel (x) at all 15 resolutions (r) was computed (equation 2).

$$RPctW_{x,r} = Max\left(PctW_{x,r}\right) - Min(PctW_{x,r})$$

Equation 2.2

Where $Max(PctW_{x,r})\ and\ Min(PctW_{x,r})$ are respectively the maximum and the minimum percent wheat value for pixel x at resolution r over 6 years.

Figure 2.6 presents a series of images for western Kansas depicting the RPctW values over 6 years in an area with high crop rotation rates. At the finer resolutions, (i.e. 250m) RPctW values were close to 100 indicating that in some years no wheat was planted in that location and in other years the pixel was purely wheat (figure 2.6 shown in red). As pixel size was increased, the variability of percent wheat within a given pixel decreased and stabilized. This effect can be assessed visually in the example from western Kansas presented in figure 2.6

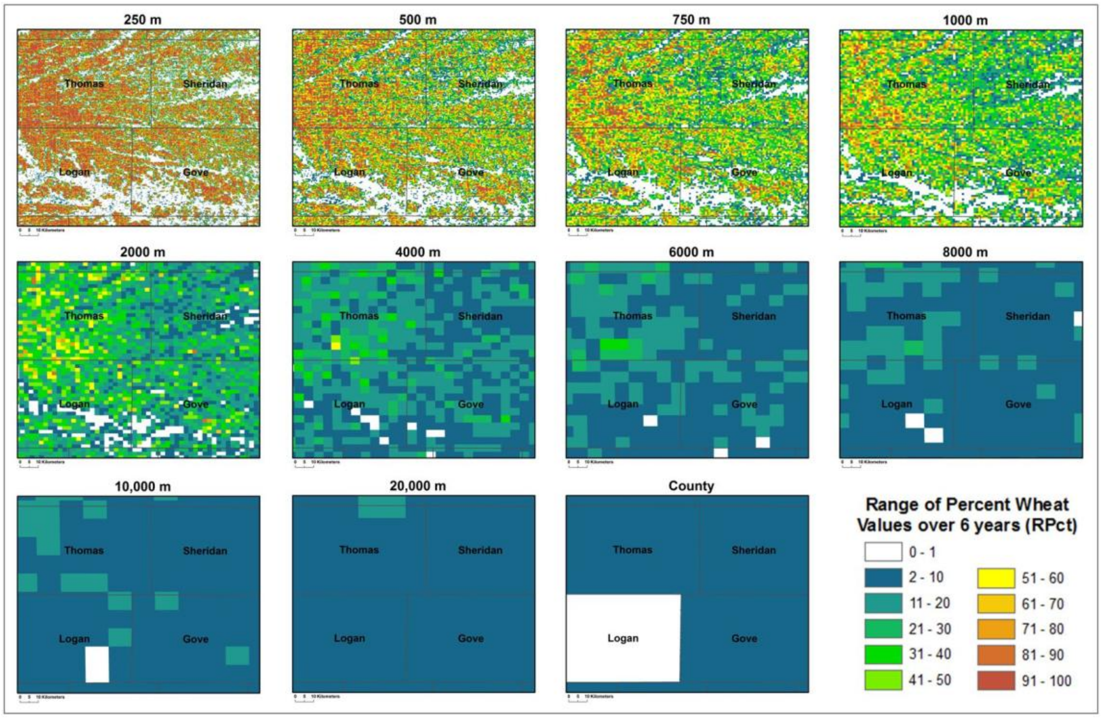


Figure 2.6 Example of RPct values computed from 6 annual wheat masks for increasingly coarser resolutions over western Kansas where crop rotation is common practice. Upper left corner 250m resolution, lower right corner treating each county as a single pixel. Red indicates high variability in per pixel percent wheat, blue indicates near constant percent wheat across years.

To quantify and characterize this percent-wheat 'stabilization' effect over the entire state, the median RPctW (MRPct) was computed for all 105 counties (equation 2.3) at each of the spatial resolutions and is presented in figure 2.7. These results indicate that the percent wheat variability drops below 10% starting at the 4km resolution for the majority of counties in Kansas.

$$MRPct_{c,r} = Median\left(RPctW_{x,r}\right) |\ x \in c$$

Equation 2.3

Where $MRPct_{c,r}$ is the Median Range Percent Wheat for county c at resolution r.

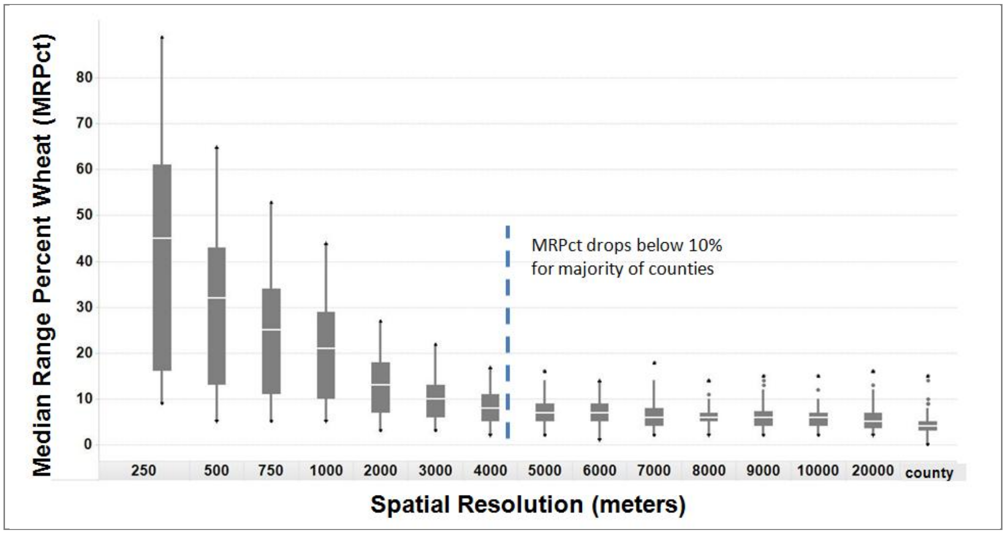
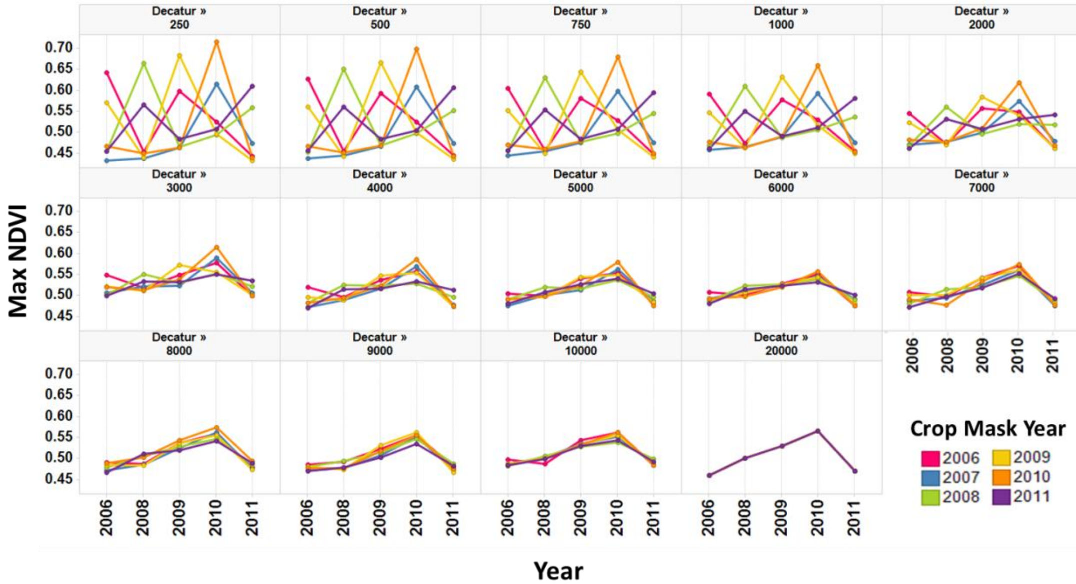


Figure 2.7 Boxplot of median range percent wheat (MRPct) for all counties in Kansas, computed for each spatial resolution using the 2006-2011 wheat masks.

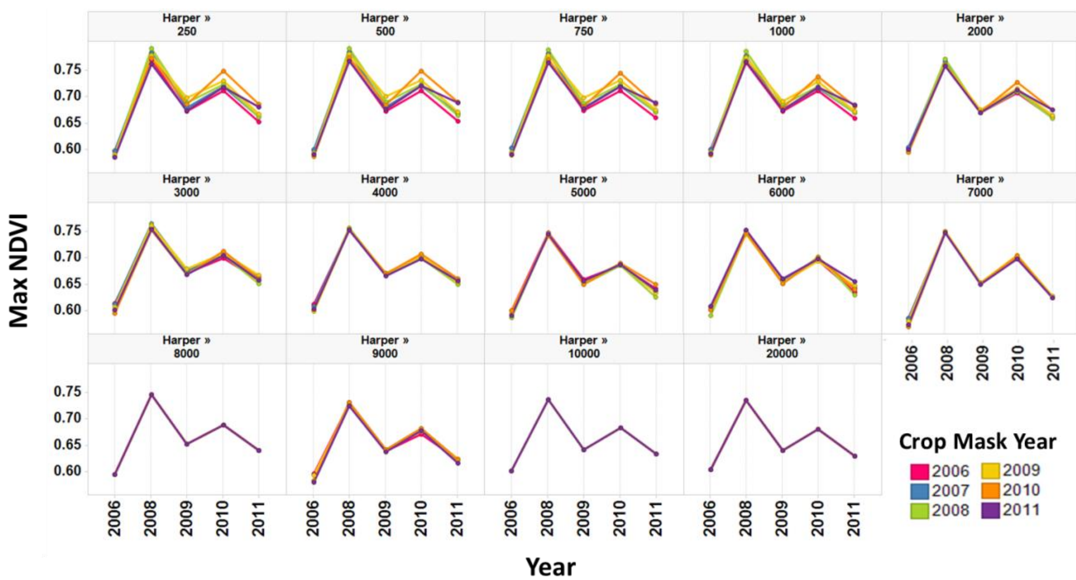
2.3.4 Wheat Specific NDVI Time Series

The next step was to evaluate the effect of using a single season percent wheat mask for extracting NDVI temporal profiles over multiple years (2006– 2011) for the range of pixel resolutions.

The percent wheat masks were used as a filter to select the purest wheat pixels within each county at each spatial aggregation level. Each seasonal mask was used to extract the maximum seasonal NDVI (MA_NDVI) signal from its corresponding season as well as for the other years (2006-2011) at all spatial resolutions. The MA_NDVI signal was adjusted for background noise by subtracting the minimum mean NDVI signal (Becker-Reshef et al. 2010b). Figures 2.8a-b show the results of this step for two contrasting types of counties: Figure 2.8a for Decatur County where crop rotation is common and Figure 2.8b Harper County, where wheat monoculture is wide spread. Each time-series graph depicts the MA_NDVI signal from 2006 through 2011 extracted using the 6 annual crop masks produced in this step, at all spatial resolutions. In the case of Decatur County, it is evident that a single, season-specific, crop mask cannot be used to extract the MA_NDVI at the higher resolutions due to the effect of crop rotations. Yet, as the resolution is coarsened the extracted signal from each of the crop masks converge, indicating that at the coarser resolution a single mask can be used over multiple years to extract a consistent signal. On the other hand, in Harper County almost all the masks, even at the finer resolutions, can be used to extract a consistent signal, since wheat fields are not heavily rotated between years. The trade-off for decreasing the impact of the out of season crop mask by coarsening the spatial resolution is the dampening of the wheat signal due to the effect of mixed pixels. The explanation for this effect is that winter wheat is generally surrounded by fields planted with crops and it greens up before the summer crops. Therefore as the spatial resolution is coarsened the wheat signal is mixed with the signal from surrounding bare ground and emerging summer crops such as corn. An example of this effect is presented in figures 2.9a-b. Figure 2.9a presents the 2010 seasonal maximum NDVI values of the purest wheat pixels for Decatur and Harper counties at increasingly coarser spatial resolutions. The circle size is proportional to percent wheat. It is evident that the maximum NDVI signal is reduced as the percent wheat decreases. Figure 2.9b summarizes this effect in KS in a boxplot of the distribution of the 2010 maximum NDVI values extracted from all counties at increasing spatial resolutions.



2.8a Decatur County



2.8b Harper County

Figure 2.8 a-b Maximum Seasonal NDVI extracted for 2006 through 2011 using 6 seasonal wheat masks (2006-2011). Line colors are presented according to the year of the wheat mask. Data were extracted at increasingly coarser resolutions. Upper left 250m, lower right 20km. a) Data from Decatur County where wheat fields are commonly rotated. b) Data from Harper County where wheat monoculture is the dominant practice.

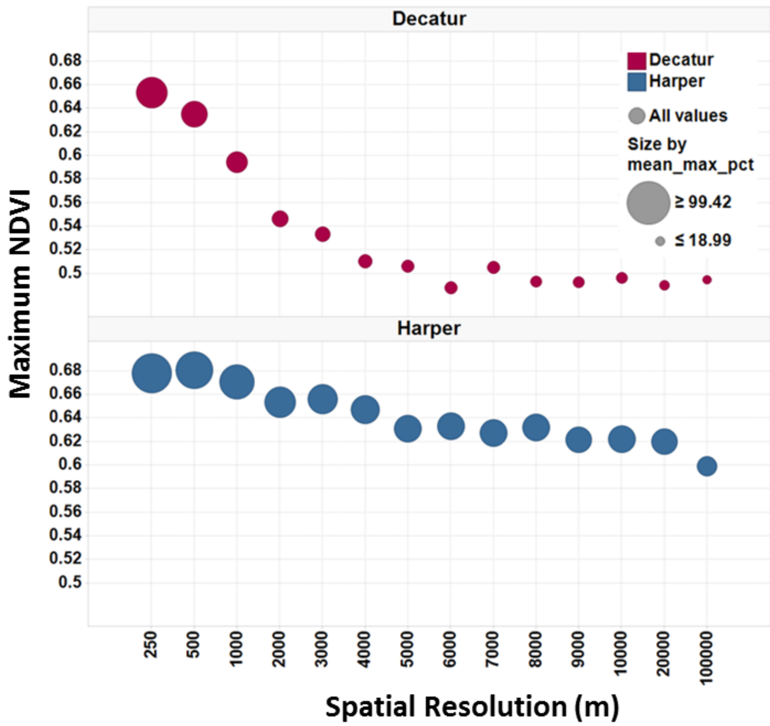


Figure 2.9a 2010 Maximum NDVI values for Decatur (top) and Harper (bottom) counties extracted at increasing spatial resolutions. Circle size is proportional to percent wheat at each resolution.

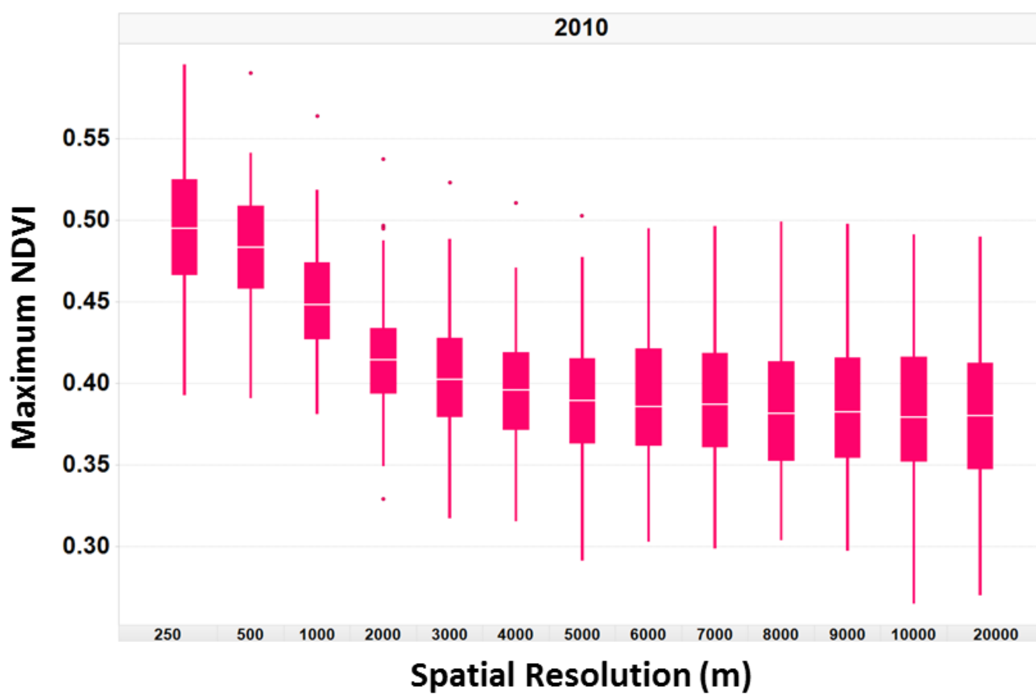


Figure 2.9b Boxplot distribution of 2010 maximum NDVI values from all counties in Kansas extracted at increasing spatial resolutions.

In order to select the optimal level of spatial aggregation for yield forecasting given this tradeoff in cases when within-season masks are not available and, a yield model (fully described in chapter 3 and in Becker-Reshef et al. (2010b)) was run under 2 scenarios of wheat mask availability. The model used the extracted MA_NDVI and percent wheat as inputs and was run for the full range of pixel spatial resolutions for two scenarios.

2.3.5 Yield Estimation under two crop mask availability cases

Many studies have found that crop yields can be successfully forecast by deriving a regression based relationship between NDVI derived metrics (Maselli 2001, Tucker et al. 1980, Lewis, Rowland and Nadeau 1998, Hamar et al. 1996, Manjunath, Potdar and Purohit 2002, Groten 1993, Rasmussen 1992) and yield. Time-integrated NDVI measures during the crop reproductive stages and single NDVI observations around the time of the seasonal maximum NDVI (which is closely associated with the booting-flowering stage in wheat), are common RS metrics in such empirical models, as they are indicative of crop conditions once the majority of the green biomass is established (Hochheim and Barber 1998, Tucker et al. 1980, Labus et al. 2002, Benedetti and Rossini 1993, Rasmussen 1997). A maximum-NDVI based wheat yield model, described in (Becker-Reshef et al. 2010b) was used in this chapter to assess the impact of spatial resolution on yield forecasting.

