14

Agricultural Case Studies for Measuring the Value of Information of Earth Observation and Other Geospatial Information for Decisions

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CONTENTS

14.1 Introduction

In this example, geospatial information is applied by using Earth observation (EO) data to the agricultural sector. Two case studies that involve the quantitative estimation of the value of information (VOI) in specific adaptation and mitigation decisions are summarized. The first case study focuses on adapting land use to sustain drinking water quality and to avoid an increase in the contamination of groundwater by agrochemicals. The second case study concentrates on mitigating drought disasters by determining farmer eligibility for financial assistance by the U.S. Department of Agriculture (USDA). In both of these instances, the EO data are transformed into information and is convolved with other science-based indicators as well as with socioeconomic data to assist individuals and communities. The two case studies demonstrate the relevance and benefit of EO as a frequent, objective, and timely monitoring system of terrestrial conditions for cost-effective resource management.

14.2 Expected Societal Benefits of a Decision with and without Earth Observation

The EO data and other remotely data are collected in many forms and at many scales. However, the data require translation to deliver information for systematic use in decisions. Economists regard EO and other geospatial information as an intermediate good that provides a link between economic sectors in an economy (Bernknopf et al. 2016, in press). The two case studies demonstrate how observations of land use and land cover can be coupled with other models and data to create information for decisions. When EO can be linked to other types of models and data to create new geospatial information, as in the two case studies summarized here, the decisions involve spatiotemporal change.

In the case studies, the economic value for geospatial information depends on what is at stake in a decision and how uncertain a decision-maker is. The VOI is defined as the gains that result from making better decisions that are based on additional information in the presence of uncertainty. The economic value is measured as the expected change to an economy that could occur with EO compared with a baseline without EO. Economic benefits accrue to society if the spatial data are more precise to help inform government operations to function efficiently (i.e., at less social cost).

The EO data are digital, which makes it possible to build a comprehensive archive of global land cover and land use. The data require translation to information for systematic use in decisions. The economic value is derived by delivering strategically relevant information to decision-makers. The case studies are focused on specific policy-relevant decisions that take advantage of the spatiotemporal attributes of EO.

Below are two retrospective analyses. In the first example, the Landsat* archive is used to evaluate the societal benefits to adapt agricultural land management to reduce nonpoint-source groundwater contamination. For the second example, the Gravity Recovery and Climate Experiment (GRACE) provide data to assess