Ideally, annually-updated wheat maps would be readily available during the growing season at an adequate spatial resolution to extract NDVI time series profiles of the target crop. At this time within-season crop-specific masks are rarely available for the majority of agricultural regions. However, a single or a series of crop type maps are often available or can be more easily generated for previous seasons after the growing season is complete and coarse resolution data with frequent overpasses are freely accessible for monitoring crop development.

This study therefore sought to assess the optimum spatial resolution for the model to be run on, in order to maximize estimated yield accuracy and to estimate the tradeoff between the 'optimal' situation (case 1) where season-specific wheat masks are available during the growing season (control case) and the most likely situation where only a single mask from a previous recent season is available (case 2).

To accomplish this task the yield model was run for the two cases at all spatial resolutions. Case 1 was treated as the 'control' case representing 'optimal' data availability. As such, case 2 results were assessed relative to the control case. The estimated yields were also assessed against the official NASS reported yields and the RMSE and corresponding percent error were computed for each case and at each spatial resolution. The model estimates were also compared to yield estimates based on the 6-year average yields to ensure that method is relevant and performs better than simply using the average as an estimate.

Season specific wheat masks were available for 2006 through 2011 from NASS. Therefore, case 1 could only be evaluated on these years. The yield model was run on these years with the exception of 2007 since during 2007 large parts of the state experienced late spring frosts which caused floral sterility and low yields. As a result for that year, the NDVI signal was relatively high, reflecting the well-developed crop, but the end of season yields were very low as a result of the freeze damage that was not reflected in the NDVI (Woolverton 2007, NASS 2007a, NASS 2007b). It is acknowledged that such cases present a limitation to current RS yield models which are based on the relationship between crop photosynthetic capacity and yield.

In case 2, which represents instances when only a single seasonal wheat mask is available, each of the 6 single-season wheat masks (2006-2011) were used separately to extract the MA_NDVI for all years (excluding the season of the mask) and at all spatial resolutions. In other words, the 2006 mask was used to extract the seasonal MA_NDVI for 2008-2011, followed by the 2007 mask and so on. A similar case 2b was also run. In case 2b only the previous season's mask was used to extract the NDVI signal, except for 2006 which did not have a preceding season's mask and therefore the 2007 mask was used. In other words, the 2010 mask was used to extract the 2011 growing season NDVI signal and so on. As for case 1 the RMSE was computed for all case 1, case2 and case 2b model runs.

2.4 Results

The EO regression-based winter wheat yield model was run for the cases described. In this model, yield was estimated as a function of percent wheat and the maximum seasonal NDVI signal (adjusted for background noise).

For the model to be useful model forecasts should be more accurate than forecasts based on using the mean yield to estimate yield. Thus, the RMSE and percent error were computed over the study period where the 6-year average yield was used as the estimator. The RMSE was 0.33 tons per hectare (t/ha) which is equivalent to a 12.5% error (relative to average yield).

The results for cases 1, 2, and 2b are presented in figure 2.10 and table 2.1. In figure 2.10, the results are summarized according to case and spatial resolution versus yield percent error. Case 1 (pink in figure 2.10), as expected, had the overall lowest errors (6.15%). The model error was lowest at the 500m resolution and increased with increasing resolution. Case 1 used the best available data and as such represented the 'optimal' model runs and was treated as the control case. The subsequent model runs of cases 2 and 2b were assessed relative to the performance of this case.

Case 2 and case 2b, performed poorly relative to case 1 at the finer resolutions due to the effect of crop rotations, though performed remarkably well as the spatial resolution was coarsened. The error was highest (~30% at the 250m) at the finest resolutions, and rapidly declined with increasing resolution. The lowest percent error for case 2 and case 2b was 7.4% and 7.2% respectively, and was found at the 5km resolution and 4km resolutions.

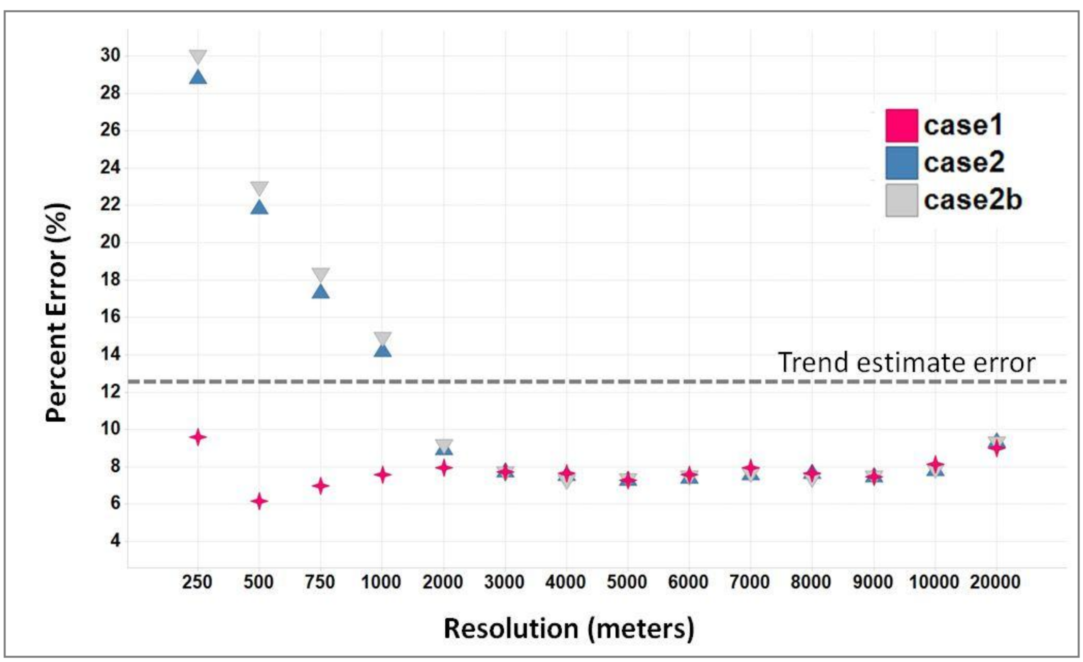


Figure 2.10 Model percent error for each case. The gray line indicates the % error if the mean yield is forecast every year

These results are quite promising as they indicate that a single percent wheat mask derived from a recent season's crop-type mask (within 6 years in the case of KS) can be used in combination with coarse resolution NDVI to forecast yields prior to harvest, in the absence of a timely seasonal crop-type mask by spatial aggregation to a coarser resolution percent wheat mask. The tradeoff of using a single mask (case 2 in terms of percent error relative to the case 1 minimum error (6.15%) is 1.05% (case 2b) to 1.25% (case 2) (table 2.1).

Table 2.1 accuracy of yield forecasts by case and resolution

Case 1

resolution	rms (T/Ha)	% Error	case
250	0.248	9.60	case1
500	0.159	6.15	case1
750	0.180	6.97	case1
1000	0.196	7.58	case1
2000	0.206	7.97	case1
3000	0.20	7.74	case1
4000	0.198	7.66	case1
5000	0.188	7.27	case1
6000	0.196	7.58	case1
7000	0.206	7.96	case1
8000	0.197	7.64	case1
9000	0.193	7.47	case1
10000	0.210	8.14	case1
20000	0.233	9.00	case1

Case2

resolution	rms (T/Ha)	% Error	case
250	0.74	28.91	case2
500	0.56	21.93	case2
750	0.45	17.41	case2
1000	0.37	14.29	case2
2000	0.23	9.03	case2
3000	0.20	7.83	case2
4000	0.19	7.66	case2
5000	0.19	7.40	case2
6000	0.19	7.50	case2
7000	0.19	7.70	case2
8000	0.20	7.76	case2
9000	0.19	7.60	case2
10000	0.20	7.91	case2
20000	0.24	9.44	case2

Case2b

resolution	rms (T/Ha)	% Error	case
250	0.774	29.91	case2b
500	0.592	22.89	case2b
750	0.472	18.24	case2b
1000	0.383	14.81	case2b
2000	0.234	9.07	case2b
3000	0.197	7.62	case2b
4000	0.185	7.18	case2b
5000	0.188	7.26	case2b
6000	0.191	7.38	case2b
7000	0.195	7.54	case2b
8000	0.188	7.27	case2b
9000	0.1	7.39	case2b
10000	0.200	7.76	case2b
20000	0.238	9.23	case2b

2.5 Discussion and Conclusions

Crop yield forecasting is hampered due to limited availability of crop type masks prior to the end of the growing season. The objective of this study was to develop and evaluate a practical approach to winter wheat yield forecasting that utilizes readily accessible data to forecast yields at sub-national and national scales with minimized tradeoff in accuracy relative to a control case.

This study found that the higher temporal resolution data (8-day composites) were better able to capture the seasonal NDVI peak for wheat and that the best yield estimates were attained when moderate resolution wheat masks were available for every season analyzed. This study found that the tradeoff between using a coarse resolution, static mask derived from a single preceding season was surprisingly low (1.05% case2b and 1.2% case2). These results suggest that in the absence of within-season crop-specific masks yield can be forecast at the state level with a small tradeoff in accuracy, using readily available coarse resolution data and a preceding season, static percent wheat mask.

It should be noted that the best results for case 1 were found at the 500m resolution rather than at the 250m resolution. This is likely due to several factors including the accuracy of the cropmasks, artifacts of 250m gridding and shifts (it has been shown that at the 250m resolution there can be up to a 0.5 pixel shift) and pixel growth (Tan et al. 2006, Wolfe, Roy and Vermote 1998). This topic should be further explored.

While one would assume that for agricultural remote sensing it is best to work at the finest spatial resolution so that individual fields can be resolved, this study provides a counter-intuitive result that suggests that coarse resolution data can offer a viable alternative in the absence of finer spatial data and up-to-date crop specific masks with a small tradeoff in accuracy. By monitoring crops at a coarser resolution, the noise in the signal introduced by year to year variability due to crop rotations is reduced. This is in keeping with results presented Markham and Townshend (1981), Malingreau and Belward (1992) and Nelson et al. (2009), albeit at finer spatial resolutions and for different land cover types.

This chapter presents a viable and efficient method for isolating a coherent, crop-specific signal over multiple growing seasons using a static, fine resolution crop mask aggregated to a coarse resolution. A fundamental condition for this approach is low overall inter-annual variability in planted wheat area. This implies that in regions where there are major shifts in planted area between years due to biofuel demand or market incentives, this approach would not work. Nevertheless, according to USDA national level statistics this condition does seems to hold true, at least at the national level, for many of the main wheat producing countries where the variation in planted area over the past ten years is below 10% (USDA 2010). In the case of Kansas, where six annual wheat masks were available from the USDA NASS, the analysis suggests that over a period of at least five years this assumption holds true and that per-pixel percent wheat variability in Kansas stabilized (below 10%) at approximately 4km pixel resolution.

The main advantage of the results presented for crop monitoring and specifically for yield forecasting models that rely on remotely sensed inputs is that a single, coarse resolution percent wheat mask is sufficient to extract a consistent wheat temporal profile over multiple years. Therefore a single mask, from a previous year would likely suffice. Second, this method eliminates the challenge of generating a timely and accurate crop type mask prior to the end of the growing season to in order to forecast yields. Nevertheless producing accurate crop type masks play a critical role for deriving seasonal crop area estimates.

Finally, the findings from this chapter indicate that higher temporal resolution data is better able to capture crop phenologic development, and specifically the seasonal NDVI peak. Furthermore, in the case of KS, the percent wheat stabilized at the 4km spatial resolution. As such the next study described in chapter 3 used a daily dataset NDVI data set at available at 0.05 degree latitude longitude (equivalent to approximately 4.5km in Kansas) to develop the yield model and evaluate its transferability.

Chapter 3: A generalized regression-based model for forecasting winter wheat yields in Kansas and Ukraine using MODIS data[3]

3.1 Introduction

A range of techniques such as visual field estimates, multiple frame-based sample surveys, analog-year approaches, crop-simulation models and regression approaches have been used for forecasting pre-harvest yield estimates with varying degrees of success (Pinter et al. 1981, Wall et al. 2007, Doraiswamy et al. 2003, Chipanshi, Ripley and Lawford 1999, Maselli and Rembold 2001). Earth observations (in particular surface reflectance and thermal data) owing to their synoptic, timely and repetitive coverage, have been recognized as a valuable tool for yield and production forecasting (Prasad et al. 2006, Manjunath et al. 2002). Agricultural monitoring from space, in particular pre-harvest assessments of crop yield and production, has been a topic of research since the early 1970's (Wall et al. 2007).

The utility of EO for crop yield forecasting has been demonstrated across a wide range of scales and geographic locations (Mkhabela and Mashinini 2005, Labus et al. 2002, Kastens et al. 2005, Funk and Budde 2009, Weissteiner and Kuhbauch 2005, Salazar, Kogan and Roytman 2007, Rojas et al. 2007, Quarmby et al. 1993, Mika et al. 2002, Hayes and Decker 1996, Hatfield 1983). In particular, the Normalized Difference Vegetation Index (NDVI) has been recognized since the 1970's for its value in monitoring crop conditions and forecasting crop yields (Tucker et al. 1980, Quarmby et al. 1993, Doraiswamy and Cook 1995, Boken and Shaykewich 2002).

[3] The material presented in this chapter was previously published in Becker-Reshef, I., Vermote, E., Lindeman, M., & Justice, C. (2010). A generalized regression-based model for forecasting winter wheat yields in Kansas and Ukraine using MODIS data. *Remote Sensing of Environment, 114*, 1312-1323

The basic assumption behind the empirical statistical approaches is that measures of photosynthetic capacity, estimated from spectral vegetation indices such as NDVI, are directly related to yield. This is because many of the conditions that favorably or adversely affect plant development and ultimately yield (i.e. fertilization treatment, rust infection, drought, or precipitation-events) result in a corresponding increase or reduction of the crop's photosynthetically active biomass and this response can often be captured though spectral measures such as NDVI (Tucker 1979). Thus, a limitation of such an empirical, NDVI-based approach is that estimates of yield are often inaccurate when photosynthetic capacity at the time of measurement is not the main determinant of grain yield.

Pioneering work carried out in this field such as by Fischer (1975) found that wheat yields could be forecast as a function of the leaf area at the onset of the reproductive stage which corresponds to the timing of maximum crop green leaf area. Tucker et al. (1980) found significant linear relationships between wheat yields and time-integrated NDVI measures during the growing season, and determined that the strongest correlation of yield with NDVI occurred around the time of maximum green leaf biomass. Pinter et al. (1981) found that wheat and barley yields could be related to accumulated NDVI over the growing season. The findings from such studies established the ground work for numerous subsequent studies relating spectral vegetation indices to crop yields at regional and national scales as well as for this study.

For example, in field experiments in the Punjab region of India, Mahey et al. (1993) found that NDVI measurements during maximum green crop canopy cover were highly and linearly correlated with wheat yields. Dubey et al. (1994) developed linear regression models to forecast wheat yields at the district level in Punjab using the NDVI derived from the Landsat Multispectral Scanner System (MSS) and the Indian Remote Sensing (IRS) Satellite Linear Imagine Self Scanning Sensors (LISS-1). Similar methods were used by Sridhar et al. (1994) to forecast wheat yields in Madhya Pradesh, India. Manjunath et al. (2002) derived linear regression models to forecast wheat yields in Rajasthan utilizing NDVI data derived from the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR), in conjunction with rainfall data and yield data.

In a study in Canada, Boken et al. (2002) enhanced a pre-existing operational, district-level wheat yield forecasting model, driven by a monthly cumulative moisture index (CMI) by incorporating NDVI data into the model, and found that the average NDVI during the peak of the growing season and the average NDVI of the entire growing season were the best predictor parameters for wheat yield. A subsequent study comparing the explanatory power of NDVI for wheat yield modeling versus that of CMI found that the NDVI-based model could forecast yields four weeks earlier than the CMI–based model (Wall et al. 2007). Basnyat et al. (2004) conducted field studies in the Canadian prairies and found significant correlations between NDVI and grain yield and determined that the optimal timing for obtaining NDVI measurements for spring-planted wheat was approximately one month prior to harvest.

In Senegal, Rasmussen (1997) developed a linear regression model driven by integrated NDVI measures to estimate millet yields. Maselli and Rembold (2001) used regression models utilizing multi-year NDVI data to estimate wheat yields at the national level in North African countries. In Zimbabwe, Funk and Budde (2009) found that phenologically-adjusted, crop-weighted NDVI-anomaly time-series data were correlated with crop production anomalies and could be used by the Famine Early Warning Systems Network (FEWS) to provide an early and objective evaluation of production. Other methods explored by the famine early warning community include utilizing the relationship between NDVI anomalies and the Pacific Sea Surface Temperature (SST) anomalies in Southern Africa to forecast NDVI anomalies at the onset of the growing season which can then be related to crop production (Verdin et al. 1999).

In China, Ren et al. (2008) developed a linear regression model to forecast winter wheat yields in the Shandong Province. Their model regressed spatially- accumulated NDVI measurements at the county-level during the growing season with county-level production statistics. Yield was then derived from the model's predicted production divided by acreage statistics to forecast yields within 10 percent of official statistics. In the U.S. Doraiswamy et al. (2003) used several input parameters retrieved from satellite imagery in a crop growth model to simulate spring wheat yields at the sub county and county levels in North Dakota.

Despite extensive studies on crop yield forecasting, crop models have rarely progressed successfully into operational implementation and are typically only applicable in the region for which they are developed as in general, both empirical and biophysical models require local calibration

This study takes advantage of considerable recent improvements in sensor technology (i.e. in spectral resolution, calibration, signal to noise ratio) and uses the new surface reflectance, BRDF-corrected, daily product from NASA's MODIS data (Vermote, Justice and Breon 2009) to develop a robust wheat yield forecasting approach.

3.2 Materials

This study combined coarse resolution NDVI time-series data and wheat masks, with reported crop statistics to develop an empirical, generalized, regression-based, winter wheat yield forecasting model. This study first developed and tested a regression-based model in Kansas, a major wheat producing region that has detailed agricultural statistics. Once developed, this Kansas regression model was directly applied to Ukraine, a major wheat growing country. According to USDA statistics, Ukraine is the sixth largest wheat exporter, on average accounting for 6% of total wheat exports between 2007 and 2009 (FAS 2009).

Building on the findings from chapter 2, three data-sets were selected for this study: winter wheat crop type masks; daily, BRDF-corrected MODIS surface reflectance time-series at 0.05 degree latitude longitude; and county-level crop statistics on winter wheat yields (Table 3.1). Crop type masks were used to identify the winter wheat areas. The Kansas yield statistics were then used with the MODIS NDVI data to develop an empirical relationship between NDVI and yield which was then applied uniformly to Kansas and Ukraine.

Table 3.1 Data used in the study

Category	Data	Source	Spatial resolution
Crop statistics	NASS quick stats yield, production, area harvested, area planted	USDA NASS	State, county
	Ukraine crop statistics	State Statistical Committee of Ukraine (SSC)	Oblast, country
Crop type	Kansas: USDA NASS Cropland Data Layer (CDL)	USDA NASS	56 m
	Ukraine: crop type data layer produced using a decision tree approach and AWiFS imagery, May 2008, July 2008.	AWiFS	56 m
	16 day composite MODIS Surface Reflectance time-series (2007–2008)	MODIS	250 m
Time-series earth observations	MODIS, daily BRDF-corrected surface reflectance and NDVI (2000–2008)	MODIS	0.05°

3.2.1 Study site and official crop statistics

As in chapter 2, the state of Kansas was chosen as the study site for developing the winter wheat yield forecasting model, as it is the main winter wheat producing state in the U.S., it has large areas of consecutive wheat fields which generally range from 30 to 150 ha, and it has a comprehensive and reliable county-level archive of crop statistics. In 2008, the state of Kansas produced 9.7 million tons of winter wheat, approximately one fifth of the total U.S. wheat production (NASS 2012b). Winter wheat production is concentrated in the western two-thirds of the state (Figure 3.1). A reliable archive of county-level statistics on yield, area harvested, and production is available from the USDA National Agricultural Statistics Service (NASS) Quick Stats database (NASS 2008). NASS is the agency responsible for administering the USDA's U.S. program for collecting and publishing agricultural statistics at the national, state and county levels. It is considered a world leader in agricultural statistics providing, a comprehensive, uniform, and reliable data set on U.S. crop statistics. The NASS crop statistics are based on data obtained from multiple frame-based sample surveys of farm operators, objective yield surveys, agribusinesses, shippers, processors and commercial storage firms and are designed to forecast production at the state (rather than county) level (NASS 2007c). The time-series of NASS county-level crop statistics from 2000 to 2008 were used to train and develop the basic regression model in Kansas.

For Ukraine, oblast-level crop statistics were obtained from the State Statistical Committee of Ukraine (SSC) for winter wheat area harvested and yield. (An Oblast is a sub-national unit approximately three times the size of a Kansas county). These official statistics are based on farm surveys collected from all the agricultural enterprises (large-scale farms that produce commodities exclusively for sale) which account for over 75 percent of Ukraine's grain production, and from a sample of house-hold farms (small farms and household plots that produce crops both sale and for personal consumption) which accounts for the remainder of the grain production (Personal communication, Oleg Prokopenko, Chief Agricultural Section, State Statistical Committee of Ukraine, April 2009). These official Ukrainian statistics were used for validation purposes only.

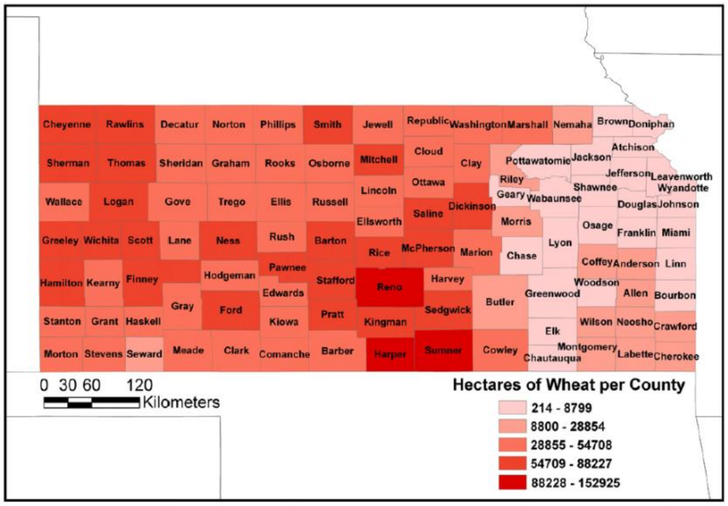


Fig. 3.1 Kansas winter wheat distribution based on USDA NASS average planted area (hectares) statistics from 2000 to 2006. Dark reds indicate higher per-county planted area and pinks indicate lower per-county planted area.

3.2.2 Crop type maps

As explained in chapter 2, identification of winter wheat fields is an important component of the model development and implementation as it allows for retrieval of winter wheat specific remotely sensed parameters. In this chapter the Kansas 2006 and 2007 CDL layers were scaled up as percent wheat masks to the 0.05 degree resolution and used to identify winter wheat growing areas. A winter wheat map for Ukraine was also necessary for the application of the regression model in Ukraine. As no winter wheat maps were available for Ukraine, a rasterized winter wheat map was produced using a decision tree, similar to that used to produce the NASS CDL and other land cover classifications such as those described by Pittman et al. (2010) and Hansen et al. (Hansen et al. 2000). Training data covering 37660 hectares, equivalent to 0.53% of 2008 planted wheat area, were collected from moderate resolution AWiFS images (56m) from May, 2008 (timing in Ukraine of the winter wheat flowering growth stage) and from June and July 2008 (timing of maturity and harvest of winter wheat in

Ukraine). These training data were supplemented with field data collected during the USDA FAS crop travel to Ukraine. The distribution of the wheat training data is presented in figure 3.2A. The classification tree was then run on one year of time-series of MODIS surface reflectance 16-day composite data (August 2007 – August 2008) to produce a winter wheat map for Ukraine at the MODIS 250m resolution (figure 3.2B). In order to validate this map, the classified winter wheat was aggregated at the oblast scale and compared with the official Ukraine SSC winter wheat planted area statistics. When compared at the oblast level, the classified area from the 250m mask had a bias of 28% (SSC area = Classified mask estimate * 0.722439) and a precision accuracy of 4.5% (Figure 3.2C).

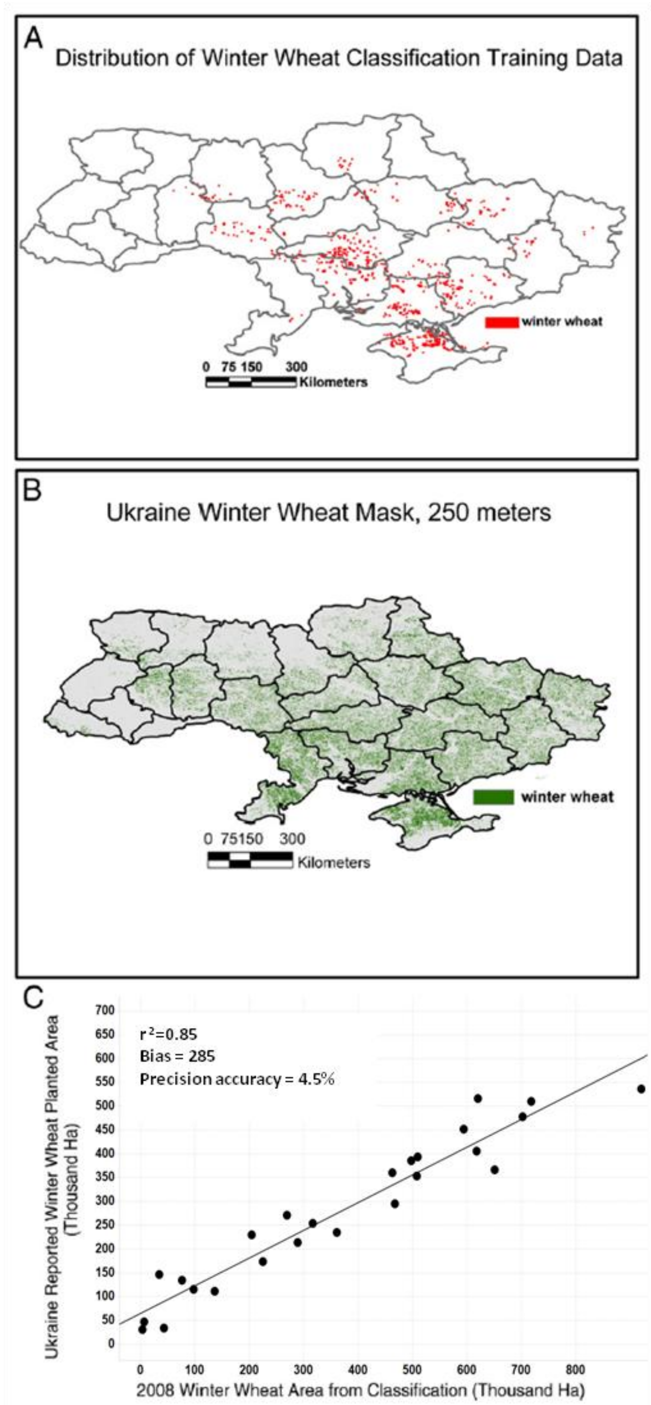


Fig. 3.2 Ukraine winter wheat mask. Panel (A) shows the distribution of the training data collected from AWiFS imagery for 2008 winter wheat crop type map for Ukraine. Panel (B) is the 2008 classified Ukraine winter wheat map at 250 m resolution. Panel (C) is the validation of the winter wheat classification map (X-axis) against the official Ukrainian SSC winter wheat oblast-level, planted area statistics (Y-axis). When compared at the oblast level, the area computed from the classified mask had a bias of 28% (SSC area=Classified_Mask_estimate * 0.72) and a precision accuracy of 4.5% relative to the official national level wheat area statistics.

3.2.3 MODIS daily Climate Modeling Grid (CMG) time-series

Traditionally NDVI composite data from the AVHRR have been used to drive remotely sensed based crop yield forecasting models (Weissteiner and Kuhbauch 2005, Salazar et al. 2007, Benedetti and Rossini 1993, Mika et al. 2002, Doraiswamy et al. 2003, Ferencz et al. 2004, Manjunath et al. 2002, Hayes and Decker 1996, Smith et al. 1995). Daily data from AVHRR had significant levels of noise due to effects of such factors as aerosols, clouds, and water vapor and off-nadir viewing. To minimize noise due to these effects, temporal composite data derived using the Maximum Value Composite (MVC) method were preferred over daily data, as the highest quality pixels from each composite time-frame are selected (Holben 1986). With time, the quality of remotely sensed data has significantly improved due to advances in sensor technology, such as with the MODIS instrument, and to significant methodological enhancements to atmospheric correction, cloud detection, BRDF correction algorithms and data quality flags (Vermote et al. 2002, Justice et al. 1998).

Recently, a new high quality, coarse resolution (0.05 degree latitude longitude), daily-updated, BRDF-corrected, surface reflectance data set from MODIS has been developed, enabling reliable daily monitoring of agricultural regions (Vermote et al. 2009). This is a daily-updated product which means that clear, high-quality pixels are identified daily, and cloudy, low quality pixels are flagged and replaced by linearly interpolated values until high-quality data become available. In this way, this dataset preserves all of the useable data rather than just a single data point selected by the compositing procedure. This daily product is similar to the 'objective analysis' scheme that was applied to AVHRR Sea Surface Temperature (SST) (Santoleri, Marullo and Bohm 1991). The objective analysis method was used to produce a daily SST product where cloud-free, good quality data were preserved and cloudy pixels or atmospherically contaminated pixels were removed and replaced by values that were interpolated between irregularly spaced observations. In their study Santoleri et al. (1991) compared daily objective analysis AVHRR SST maps to their corresponding composite images and found that the objective analysis images were able to more accurately characterize SST values in areas of rapid variability than in the composite images.

Similar to the objective analysis approach, the Climate Modeling Grid (CMG) MODIS daily-updated surface reflectance is able to preserve the temporal signal over cropped areas better than the corresponding standard composite products trading spatial resolution for temporal resolution. As such it should allow for better estimation of remotely sensed-based growing season parameters such as the seasonal peak NDVI than the corresponding composite product.

3.3. Methods

3.3.1 Regression Model Development for Kansas

The first step in the model development was to scale up the NASS CDL to the MODIS CMG scale (0.05 degrees) as a percent wheat crop-type mask using the same method described in chapter 2. (equation 2.1)

Once the percent wheat mask was produced it was used to select the 5% purest winter wheat pixels at the 0.05 degrees from each county in Kansas. Using these pixels as a mask, a wheat specific NDVI time-series derived from the daily CMG product was retrieved for every year of data from each county. The result was an eight year (2000-2008) daily NDVI time-series for each county in Kansas. As is evident from the example in figure 3.3, the yield values co-vary with the maximum NDVI values from each season. This is apparent in all years with the exception of 2007 where the maximum NDVI value is high and the yield value is relatively low due to the late spring freeze damage (noted in chapter 2).   Therefore, for the purposes of establishing the generalized regression model, data from 2007 were excluded.

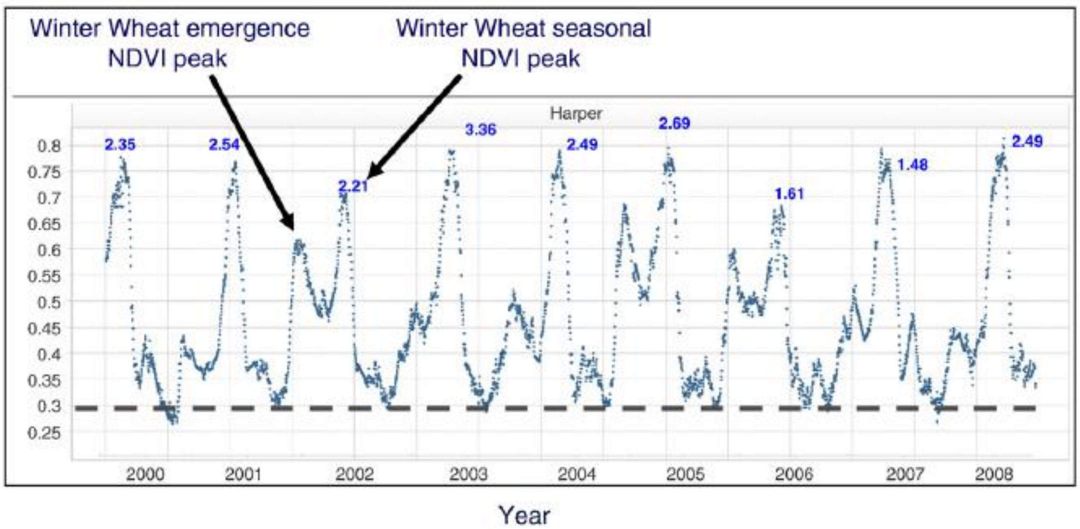


Fig. 3.3 NDVI time-series for Harper County, one of the highest wheat producing counties in Kansas. date on the X-axis and NDVI values on the Y-axis. The daily NDVI values were extracted from the winter wheat areas for 2000 through 2008. The numbers in blue are the final yield values for Harper County. The figure shows that the yield values co-vary with the maximum NDVI values from each season. This is apparent in all years with the exception of 2007 where the maximum NDVI value is high and the yield value is relatively low.

In this study the seasonal maximum NDVI was used as the main remotely sensed input parameter. The seasonal maximum NDVI was chosen since it enabled a timely prediction of production approximately a month and a half prior to harvest. To retrieve the maximum NDVI the 95th percentile seasonal NDVI value was extracted from the county, wheat specific daily time-series for each year of data (2000-2008). The maximum NDVI values were then adjusted to reduce the influence of non-wheat noise, such as soil, on the wheat NDVI signal. This was achieved through applying a method similar to that suggested by Rassmusen (1998) where the pre-growing season average low vegetation index value for each pixel was subtracted from the maximum NDVI growing season values, as expressed in equation 3.1.

$$\mathrm{MA-NDVI}_y = VI_{max95,y} - \frac{1}{N}\left[\sum_{y=1}^{N} VI_{min5,y}\right] \quad (3.1)$$

Where N is the number of years (2000 through 2008), y is the year, $VI_{max95,y}$ is the maximum 95th percentile NDVI for Year y, $VI_{min5,y}$ is the minimum 5th percentile NDVI for Year y.

The maximum adjusted NDVI (MA-NDVI) from 2007 was excluded from the time-series due to the April freeze.

Once the winter wheat MA-NDVI values were retrieved from each county for the 8 years of data, percent-wheat specific, linear relationships were derived between the retrieved MA-NDVI and the NASS reported yield statistics for each county. To derive these relationships, the maximum percent (Mpct) wheat value for each county was computed as a weighted average of the percent-wheat values of the top 5 percent purest pixels in each county (figure 3.4).. A linear regression was then derived for each county (with intercept set to 0), regressing eight years of the averaged maximum MA-NDVI against eight years of NASS yield statistics for each county. The county specific regression slope and maximum percent wheat values were then used in the next step for generalizing the MA-NDVI to yield relationship as a function of percent wheat.

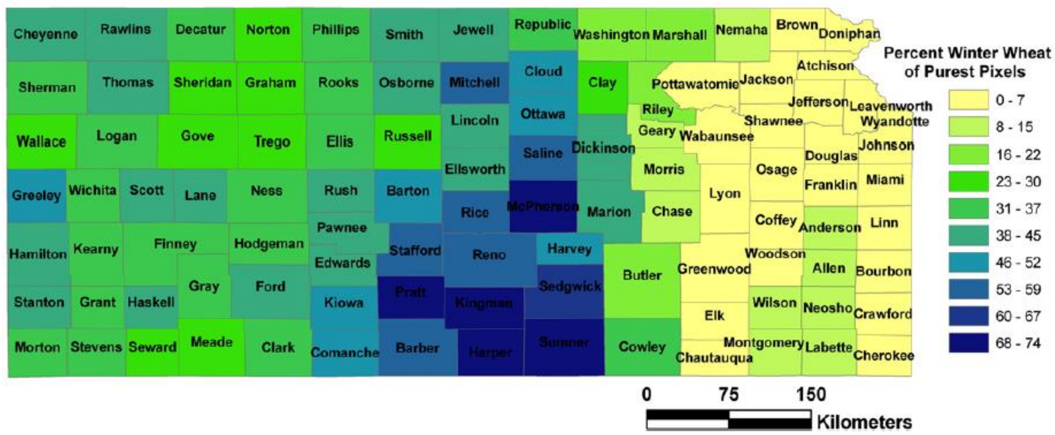


Fig. 3.4 Distribution by county of the maximum percent winter wheat computed as a weighted average of the 5% purest pixels in each county in Kansas.

The assumption was that the MA-NDVI value from each county is a mixed signal composed of the proportional signals from MA-NDVI of wheat and the MA-NDVI of the other land cover (Equation 3.2).

$$MA-NDVI_{Pixel\_x} = (MA-NDVI_{wheat} * Pct_{Wheat}) + (MA-NDVI_{other} * (1-Pct_{wheat})) \qquad (3.2)$$

As winter wheat fields are generally located in widely cultivated areas and are surrounded primarily by fields sown with spring-planted row crops rather than by forests or other land cover classes, the MA-NDVI signal from the other land cover types is likely dominated by non-wheat cultivated lands. Winter wheat is sown in the fall and by mid-spring reaches its maximum green canopy while the other, non-wheat fields are still bare or at the start of their vegetative growth phase. It was therefore assumed that $MA-NDVI_{other} < MA-NDVI_{wheat}$. In this case it follows that where the percent wheat is low, the MA-NDVI signal will be lower than the MA-NDVI signal where the percent wheat is higher, as the bare-ground and emerging row-crop signal will dominate the MA-NDVI signal. Given these assumptions and since the averaged maximum percent wheat (Mpct) varies by county, the county-specific regression slopes of yield to MA-NDVI were expected to vary as a function of percent wheat. In other words, in cases where winter wheat percent is low, the slope was expected to be proportionally larger than in cases where percent wheat is higher, in order to account for the weaker $MA - NDVI_{wheat}$ signal which is due to the lower percent wheat. At the county level the MA-NDVI was found to be a good predictor of yield and the slopes of these linear relationships varied between counties primarily as a function of the averaged maximum percent wheat. As expected, counties with lower maximum percent wheat had larger slopes than those with higher maximum percent wheat values. An example from two counties, Harper and Dickinson Counties is presented in figure 3.5. Harper County had a maximum percent wheat value of 74 and a MA-NDVI to Yield regression slope of 5.3. On the other hand, Dickinson County had a lower percent wheat value of 41 and a regression slope of 7.8.

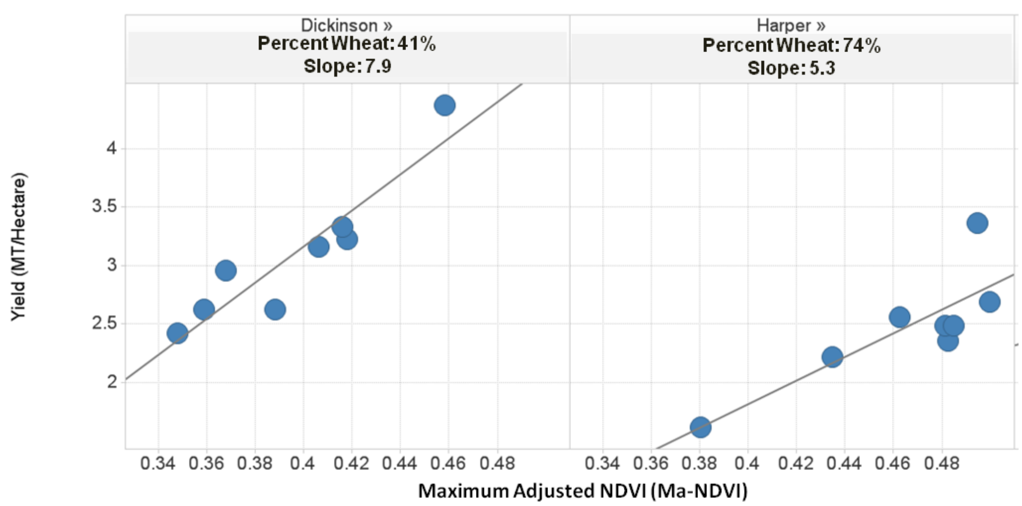


Fig. 3.5 Example of two MA-NDVI to Yield regressions from two Kansas counties with differing maximum percent wheat county values. Harper County which has a maximum percent wheat of 74 and has a MA-NDVI to Yield regression slope of 5.3 whereas Dickinson County which has a lower percent wheat of 41and has a higher regression slope of 7.9

Once the percent wheat dependent slopes were derived, the next step was to obtain a generalized yield-MA-NDVI relationship that could capture the percent-wheat dependent variation in slope, and be applied uniformly to the entire state. To accomplish this, a linear relationship was derived, regressing the individual county slopes computed in the previous step, against the county averaged maximum percent winter wheat. Three filters were applied to the data to select the best-suited data points for the regression: i) county average harvested area > 4000 hectares ii) RMSE of yield to MA-NDVI regression < 0.43 MT/hectare iii) regression correlation coefficient > 0.6. Once the filters were applied, the remaining data points were used to derive the percent wheat to slope regression (figure3.6) .where as the percent wheat increases the slope decreases. In addition, dispersion in slope values increases at low maximum percent crop values. The derived regression is presented in equation 3.3. The regression Root Mean Square Error (RMSE) was 0.87, which is equivalent to a 10% error and the r^2 was 0.49.

$$\mathrm{S}_{Mpct} = 9.61 + \left(-0.05 \times Mpct\right)$$

Equation 3.3

Where $Mpct$ is maximum percent wheat and S_{Mpct} is the corresponding slope of the yield to MA-NDVI regression as a function of Mpct.

Although the averaged maximum percent wheat in some counties is relatively low (below 50%), and as such the majority of the MA-NDVI signal is from $MA-NDVI_{other}$, this generalized regression proportionally adjusts the MA-NDVI with a higher slope thus giving a proportionally higher weight to the $MA - NDVI_{wheat}$ allowing the extraction of the MA-NDVI wheat signal even where it is proportionally low.

This linear regression was used to compute the slope of the yield to MA-NDVI regression as a function of the maximum percent wheat value. It was applied uniformly to the entire state of Kansas to obtain winter wheat yield in tons/hectare for each county, by multiplying the MA-NDVI value for each county by the corresponding slope derived from equation 3.3. The annual per county yield was then multiplied by the NASS county area harvested statistics, to derive a statewide annual production number in million metric tons (MMT) (Equations 3.4 and 3.5). Using this generalized regression model, production statistics were estimated for 2000 through 2008 for the state of Kansas.

$$Forecast\ Yield = MA\_NDVI_{Mpct,y} \times S_{Mpct}$$

Equation 3.4

$$Forecast\ Production = Forecast\ Yield\ \times Official\ Area\ Harvested$$

Equation 3.5

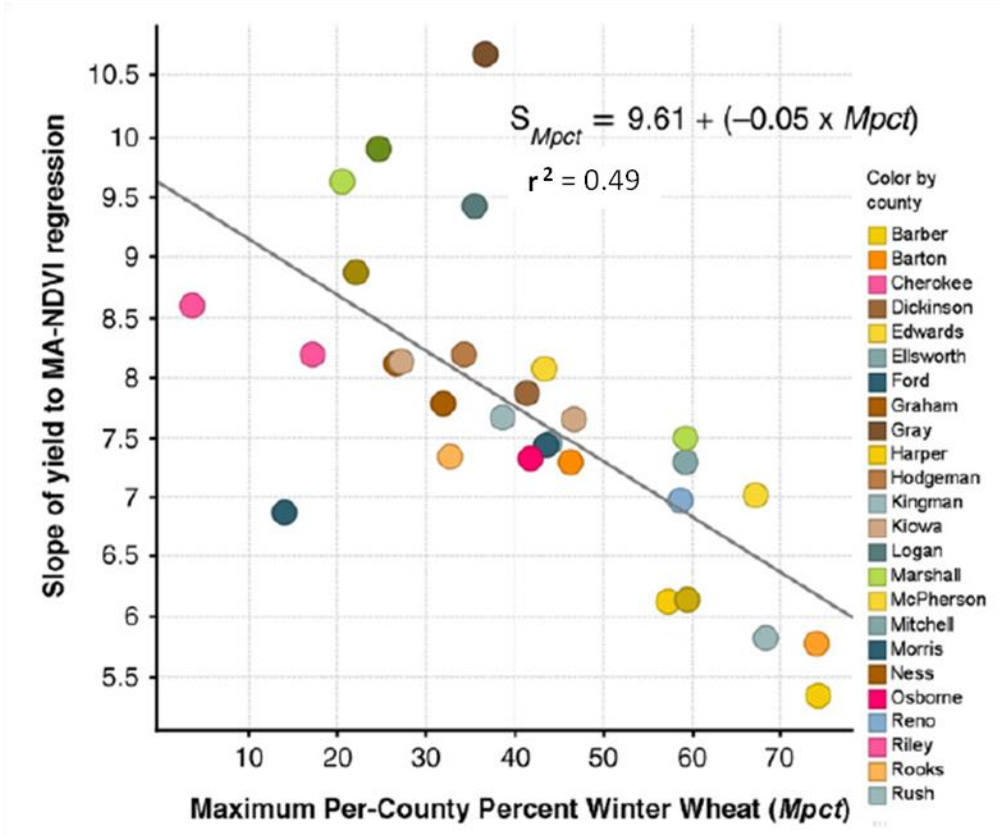


Fig. 3.6 Derived linear relationship between the individual county slopes (such as those shown in Fig. 3.4) and the per-county maximum percent winter wheat. The X-axis is the county maximum winter percent wheat value and the Y-axis is the regression slope derived from the individual counties. It should be noted that the slope and maximum percent wheat are negatively and linearly correlated. As the percent wheat increases the slope decreases. In addition, dispersion in slope values increases at low maximum percent crop values. The regression equation is at the top of the graph. The regression Root Mean Square Error (RMSE) is 0.87, and the $r^2 = 0.49$.

3.4 Results

The regression model trained on agricultural statistics from Kansas, was applied first in Kansas and then directly applied to Ukraine, in order to evaluate its portability to another major wheat producing region of the world.

3.4.1 Kansas

The Kansas regression model was run for 8 years of data from 2000 through 2008 excluding 2007 to predict state level yields. Winter wheat production was predicted by multiplying the predicted yields by the NASS reported area harvested statistics.

The model predictions were validated against the official yield and production NASS statistics (figure 3.7). The RMSE of the official versus predicted yields was 0.18 MT/ha which is equivalent to a 7 percent error. The RMSE of the official versus predicted production was 0.67 MMT which is equivalent to a 7 percent error.

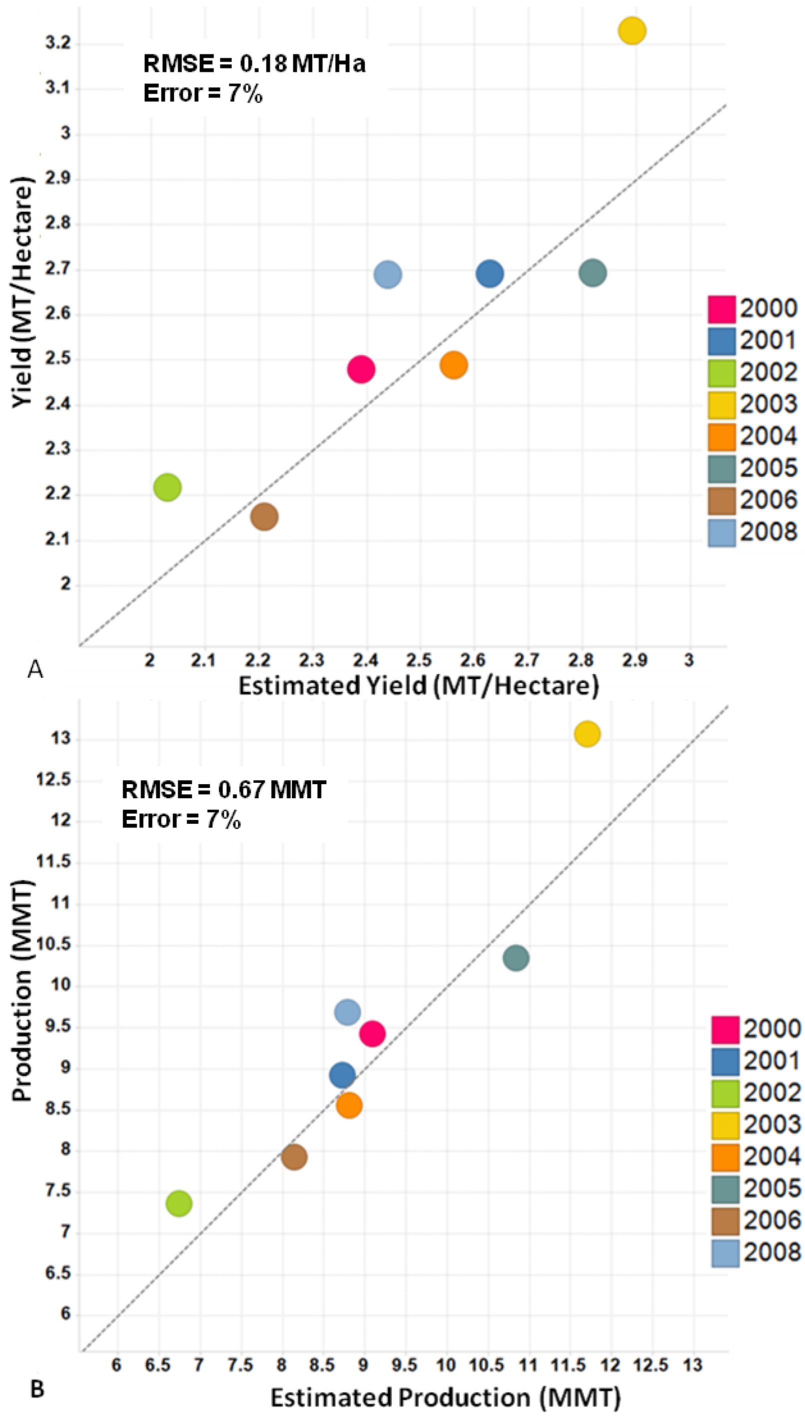


Fig. 3.7 Results from running the regression model in Kansas. Panel (A) is a scatter plot of the estimated versus the official yield statistics and Panel (B) is a scatter plot of the estimated versus official production statistics. The RMSE of the official versus estimated yields estimates is 0.18 MT/ha which is equivalent to a 7% error. The RMSE of the official versus estimated production is 0.67 MMT which is equivalent to a 7% .

3.4.2 Ukraine

To directly transfer the regression model (equation 3.3) developed in Kansas to Ukraine, a percent winter wheat mask and a time-series of MA-NDVI were required. A percent wheat mask at the 0.05 degree resolution was produced from the MODIS-derived 250m winter wheat map (using equation 2.1) (figure 3.8A). As for Kansas, it was assumed that at the 0.05 degree scale, the per pixel percent wheat remains relatively static between years. According to Oblast-level planted area statistics from the Ukraine SSC there is an average 11% difference between 2008 planted area and the mean planted area (2000-2008).

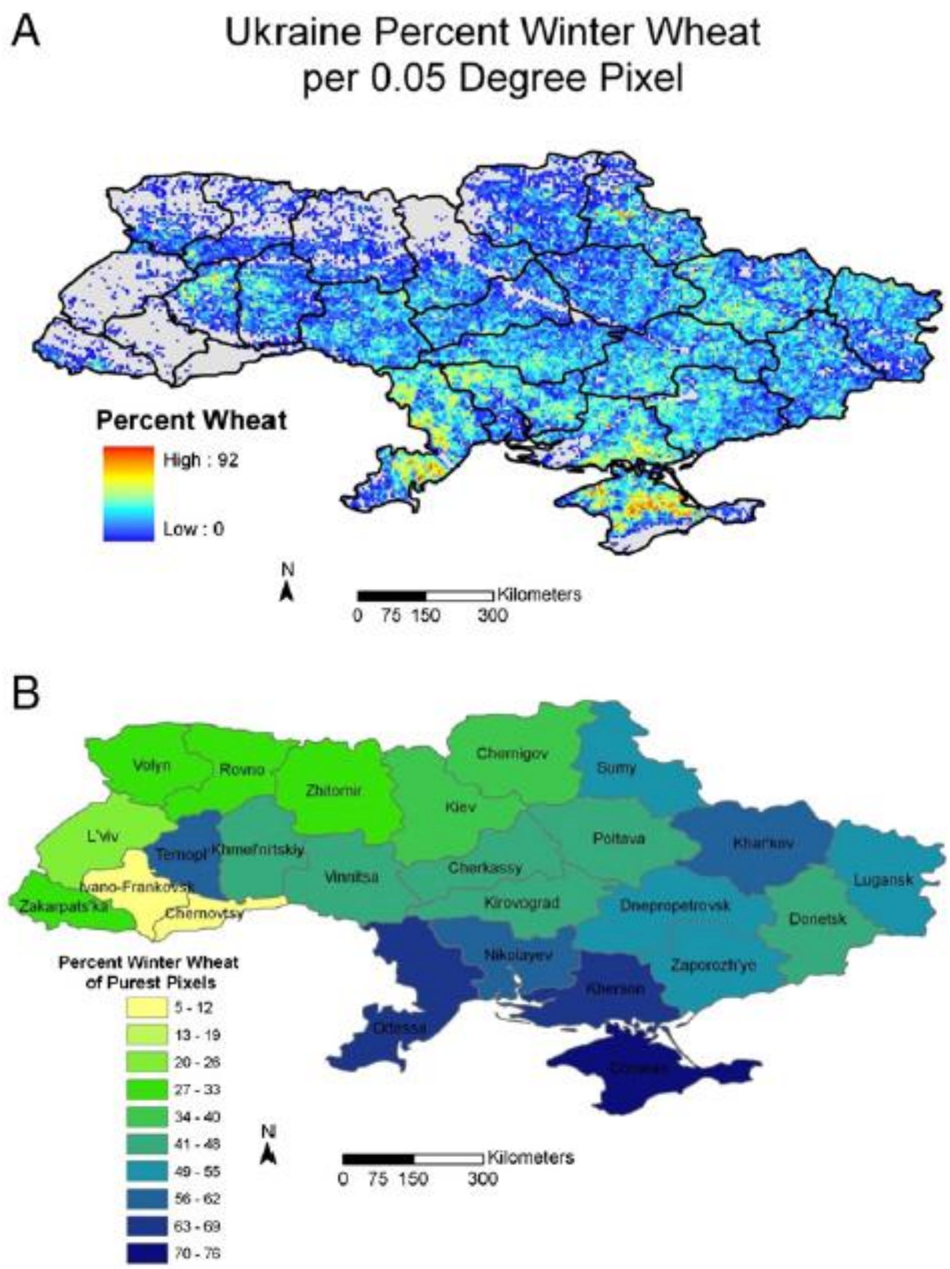


Fig. 3.8 Panel (A) is the percent winter wheat mask (0.05°) scaled up from the 250 m classified winter wheat mask. Panel (B) shows the distribution by oblast of the maximum percent winter wheat computed from (A), as a weighted average of the 5% purest pixels within each oblast.

The same methods used in Kansas to retrieve a MA-NDVI a time-series were used in Ukraine. First the 5 percent purest pixels in each oblast used for retrieving the MA-NDVI. The weighted average of these purest pixels for each oblast is shown in figure

3.8B. For each year of data between 2000 and 2008 the maximum seasonal NDVI was extracted for the purest winter wheat pixels from each oblast (the peak of the winter wheat growing season in Ukraine is between mid April and early June). The MA-NDVI was computed in the same way as it was computed in Kansas (Equation 3.1). The percent wheat dependent Kansas model, equation 3.3, was then directly run on the entire country. As in Kansas, the model-predicted yields were multiplied by area harvested statistics from the Ukraine State Statistical Committee to obtain production estimates.

The regression model developed in Kansas proved to be directly applicable to Ukraine without calibration against Ukrainian yield statistics. The model results were validated against the official Ukrainian statistics (figures 3.9 and 3.10). A time-series graph of the official production statistics, in pink, are compared to the predicted production, in blue, where the year is on the x-axis and winter wheat production in thousands of Metrics Tons is on the Y-axis (figure 3.9). The regression model predictions were in good agreement with the official Ukrainian statistics capturing the fluctuations through time of winter wheat yields and production. For example, in 2003 over 60 percent of winter wheat in Ukraine was destroyed due to December frost damage and to a persistent ice crust that formed in February as a result of repeated cycles of thawing and re-freezing (FAS 2003). In contrast the 2008 the winter wheat crop benefited from excellent weather throughout the growing season and the yields reached a 15-year high (FAS 2008). The Kansas model was able to capture the dramatic drop in yield in Ukraine in 2003 and the sharp increase in yield in 2008, six weeks prior to harvest. The model predictions were validated against the official

Ukrainian crop statistics (figure 3.10). The RMSE of the official versus predicted yields was 0.44 MT/ha which is equivalent to a 15% error. The RMSE of the official versus predicted production was 1.83 MMT which is equivalent to a 10% error.

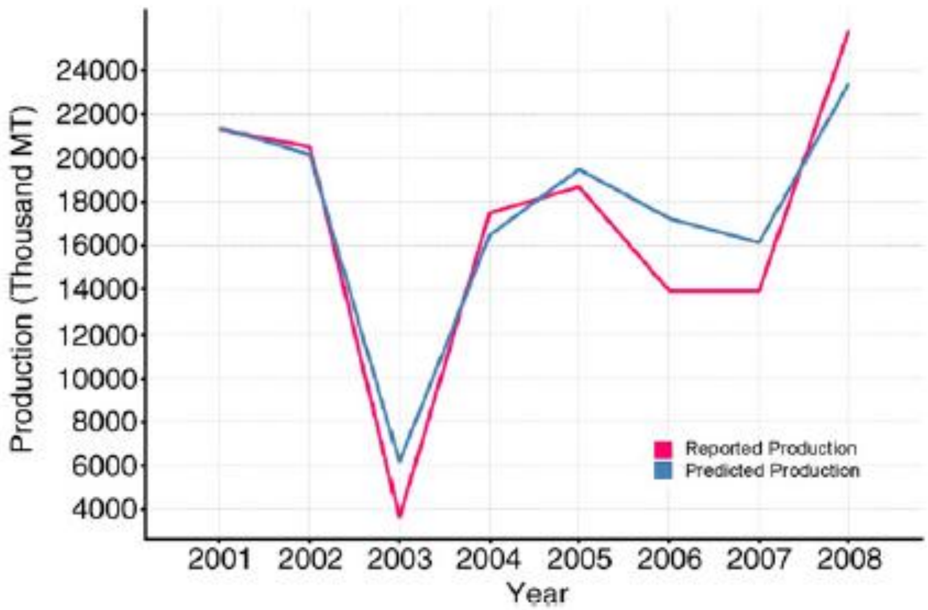


Fig. 3.9 Results of directly applying the regression model developed in Kansas to Ukraine. In this time-series graph the official production statistics, in pink, are compared to the predicted production, in blue, where the year is on the X-axis and wheat production in thousands of metrics tons is on the Y-axis.

To further evaluate the model, it was run in real-time in May of 2009 and again in May of 2010 to forecast winter wheat production in Ukraine in support of the USDA crop analysts. The model forecasted 19.2 MMT of wheat for the 2009/10 season and 17.4 MMT for the 2010/11 season. According to the official Ukrainian SSC statistics, which became available at the end of the season, winter wheat production was 20.5 MMT in 2009, and 16.8 MMT in 2010 which means that the model forecasts were within 6.3% of the official 2009 statistics and within 3.1% in 2010.

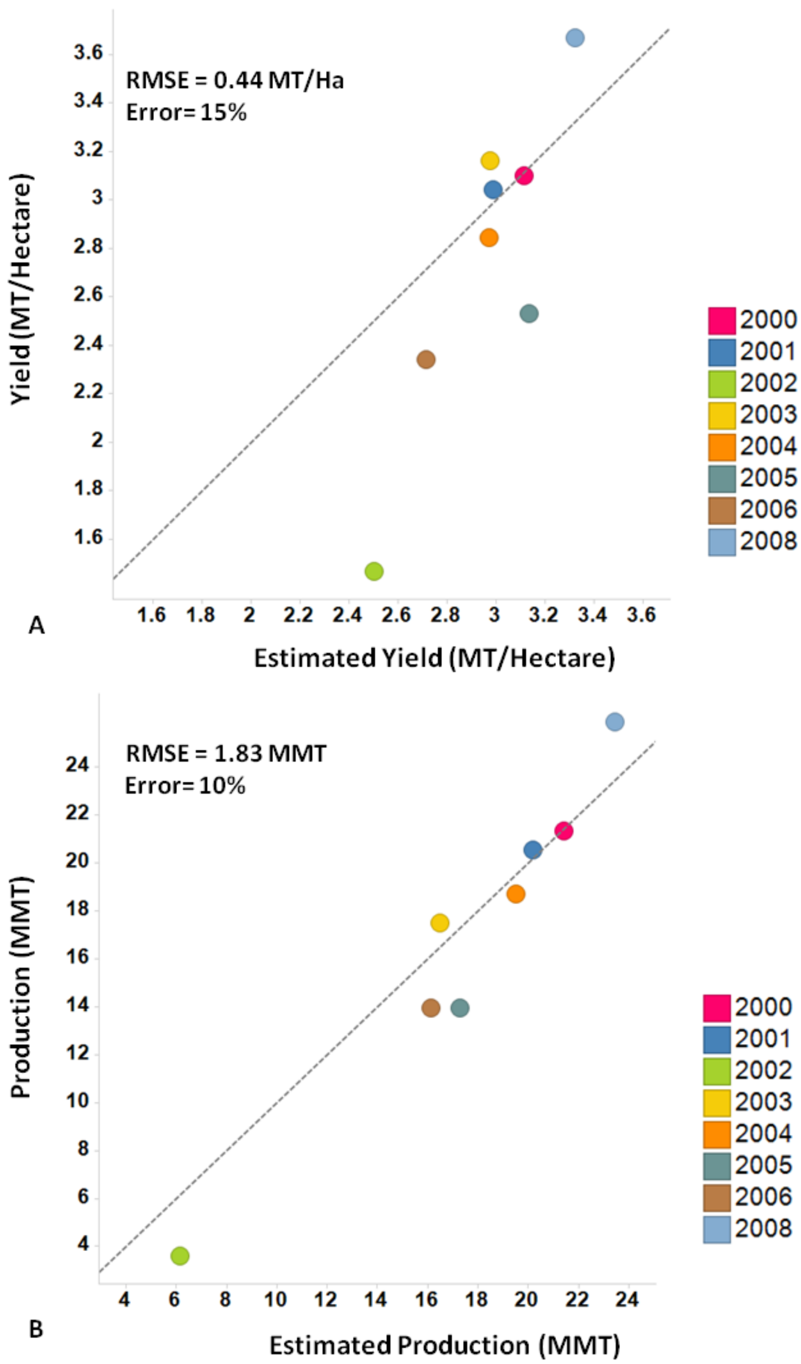


Fig. 3.10 Two scatter plots validating the Ukraine predictions produced by the model developed in Kansas against the official Ukrainian yield and production statistics. The RMSE of the official versus estimated yields (top panel) is 0.44 MT/ha which is equivalent to a 15% error. The RMSE of the official versus estimated production (bottom panel) is 1.83 MMT which is equivalent to a 10% error.

3.5. Discussion

The regression-based model developed in this study was empirically-based and utilized official crop statistics from Kansas to derive a relationship between winter wheat specific remotely sensed parameters and reported yield statistics. In general one of the main drawbacks of remotely sensed based empirical yield models is that they can only be successfully applied to the areas where they have been developed or otherwise require local calibration for application in other regions. (Doraiswamy et al. 2003). The primary advantage of this study is that it developed a single generalized-model that was applied at the state-level in Kansas and was proven directly applicable to Ukraine.

The winter wheat regression-based model developed in this study assumes, like many other empirical remotely sensed based yield models that the canopy vigor of winter wheat estimated by NDVI measurements is directly related to final winter wheat yields(Ferencz et al. 2004). Specifically, NDVI measurements around the time of the maximum, which encompass the ‘critical period’ for grain production, have been found to be strongly correlated with final yields (Tucker et al. 1980, Doraiswamy and Cook 1995, Benedetti and Rossini 1993, Labus 2002). The majority of such studies developed approaches which rely on NDVI measurements from composite rather than daily data sets, as the data quality and data volume was an issue. In this study, owing to the new, coarse resolution, high quality daily, BRDF-corrected CMG MODIS surface reflectance data the seasonal peak NDVI was estimated with high confidence from the daily data improving the accuracy relative to using 8-day composite data by at least 0.5%.

As has been well documented in the literature, this study found that yield was positively and linearly correlated to the seasonal maximum NDVI at the county scale. The goal of this study was to go beyond this finding and develop a regression model that was transferable and directly applicable at the state and national levels. The assumption underlying the generalization of the model was that the positive and linear relationship between the maximum NDVI signal of pure winter wheat pixels and yield is constant between locations. Therefore if the maximum $NDVI_{wheat}$ signal can be unmixed from the maximum NDVI signal it can be used directly to predict yield. Two steps were taken to generalize the linear relationships found at the county scale so that it could be widely applied and transferred The first step towards isolating the wheat signal was to minimize the noise in the maximum NDVI signal retrieved from the primarily wheat areas by removing the background signal such as the soil signal. This was accomplished by subtracting the average minimum NDVI from the maximum seasonal NDVI. This adjusted measure was termed the Adjusted Maximum NDVI (MA-NDVI). The MA-NDVI allowed for generalization and direct comparison between the maximum NDVI signals retrieved from different locations. The second step was to un-mix the $MA - NDVI_{wheat}$ signal from the $MA - NDVI_{other}$ signal by accounting for percent wheat. This was accomplished by deriving a set of relationships between yield and MA-NDVI and then generalizing the slopes of these regressions as a function of percent wheat. As expected, the slope of the MA-NDVI to yield regression decreased linearly as a function of increasing wheat purity. The explanation for this variation in slope as a function of winter percent wheat is based on the fact that wheat is generally located within cropped areas sown with spring-planted row crops rather than by forests or other land-cover classes. In Kansas and Ukraine, where winter wheat is sown in the fall, wheat reaches its maximum green canopy by mid-spring while the other, non-wheat fields are still bare or at the start of their vegetative growth phase. Therefore, in the cases of low wheat-percentage, the wheat reflectance signal is relatively weak as it is suppressed by the bare-ground and emerging row-crop signal. Consequently the MA-NDVI signal in these circumstances is lower than the MA-NDVI of purer pixels where a larger portion of the MA-NDVI signal is from wheat. This negative linear relationship between slope and percent wheat was used to derive a single, broadly applicable regression model.

These two steps for un-mixing the maximum wheat NDVI signal, namely the maximum NDVI noise reduction and the depiction of the regression slope as a function of wheat purity, enabled the development of a robust, simple, remotely sensed based generalized-model which was applicable at the state level in Kansas, at national level in Ukraine and potentially directly applicable to other major wheat growing regions in the world (e.g. Australia, Russia, Argentina, China).

There are several limitations to utilizing such an empirical, remotely sensed based regression model which relies on measurements of vegetation photosynthetic capacity to estimate yields. One of these limitations is that it cannot capture the impact of events that reduce yield but do not reduce the peak green biomass. As in the 2007 late spring frosts in Kansa. Such events can have devastating impacts on yield though this impact is not captured by the presented regression model. One possible way to address this is to incorporate minimum-daily temperature along with a growing-degree-day phenology model that may be able to detect frost events around the time of anthesis. Another challenge of this approach is that it requires a minimum of one, representative, winter wheat crop-type map, which is often not available. In addition, large-scale shifts in winter wheat planted area, due to market pressures, tax laws, etc. would limit this model application since the underlying percent wheat map would no longer be valid. In such a case, a new representative crop percent map would be required.

3.6 Conclusions

In this chapter an empirical, generalized remotely-sensed based yield model was developed and successfully applied at the state level in Kansas using daily, high quality 0.05 degree NDVI time-series data to drive the regression model, a percent crop mask as a filter to identify the purest winter wheat pixels, and USDA NASS county crop statistics for model calibration. The model predictions of production in Kansas closely matched the USDA/NASS reported numbers with a 7% error. This empirical regression model that was developed in Kansas was successfully applied directly in Ukraine. The model forecast winter wheat production in Ukraine six weeks prior to harvest with a 10 percent error of the official production numbers. In 2009 and 2010 the model was run in real-time in Ukraine in support of USDA crop analysts. The model forecast production within 7% in 2009 and 3% in 2010 of the official statistics that were released after the harvest. This model is simple, has limited data requirements, and can offer an indication of winter wheat production, shortfalls and surplus prior to harvest in regions where little ground data is available.

‘Chapter 4: Strengthening the case for EO-based crop monitoring

4.1 The need for improved agricultural forecasts

The recent price surges in the global grain markets have brought the issue of food security to the forefront of the world’s attention. Between 2006 and 2011 grain prices soared twice leading to civil unrest with food riots in over 40 countries, and according to FAO estimates, pushing an additional 140 people million below the poverty line. These events highlight vulnerability of the world food security to such market shocks, as well as the limited capacity of the current systems to provide necessary accurate and timely agricultural information.

Unpredictable weather conditions are cited as the most frequent and significant factors leading to food price volatility (OECD-FAO 2011). The devastating droughts in Russia, Ukraine and Australia were primary factors leading to the recent food price surges of wheat and wheat products. According to International Monetary Fund statistics, the average price of the four main food crops (soy, corn, wheat and rice) doubled and in some cases quadrupled between 2006 and 2008. Again in 2010-2011, grain prices surged to a new high with wheat prices increasing over 80% in less than a year. The mounting concern over grain market volatility led to widespread international calls for improved agricultural information, such as the following.

“*unexpected price hikes and volatility are amongst major threats to food security and their root causes need to be addressed, in particular regarding the lack of reliable and up-to-date information on crop supply and demand and export availability*” (FAO 2010). This excerpt is from the official report of the September 24th 2010 Extraordinary Joint Inter-sessional Meeting of FAO’s Intergovernmental

Group on Grains and Intergovernmental Group on Rice, held in response to the surging wheat prices in 2010. More recently, an Inter-Agency report commissioned by the G-20 (OECD et al. 2011), states that the recent food price crises highlight the deficiencies in both national and international organizations to provide consistent, accurate and timely agricultural forecasts and calls explicitly for increased capacity for more frequent and systematic monitoring of the state of crops and for improved production forecasts using satellite data and geo-information systems (OECD et al. 2011). Furthermore, it asserts that more timely, complete and accurate information and improved capacity to identify and analyze early warning signs might have calmed the markets, re-assured populations and resulted in better readiness. Subsequently the G-20 Agriculture ministers agreed on an 'Action Plan on food price volatility and Agriculture' which was adopted at the G-20 November 2011 Summit. The action plan includes two related initiatives: the Agricultural Market Information System (AMIS), and the Group on Earth Observations Global Agricultural Monitoring initiative (GEOGLAM) focused on improving production outlooks and forecasts using EO (GEO-Agriculture 2012, G20 2011).

The factors governing the recent food price volatility are complex and the subject of intense debate, yet it is clear that improvements in terms of timeliness, transparency, and reliability of global agricultural information has a critical role to play in stabilizing grain markets, developing effective agricultural policies, and mobilizing aid in response to impending regional food shortages. In this context, the limited uptake by operational agencies of EO-based crop monitoring, which claims to provide more timely and efficient methods than conventional field data collection is perplexing (Justice et al. 2011). The question arises on what scale EO can contribute to mitigating such price volatility given that EO-based crop forecasting methods can provide reliable forecasts prior to harvest, as demonstrated in Chapter 3. The next section explores this topic using the 2010 price surge as a hypothetical case study. It is highlighted that the case study presented below is strictly exploratory and the results presented are preliminary.

4.2 Can EO-based crop forecasts reduce price volatility: a wheat case study?

As evident from the recent price hikes, the international wheat market is largely dominated by events that impact production in the largest wheat export countries. These countries, which include the US, Russia, Australia, Ukraine, Canada, Kazakhstan and Argentina are responsible for over 70% of global exports and for ~ 35% of total world production. This implies that timely and accurate wheat production estimates for these countries could plausibly provide a good indication of global wheat market trends and would be a significant step towards the goal of providing necessary wheat outlook information. Furthermore, this also suggests that major shifts between monthly production forecasts for these countries can have an impact on international price fluctuations.

As such, a case could be made that in order to effectively contribute to international market stability, EO-based monitoring efforts could focus on the main agricultural export countries, and in particular those prone to weather induced yield fluctuations. This assertion was evaluated in the case study described below.

4.2.2 Case study objectives

A case study was set up in order to demonstrate the potential benefit of EO crop forecasting in main export countries towards helping to stabilize markets and mitigate price volatility. It was conducted based on the results of the yield model presented in Chapter 3 applied to the 2010/2011 Russian production forecasts affected by the 2010 drought. It is acknowledged upfront that this case study presents an oversimplification of market behavior and makes assumptions about the accuracy and timeliness of the EO-based estimates for the 2010/2011 Russian wheat production. Nevertheless the intention was to give a sense of the potential value of RS-based crop estimates for grain market stability using existing data and methods and to substantiate the international calls for enhancing our current monitoring systems using EO.

The study was carried out in two steps in order to shed light on two objectives:

1) Explore the relationship between international monthly wheat prices and monthly production forecasts of the main wheat export counties.

2) Explore the potential impact of reliable, timely EO-based forecasts on reducing price volatility.

4.2.3 Data

The following data sets were used in this case study:

- USDA monthly wheat forecasts for 2003-2012 for the main wheat export countries (monthly forecasts provided by USDA directly and final production statistics were downloaded from the USDA Production Supply and Demand online database (USDA 2012).

- International commodity monthly prices from World Bank for the same period (World-Bank 2012)

4.2.3.1 USDA monthly forecasts

The USDA is currently the only government agency mandated to provide monthly, global crop production forecasts. Several studies have been conducted to assess the effect of the USDA announcements on market prices. Overall these studies have found that the USDA forecasts impact international price changes (Sumner and Mueller 1989, Milonas 1987, Mckenzie 2008). For example, Milonas et al. (1987) found that the first forecasts of crop year seem to be more important than the later forecasts. More recently (Marone 2008) found indications that the USDA forecasts have a stronger impact on short-term transactions than on long-term future contracts and that the information value of the USDA forecasts is declining as market participants are better able to anticipate some of the information prior to the USDA release.

The USDA forecasts are released by the 11th of every month. The May forecast is the first forecast of the marketing year, and the April forecast is the last estimate. As such, the data for this study was organized and aggregated according to the USDA crop year (May through April). It should be noted that the USDA crop forecasts are the best publically available source for timely global crop production information. The aim of this analysis was to demonstrate the potential value of remotely sensed based methods to provide complementary information for crop forecasting.

4.2.3.2 World Bank Commodity Price Data

A series of international commodity monthly prices including that of wheat, were retrieved from the World Bank (World-Bank 2012)(*pink sheet*) for a series of 75 commodities. This database is provided in US $ (nominal – not adjusted for inflation). The US, Hard Red Winter (HRW) Golf price was chosen for this study as this is a commonly used wheat price for representing the international wheat markets (OECD-FAO 2011, European-Commission 2009).

4.2.4 Analysis: Steps and Results

4.2.4.1 The relationship between international monthly wheat prices and monthly production forecasts

Given that international commodity markets are highly linked, the first step was to assess the relationships of wheat prices to other commodity prices. The wheat price relationships were assessed using linear regression as well as the maximal information coefficient (MIC) (Reshef et al. 2011). The MIC is a nonparametric measure that provides a score that roughly equals the coefficient of determination of the data relative to the regression function regardless of function type.

The results indicate that wheat prices are most highly related to other food crop commodities such as soybeans, maize, rice and sorghum as well as to crude oil and less so to natural gas (figure 4.1 and table 4.1). Of the non-food commodities, crude oil had the strongest correlation to wheat price with a linear regression coefficient of 0.85 and a MIC coefficient of 0.79. The natural gas prices were also highly correlated to the wheat price and are also closely linked to crude oil prices. Although causality is hard to establish, it is known that there is a tightened inter-dependence between energy and crop commodity markets. This is likely due to a combination of factors such as fuel use for agricultural machinery, transportation costs, application of fertilizer and chemicals which derived directly from crude oil, and competing demands from biofuels (World-Bank 2011, FAO 2011b). Figure 4.2 is a price time series graph showing the relationship between monthly wheat and oil prices.

As this case study sought to assess the response of wheat prices to production forecasts, the wheat price was de-trended using the regression between oil price and wheat price according to equation 4.1:

$$DtWPrice_t = WPrice_t - (OPrice_t * 2.25) + 72.3$$

Equation 4.1

Where $DtWPrice_t$ is the de-trended wheat price at month t, $WPrice_t$ is the monthly wheat price, and $Oprice_t$ is the crude oil price at time t. 0.25 is the slope and 72.3 is the intercept of the regression between crude oil price and wheat price (figure 4.3).

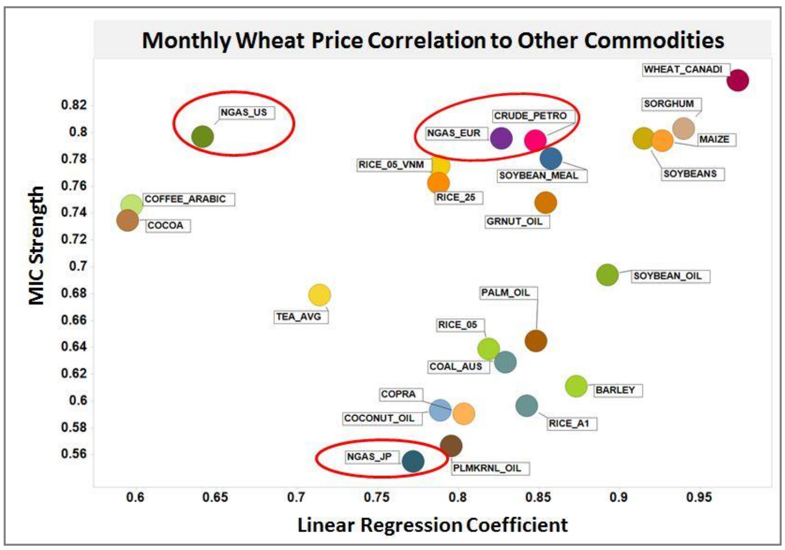


Figure 4.1 Relationship of monthly wheat prices to other commodities. Linear regression (x-axis) and MIC coefficients (y-axis).

Table 4.1. Linear regression and MIC coefficients of monthly international wheat price vs. monthly prices of other international commodities

Commodity	Lin Regression Coef	MIC
WHEAT_CANADI	0.97	0.84
SORGHUM	0.94	0.80
MAIZE	0.93	0.79
SOYBEANS	0.91	0.80
SOYBEAN_OIL	0.89	0.69
BARLEY	0.87	0.61
SOYBEAN_MEAL	0.86	0.78
GRNUT_OIL	0.85	0.75
PALM_OIL	0.85	0.64
CRUDE_PETRO	0.85	0.79
RICE_A1	0.84	0.60
COAL_AUS	0.83	0.63
NGAS_EUR	0.83	0.80
RICE_05	0.82	0.64
COPRA	0.80	0.59
PLMKRNL_OIL	0.80	0.57
COCONUT_OIL	0.79	0.59
RICE_05_VNM	0.79	0.78
RICE_25	0.79	0.76
NGAS_JP	0.77	0.56
TEA_AVG	0.71	0.68
NGAS_US	0.64	0.80
COFFEE_ARABIC	0.60	0.75
COCOA	0.59	0.73

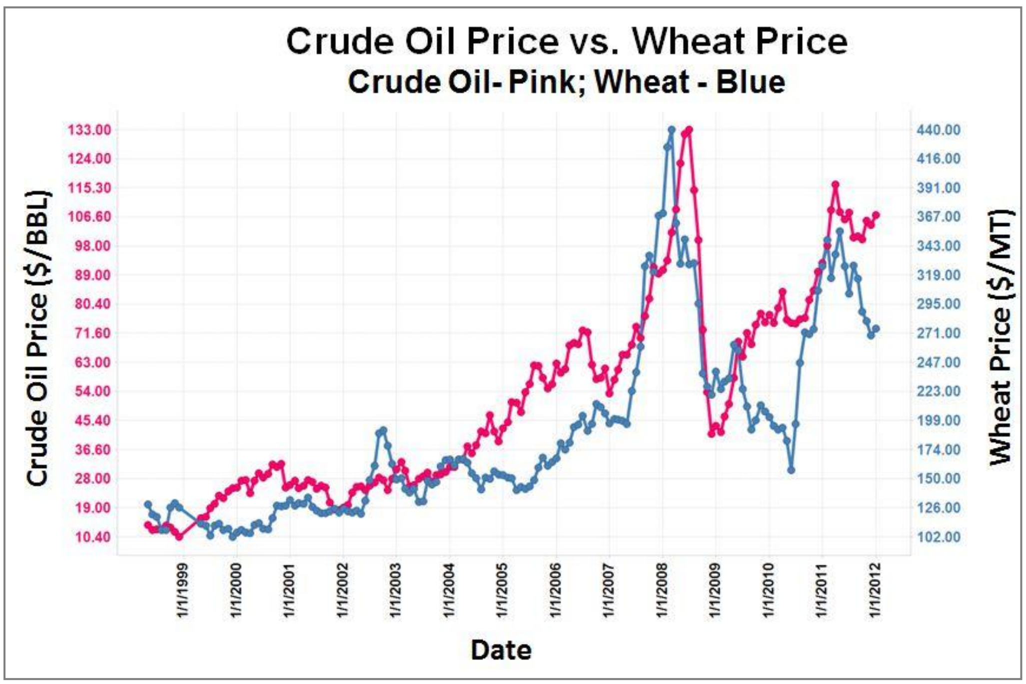


Figure 4.2 Monthly crude oil nominal price vs. monthly wheat price (1999-2012)

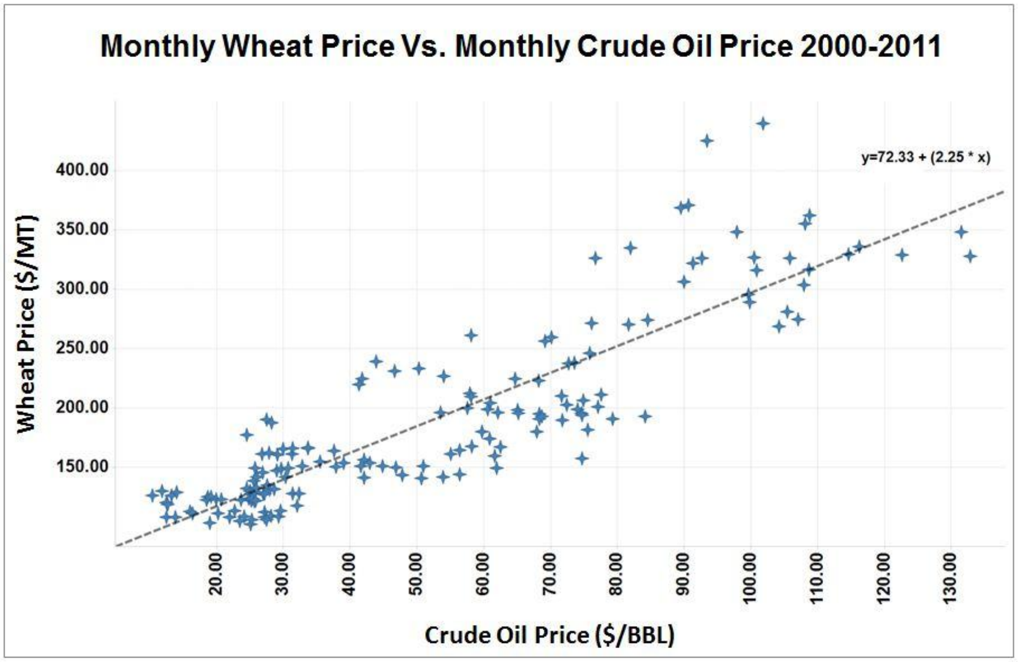


Figure 4.3 Regression between crude oil price and wheat price

Next, the USDA monthly wheat production forecasts were aggregated for the largest export countries: U.S., Russia, Canada, Australia, Ukraine, Kazakhstan, and Argentina and hereafter referred to as Group1. The production forecasts were organized according the USDA crop year calendar, where the first estimate for the upcoming market year is released in May and the last estimate is released the following April.

These aggregated production forecast data were used to assess the relationship between Group1 production forecasts and monthly international wheat price. First, the wheat production forecasts were compared with the monthly de-trended wheat prices (DtWPrice). Figure 4.4 presents a time series comparison of the DtWPrice vs. production forecasts. From visual inspection of figure 4.4 it is generally evident that when production forecasts decrease, price increases. To quantify this relationship, monthly prices were regressed against the USDA monthly Group1 production forecasts for every USDA crop year (2003-2011) figure 4.5.

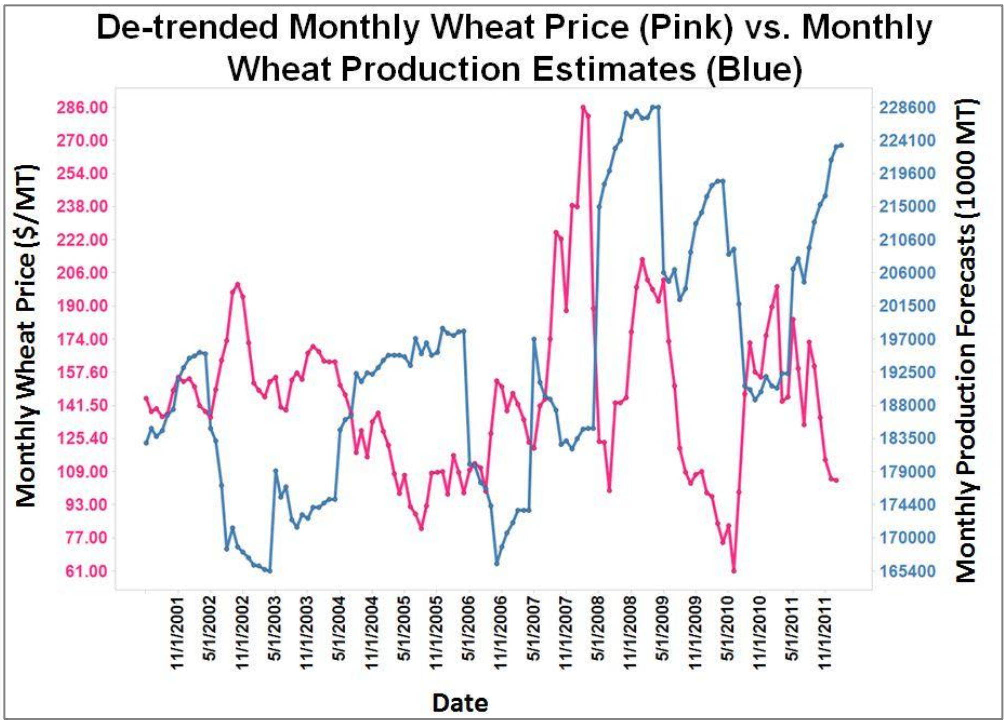


Figure 4.4 De-trended monthly wheat price vs. monthly wheat production estimates for Group 1 countries.

Not surprisingly, price was strongly and negatively correlated to Group 1 production forecasts during years of crop shortfalls, namely in 2006-2007, 2007-2008 and more recently 2010-2011. Figure 4.6 displays the final aggregate production statistics for the Group 1 countries, highlighting the crop shortfall years. Figure 4.5 displays the regressions between production forecasts and monthly de-trended wheat prices. It is interesting to note that in shortfall years, the earlier production forecasts overestimate production and then drop sometime after the 4th estimate. As such it seems, as suggested by Milonas (1987), that the earlier production forecast have a higher impact on price than do the later forecasts as the uncertainly in the estimates is reduced and more reliable information becomes available. It is also acknowledged that many other factors, such as export bans and quotas, hording, and grain stock-levels played a significant role on excess price volatility though this study is focused on exploring the empirical relationship between production forecast and price.

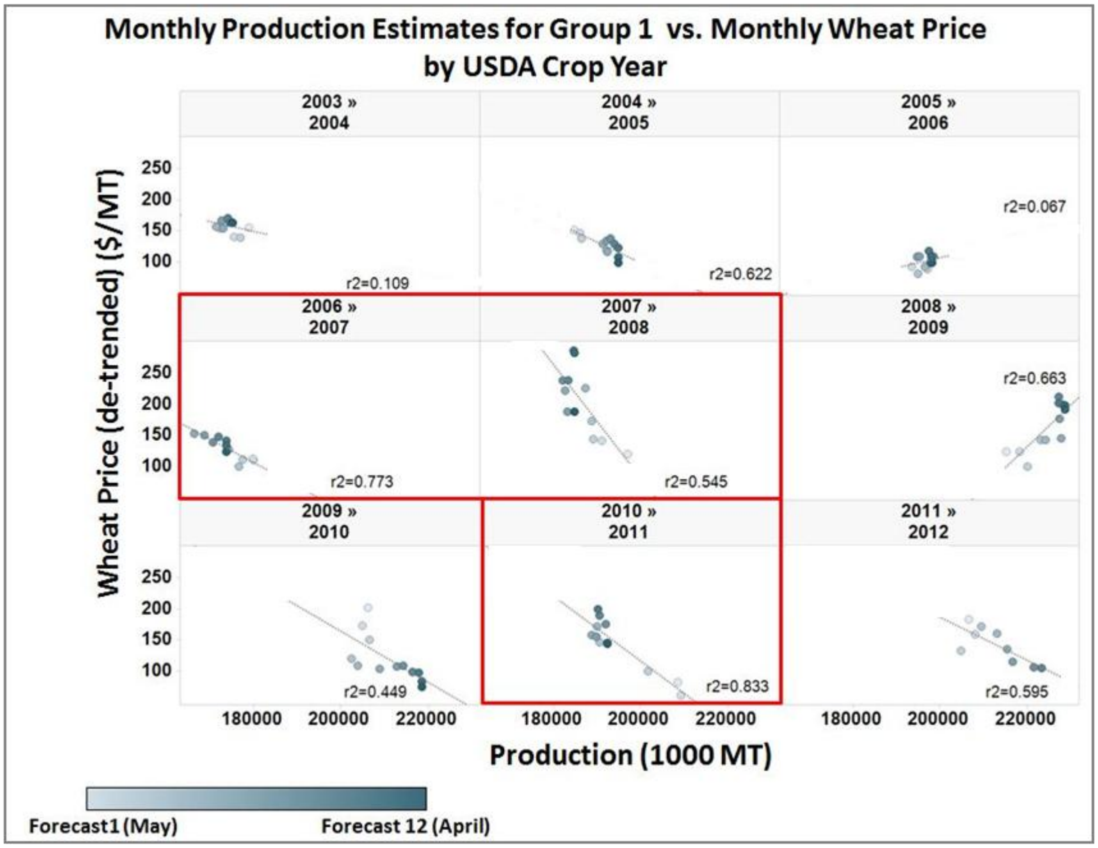


Figure 4.5 Monthly production estimates for Group 1 countries vs. international monthly wheat prices by USDA crop year (May-April). Light blue color indicates earlier forecasts and the dark blue indicates the later forecasts. Red boxes highlight years with production shortfalls due to weather events (primarily droughts).

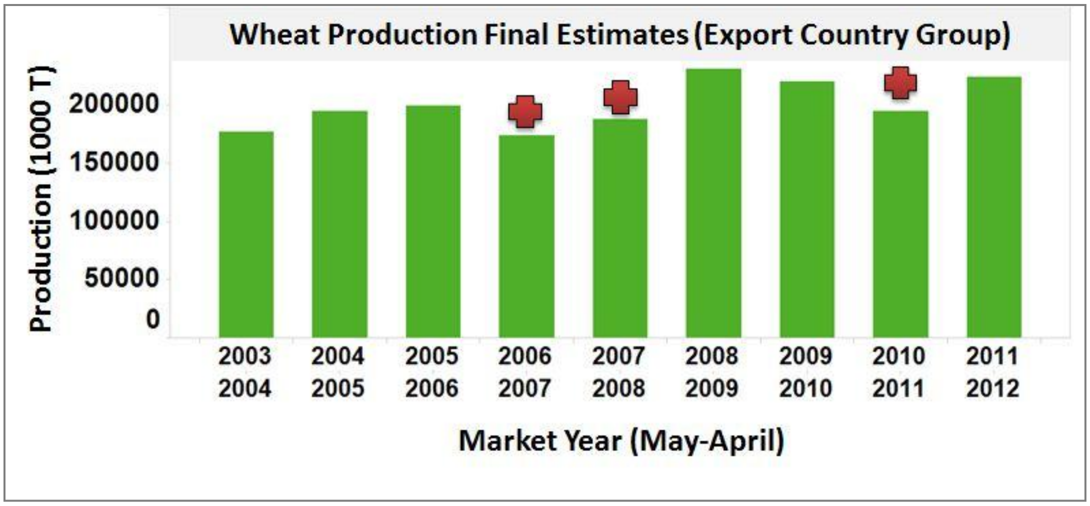


Figure 4.6 Aggregated wheat production (1000 metric tons) for Group 1 countries. Red crosses indicate crop years with wheat shortfalls.

The most recent price surge in the 2010-2011 crop year was selected for demonstrating the potential contribution of RS-based production estimates towards reducing wheat price volatility.

4.2.4.2 Impact of reliable, timely EO-based forecasts on reducing price volatility

Prolonged high temperatures and lack of precipitation in Russia were the primary reason for the 2010-2011 production shortfalls reflected in the Group1 aggregate production statistics. Initially, the monthly production forecasts were significantly higher than the final production estimates. As shown in figure 4.7 the production forecasts were within 10% of final production starting in August. (The severe impacts of the drought on vegetation were observable in the June MODIS imagery).

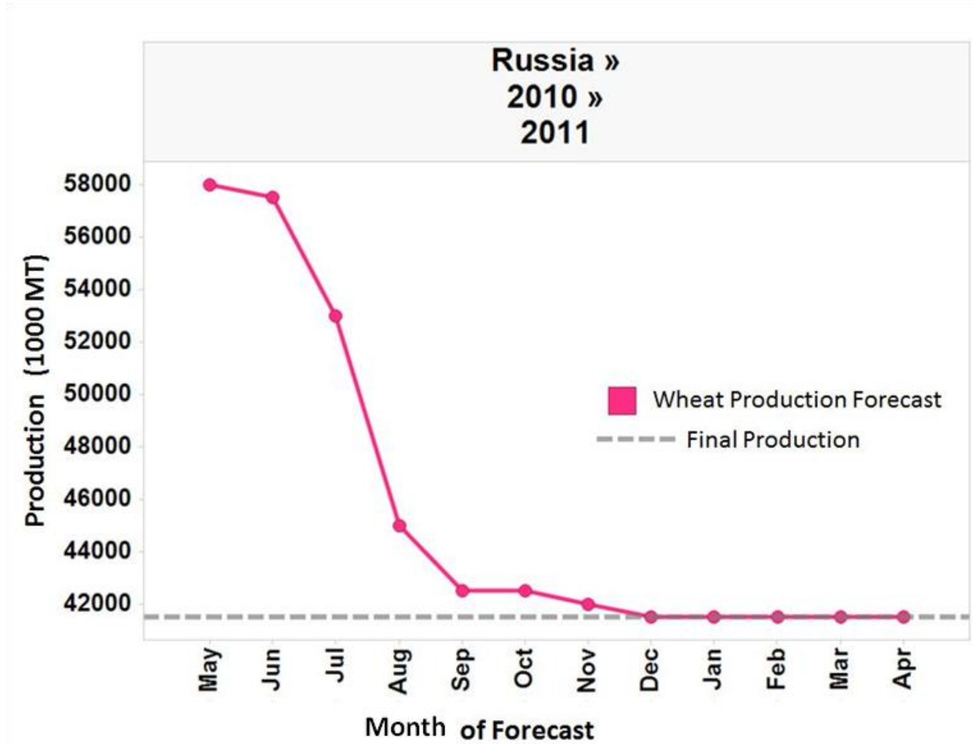


Figure 4.7 USDA Russian wheat production forecasts for the 2010/11 crop year (pink) versus the final production estimate (dashed gray line)

The following steps were carried out to demonstrate the potential impact of EO-based forecasts for international wheat prices using the 2010/11 price surges as an example.

Step 1: The forecast errors from the EO-yield model described in chapter 3 (Becker-Reshef et al. 2010b) were used to approximate viable EO-estimate accuracy for Russia in 2010. The EO-yield model was run multiple times during 2010 (for May, June, July and August) in order to forecast production in Ukraine. The errors from this analysis were applied to the 2010/11 production forecast for Russia. (figure 4.8)

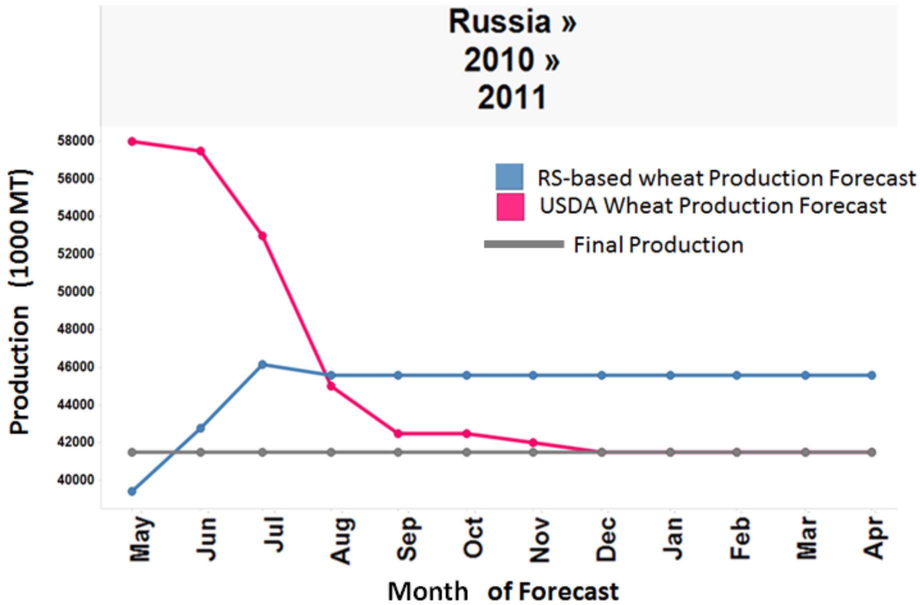


Figure 4.8 USDA Russian wheat production forecasts for the 2010/11 crop year (pink); EO-based Russian wheat production forecasts applying EO-model errors from Ukraine model runs (blue); Final production estimate (dashed gray line)

Step 2: The 2010/2011 group1 production forecast were re-aggregate using the EO-Russia forecasts (figure 4.9). This re-aggregated forecast will be referred to as the EO-forecast.

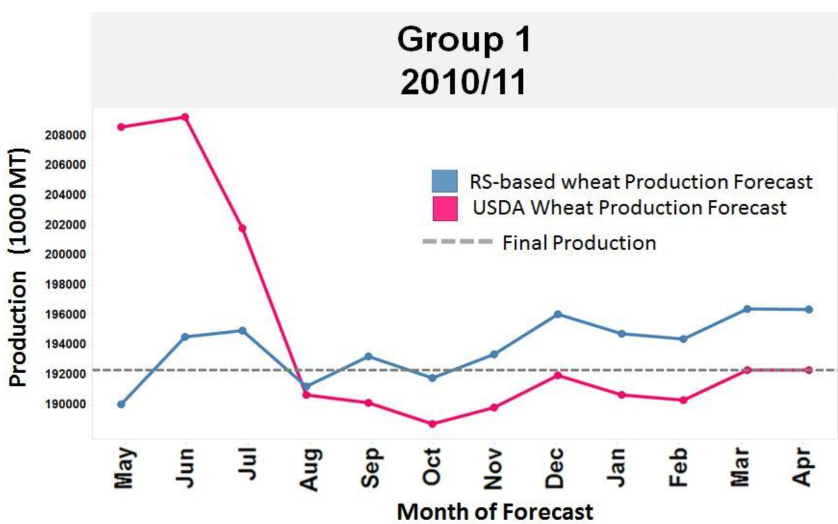


Figure 4.9 Aggregated USDA wheat production forecasts for the 2010/11 crop year for Group1 (pink); Aggregated wheat production forecasts for Group1 applying RS-model errors from Ukraine model runs to the Russian forecasts (blue); USDA final production estimate for group1 (dashed gray line)

Step 3: De-trended wheat prices were estimated using the derived 2010/11 regression between DtWprice and aggregated USDA production forecasts for Group1 (described by equation 4.2, r^2=0.83 Figure 4.10).

$$EstDtWPrice_t = -0.01 * PForecast_t + 1158.39 \qquad \text{Equation 4.2}$$

Where $EstDtWPrice_t$ is the estimated de-trended wheat price for time t and $Pforecast_t$ is the Production forecast at time t.

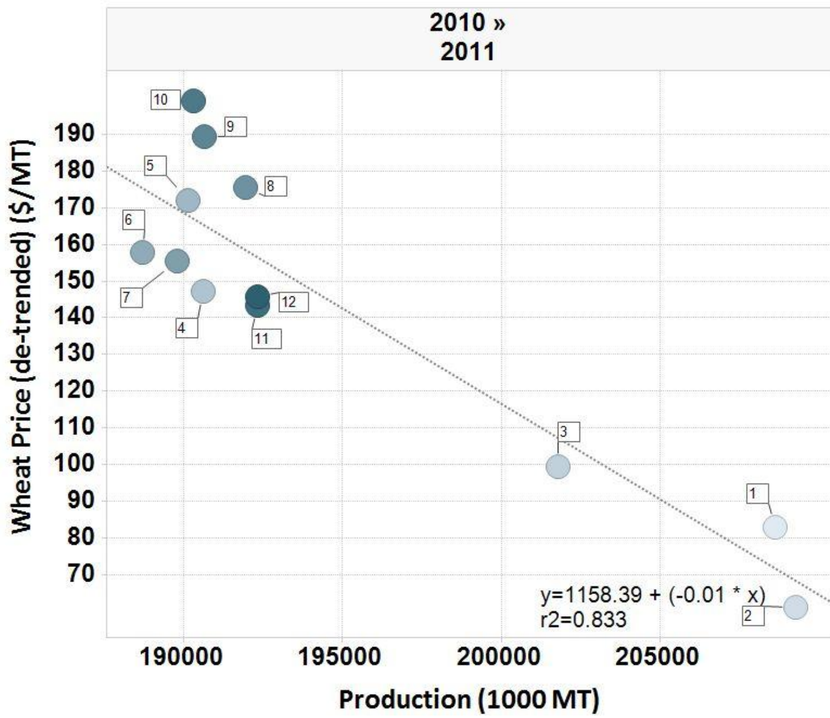


Figure 4.10 2010 Regression between USDA production forecasts and monthly wheat price. Labels indicate the forecast time step, where 1 is the May forecast. The linear regression and r^2 are displayed.

De-trended prices were estimated using a) the original production forecasts for Group1 (figure 4.11a) and b) the EO integrated forecasts for Group1 (figure 4.11b). Figure 4.11a is a time-series graph of the de-trended wheat prices (gray) vs. the de-trended price estimates based on the original forecasts (pink). Figure 4.11b is a time series graph comparing the original de-trended price estimates (pink) to the EO-based estimates (blue). This analysis suggests that earlier, reliable production forecasts for Russia could have reduced the wheat price fluctuations during the first four time-steps of the crop year.

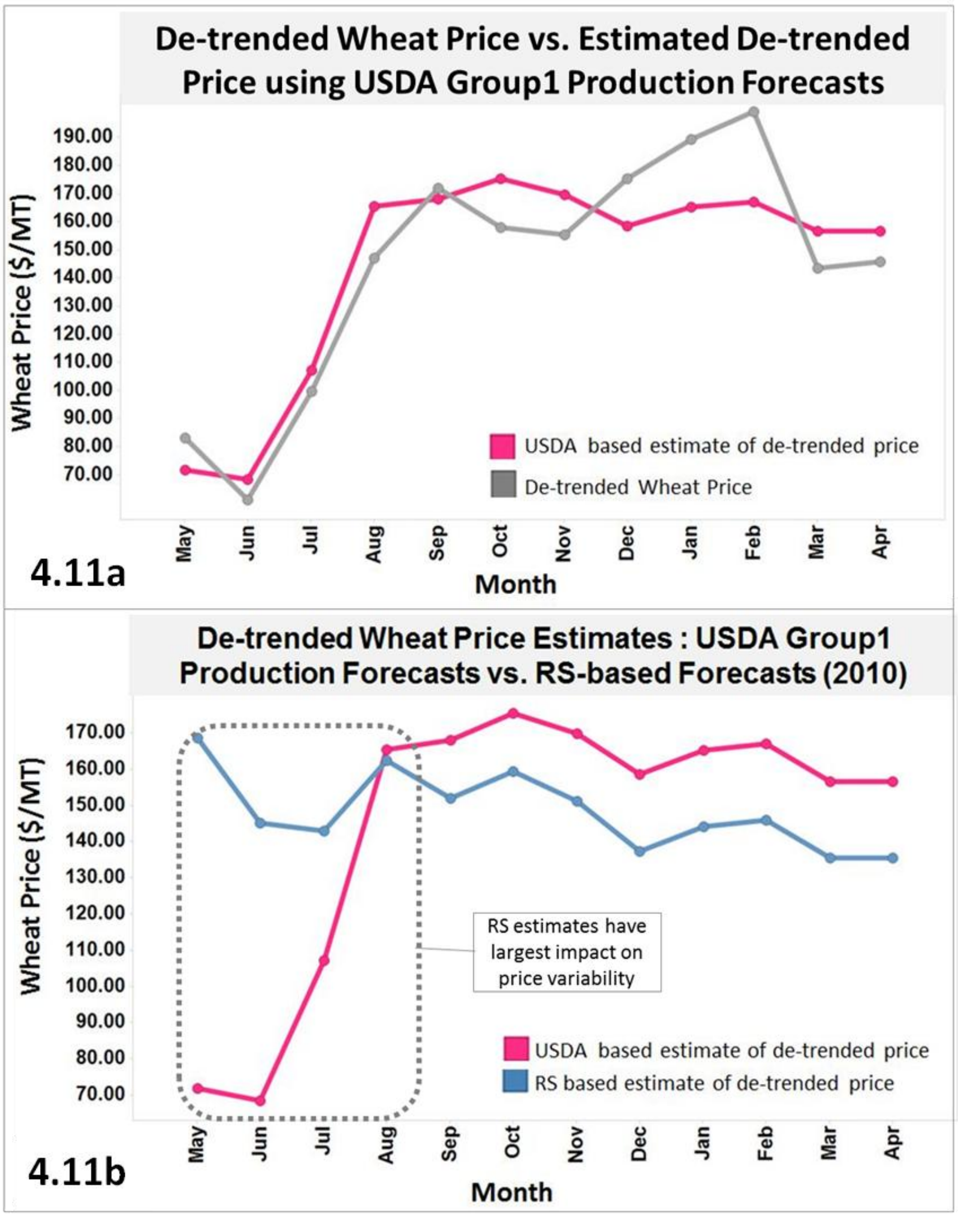


Figure 4.11a-b. a) De-trended wheat price (gray) versus estimated price using USDA forecasts (pink). b) Comparing the USDA based (pink) versus the EO-integrated (blue) de-trended wheat price estimates.

Step 4: The crude-oil trend was applied to the derived estimates of the de-trended price time series so that they could be compared with the actual wheat prices. The crude oil trend was applied using the following equation:

$$EstWPrice_t = EstDtWPrice_t + (OPrice_t * 2.25) - 73.3$$

Equation 4.3

Where $EstWPrice_t$ is the wheat price estimated for time t, $EstDtWPrice_t$ is the estimated de-trended wheat price and $Oprice_t$ the crude oil price at time t. (figure4.12). Figure 4.12a compares the original USDA based price estimates to the actual wheat price time-series, and Figure 4.12b compares the original USDA-based price estimates to the EO-based price estimates.

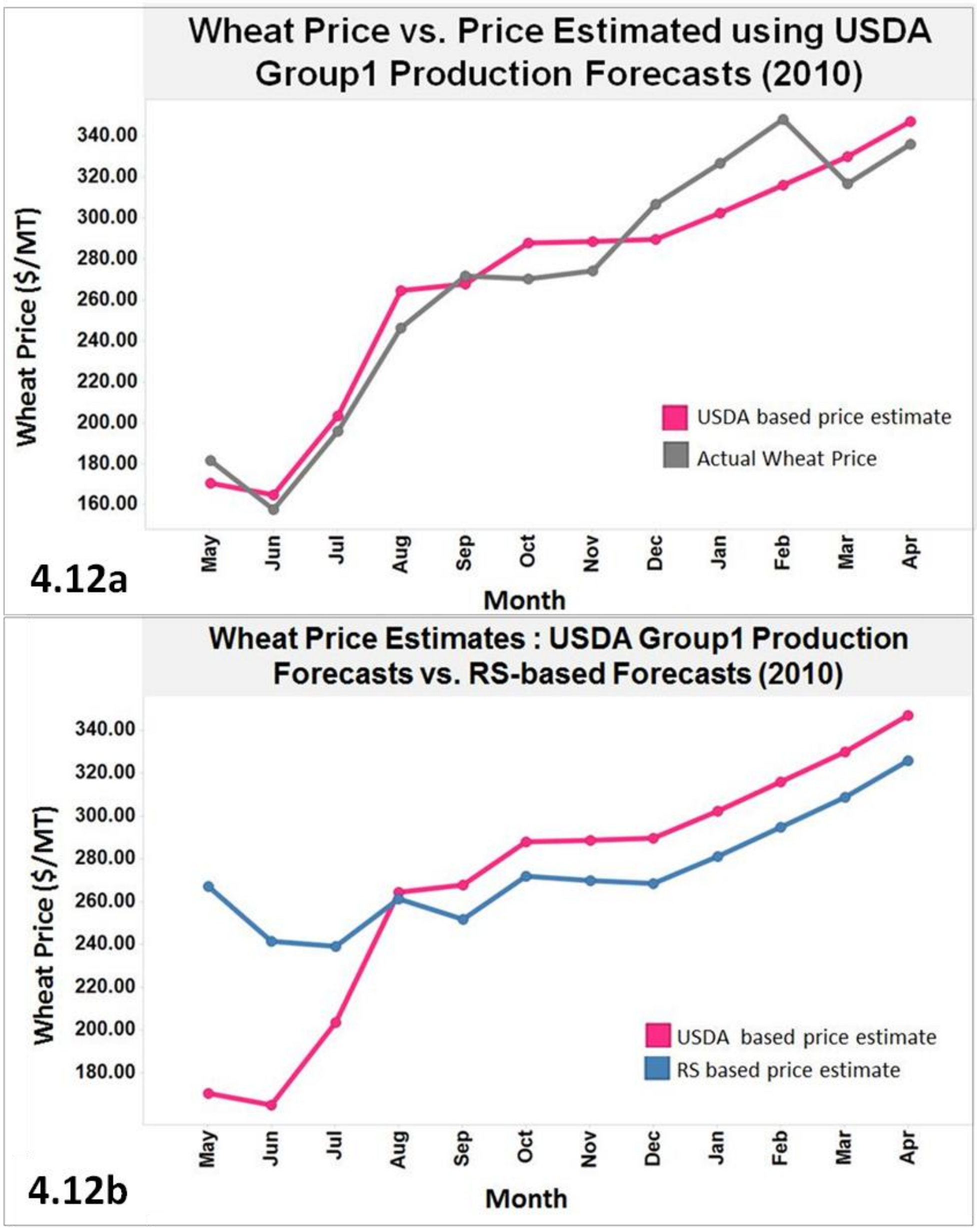


Figure 4.12a-b a) Wheat price (gray) versus estimated wheat price using USDA forecasts (pink). b) Comparing the USDA based (pink) versus the EO based (blue) wheat price estimates.

Step 5: The price volatility was computed for: 1) the EO-based price estimates, 2) the original USDA-based price estimates, and 3) the actual wheat prices. A common measure of volatility is the coefficient of variation (CoV) of a given price series. This measure reflects an estimation of variability (standard deviation) as a ratio to its mean (European-Commission 2009). The CoV of the estimated price series was the used in this example to indicate price volatility (table 4.2). Finally, the impact of the EO-integrated crop production forecasts on price volatility was assessed for the 2010/2011 crop year relative to the impact of the original forecasts. This was computed as follows:

(VolUSDA- VolRs)/ VolUSDA.

Where VolUSDA is the volatility computed based on the original USDA production forecasts and VolRS is the volatility computed based on the EO-integrated production forecasts (table 4.2).

Table 4.2 Price Volatility (as CoV)

Estimated & Actual Wheat Price Volatility

Price Source	Volatility (CoV)
actual price from World Bank (US HRW Golf)	23 %
price estimated based on original USDA production forecasts	22 %
price estimated based on EO-integrated production forecasts	9 %
reduced volatility	57 %

4.3 Discussion

The three main findings from this highly simplified hypothetical 2010/2011 case study are as follows: 1) Monitoring production in the 7 main wheat export countries can provide a good indicator of international wheat prices. 2) Price volatility in principle can be reduced in part with timely accurate production forecasts afforded by better integration of EO-based methods into operational monitoring systems. In the hypothetical case presented here, the 2010/2011 price volatility in international markets could have potentially been reduced by more than half from 22% to 9% by integrating early season EO-based production forecasts (assuming these are timely and accurate). (Table 4.2). 3) EO-based forecasts are likely to be of most value to operational monitoring systems, during the first estimates of the season, prior to harvest and the release of other reliable market information.

5. Conclusions

This dissertation set out to investigate ways to improve current EO-based methods for crop yield forecasting focusing on wheat and to demonstrate the potential impact that improved EO-based forecasts and their integration into operational monitoring systems could have on grain markets. This final chapter summarizes the context for this research, reviews the main research findings, and discusses directions for future research and the earth observation needs for agricultural monitoring.

5.1 Summary

Agriculture faces major challenges in this century. According to FAO estimates global food production will need to increase by 70% by 2050 in order to meet the growing global demand. Severe weather events in major food producing countries were primary factors in the recent food price crises which pushed the number of food-insecure people over 1 billion and led to civil unrest and riots in several countries around the world. The recent events raise important questions about the accuracy of production forecasts and their role in market fluctuations, and highlight the deficiencies in the current state of global agricultural monitoring. Earth observations methods and technologies have been used to forecast and estimate crop production and help assess the effects of severe weather events prior to harvest but have had limited uptake by operational users. As such the primary goal of this dissertation was to build on existing methods and research and utilize available EO data in order to develop a robust generalized approach for crop yield forecasting prior to harvest that can be integrated into an operational domain.

5.2 Major findings and contributions

The focus of this dissertation was on advancing EO-based crop forecasting. The research presented addresses three primary challenges:

1) **Data availability**:
   - Developing an approach to yield forecasting that is applicable in the absence of up-to-date crop distribution information using data with sufficient revisit frequency for monitoring crop development.
2) **Model transferability:**
   - Developing a robust yield forecasting model that is transferable between major wheat growing regions and is applicable at national scales.
3) **Relevance**
   - Demonstration of the value of RS crop forecasting methods towards the overall goal of helping to inform commodity grain markets.

The research was carried out within the framework of the Global Agricultural Monitoring project (GLAM) described in chapter 1 (Becker-Reshef et al. 2010a) in support of USDA FAS crop analysts. The goal of chapter 2 was to assess the appropriate spatial and temporal resolution for crop yield forecasting using freely, easily accessible data. It addressed the challenge of yield forecasting in the absence of within-season crop type masks. This was accomplished by developing an approach that utilizes time-series data at coarse spatial resolution in combination with spatially aggregated, previous year crop type masks. The study found that higher temporal resolution data, (i.e. 8-day versus 16-day composite data were better suited for extracting the seasonal crop parameters, and in particular the seasonal NDVI peak. Secondly, it found that where crop rotations are prevalent, coarsening the spatial scale of out-of-season crop type mask resulted in a constant per-pixel wheat proportion over multiple seasons. This enabled a coherent and comparable extraction of NDVI for yield estimation over multiple years using a single out-of-season mask and coarse resolution EO NDVI time series. In the case of Kansas, using a crop type mask aggregated to the 5km resolution resulted in a 1.2% tradeoff in accuracy relative to the control case where within season cropmasks were available. These findings suggest that wheat yield can be forecast with a small tradeoff in accuracy using a single, out of season crop mask and coarse resolution NDVI time series data.

The goal of chapter 3 was to build on the chapter 2 findings and develop a robust EO, regression-based model for wheat yield forecasting for use at national scales. As such this study combined daily, high quality coarse resolution (0.05 degree) NDVI time series data with a single wheat mask and detailed official crop statistics to develop an empirical, generalized approach to forecast wheat yields at the state to national scales. The regression-based model was developed as a function of seasonal maximum NDVI (adjusted for background noise) and percent wheat. The model was developed and implemented in Kansas estimating yields with a 7% error. Subsequently the same model was successfully implemented in Ukraine, estimating winter wheat yields within 10% of official estimates six weeks prior to harvest. As wheat masks are not available for Ukraine, this study developed a wheat mask based on 2008 data, which was used to forecast yields for multiple years. The results of this model were subsequently used by the USDA crop analyst responsible for Ukraine.

The strengths in the developed approach are that it has limited data requirements, utilizes freely available, coarse resolution data, and it is empirical yet transferable. These findings could have significant implications for yield forecasting at national scales in locations where accurate or timely information is limited.

The goal of chapter four was to use the model results (chapter 3) in order to shed light on the potential contribution of such EO-based crop forecasts towards helping to stabilize grain markets- a topic of major international concern, with the intention of demonstrating the utility and relevance of these methods and to highlight the need for further investment in advancing this field. The lack of international investment by governments, and in particular the agricultural monitoring agencies and space agencies, in R&D to realize the full potential of the available space assets for operational agricultural monitoring, can be attributed in large part to a lack in demonstrated relevance to their mission and since these systems are often not considered to be operational.

The case study in this chapter clearly oversimplifies market behavior and makes gross assumptions on the accuracy of EO-based crop forecasts. Nevertheless the intention was to give a sense of the potential value of RS-based crop estimates for grain market stability using existing data and methods and to substantiate the international calls for enhancing our current monitoring systems using EO. The study assessed USDA monthly crop forecasts for the primary wheat export countries against international monthly wheat prices. The study found that <u>monitoring production in the 7 main wheat export countries can provide a good indicator of international wheat prices</u>. Furthermore, it demonstrated that <u>price volatility could be reduced with timely accurate forecasts afforded by EO-based methods</u>. In this case study, <u>price volatility was reduced by 57% (from 22% to 9.5%) by integrating EO-based production estimates</u>. Finally it provided <u>indications that RS-based forecasts are likely to be of most value to operational monitoring systems, during the first</u>

estimates of the season, prior to harvest and the release of other reliable market information.

5.3 Future Research: Beyond this Thesis

A large number of interesting and exciting research topics arise from the research findings presented in this dissertation. Based on the experience gained in this dissertation a number of improvements to EO-based crop monitoring methods that can be used in the operational domain can be envisioned. The primary topics are highlighted in the following section.

- **Model Extension:**

  The model has been applied to two main wheat growing locations, namely Ukraine and Kansas. In order to further assess the model's transferability the model approach should be extended and evaluated in other large wheat producing countries such as Australia, Russia, Argentina and China. Preliminary results from this model's application to southern Russia, Australia and China are promising.

- **Model Refinement**:

  The current model is optimized for forecasting yield by utilizing the wheat NDVI seasonal peak observed roughly six weeks prior to harvest. Improving timeliness of estimates would be highly desirable. Future research should explore coupling the daily NDVI data with readily available meteorological data in order to model crop growth and forecast the NDVI peak a few weeks prior to the actual peak. Research initiated during LACIE (Idso et al. 1979a) found a strong correlation between RS measurements of growing degree days

(GDD) and wheat growth stages. Such relationships could be used in order to forecast the NDVI peak and in turn feed into the yield model forecasting yields a few weeks earlier.

Furthermore, as in the 2007 Kansas case, late spring frost events can have devastating impacts on yield, though this impact is not captured by the current model. This limitation can be addressed by incorporating a minimum-daily temperature along with a growing-degree-day phenology model that can detect frost events that occur after the majority of biomass is developed.

An additional area for model refinement is to develop an automated approach for within season wheat classification particularly in regions where planted area is highly variable. There are promising results for developing such an approach using regression trees for soy mapping using a combination of landsat-class data with MODIS 250m data (Hansen et al. 2010).

- **Assess sensitivity and errors**:

Assessing the model sensitivity to crop mask accuracy and to RS data quality is another area for future research. Such an assessment can help to provide the minimum data requirement guidelines for implementing such an RS based yield model. Sensitivity to crop mask accuracy can be assessed by introducing random errors into existing crop masks and assessing the impacts on the yield estimates. The model can also be assessed using the AVHRR data archive, which is lower quality data, however, has a long data record starting in 1982. A consistent long term data set already developed by Vermote et al. (2010) would be suitable for such a study. If the model can be run using AVHRR data this would allow for research into yield trends over the last 30 years and a more comprehensive assessment of the impacts of extreme weather and events connected to climate oscillations on yields

- **Continued assessment of the relationship between production forecasts and price variability**

  The preliminary findings from the case study on price volatility and production forecast accuracy provide valuable insights on the potential contribution of EO-based methods for improving the accuracy of early production estimates which are an important component for stabilizing markets. Given the economic component of this research, this research should be continued in cooperation with an agricultural economist, to develop guidelines for where to focus EO-based efforts for agricultural monitoring. This would include further investigation of: which countries should be prioritized for EO-based monitoring, forecast accuracy requirements, and an assessment of tradeoffs between provision of early season estimates and estimate accuracy on price. In addition the relationship between price and production forecasts of other major crops (i.e. maize, soy, rice) should be explored in order to help identify and prioritize efforts for enhancing EO-based production forecasting of the other main crops. These priorities could be used to guide the crop types and countries to focus on for assessing the applicability of the yield forecasting approach developed in this dissertation to other crop types.

5.4 Looking Forward and Future Needs and Role of Earth Observations for Agricultural Monitoring

The need for comprehensive, systematic and accurate global agricultural intelligence is clear and will continue to grow in the face of anticipated increasing pressures on our agricultural systems. As such it is fundamental that the operational agencies are able to meet these agricultural information demands in a timely reliable manner. From the remote sensing side these needs include: timely data delivery, ensuring continuity of earth observing missions particularly at coarse and moderate resolutions, enhancement of the frequency and availability of moderate resolution data (20–60 m), inter-operability between the current and future sensors, better integration across data sets at differing spatial resolutions, enhanced value -added and standardized products such as crop type maps, crop calendars, biophysical measures and vegetation indices, enhanced yield models (both mechanistic and empirical), crop area estimates, and seasonal weather forecasts (Justice and Becker-Reshef 2007, GEO-Agriculture 2012, See et al. 2012, Justice et al. 2009).

Although sensing systems are currently available to meet many of the crop monitoring needs, enhancements and continuity, particularly at the moderate resolution (20 m–60 m), are urgently needed (Wulder et al. 2008, Justice et al. 2011). Although daily and composited MODIS data can be used to monitor areas with large field sizes, findings from the Group on Earth Observations (GEO) Agricultural Monitoring Community of Practice (CoP) indicate that finer resolution data are needed two or three times every 10 days to provide the necessary cloud free coverage for monitoring many of the agricultural regions with smaller field sizes. The Landsat

7 (30 meter resolution and 185 km swath) provides 16 days coverage which is sub-optimal for many agricultural monitoring applications. In addition, the instrument was severely impacted by a scan line corrector malfunction in 2003 which further hampers use of these data for agricultural monitoring. The Landsat Data Continuity Mission (LDCM), scheduled to launch in December 2012, will have an increased global acquisition and processing capability and will provide a new source of data but will still not meet the revisit frequency requirements for many agricultural applications. Sensor redundancy is also needed at moderate resolution and there is an urgent need to develop a coordinated global acquisition strategy for the currently available and future assets.

The optimal spatial and temporal resolutions requirements for crop area estimation, and crop growth monitoring, and yield forecasting vary according to agricultural landscape, and environmental characteristics (Duveiller and Defourny 2010) and generally require data at higher temporal and spatial resolutions than what is currently available and freely accessible (Curnel et al. 2011). One of the pressing goals of the Group on Earth Observations (GEO) Agricultural Monitoring Task is to define these EO-based requirements for global agricultural monitoring (GEO-Agriculture-CoP 2011).

The G-20 GEOGLAM initiative is working closely with the Committee on Earth Observation Satellites (CEOS) to develop the EO data requirements and acquisition strategy for global agricultural monitoring (GEO-Agriculture 2012). In previous reports, the GEO agriculture community of practice recommended that 2–3 scenes are acquired every 10 days at resolutions between 20 m and 60 m during the growing season (Justice and Becker-Reshef 2007). This strategy should be extended into the future and applied to the constellation of next generation sensors at this resolution as they come online (e.g., CBERS 3, LDCM, Sentinel 2). Similarly, a strategy is needed to acquire one or two images a month at 5m to 1m spatial resolution, sampling critical agricultural areas. Smallsat satellite constellations can offer a cost-effective solution for providing global Landsat class data with a 1 to 3 day revisit frequency that is required for monitoring agriculture during the growing season (Goward et al. 2011). Data from such constellation could be cross-calibrated using properly calibrated more expensive missions.

In addition there is a need to explore and enhance methods for the integrated use of coarse and moderate resolution data for agricultural monitoring which can be used in tandem both for crop area estimation as shown by Chang et al. (2007) and for crop condition monitoring and yield forecasting. Attention also needs to be given to ensuring data product continuity and quality assurance, requiring instrument calibration and inter-calibration, product inter-comparison and validation, and definition of data quality standards.

Using current readily available data and methods, the RS community can make a big contribution towards provision of timely, up-to-date, transparent information, responding to the urgent international call for such data. These data are critical for economic, humanitarian and security perspectives.

Currently there remains a large gap between the capacity for crop production monitoring within the remote sensing research community and the current operational monitoring systems. A big challenge is that sufficient investments have not been made for full integration of EO-based methods into the operational agricultural forecasts in part because the capabilities are not considered to be operational or relevant.

Given the heightened interest in food security, calls for improved up-to-date crop forecasts, it seems that the time is ripe for a concerted international effort to integrate the advances in the research domain and in satellite technologies to transition and integrate them into the operational monitoring domain. This thesis has made a contribution to this broader agenda by developing and testing a robust EO-based method for wheat production forecasting, using available data and demonstrating the relevance for adopting such methods to provide timely information to inform crop commodity markets.

Appendix

Publications relevant to this dissertation:

GEO-Agriculture (2012) (contributing author). GEOGLAM: The G-20 GEO Global Agricultural Monitoring Initiative submitted to the G-20 Agriculture Ministers March 23, 2012

See, L., Fritz, S., Thornton, P., You, L., Becker-Reshef, I., Justice, C., Leo, O., & Herrero, M. (2012). Building a Consolidated Community Global Cropland Map. *Earthzine. Published online: January 24 2012.* http://www.earthzine.org/.

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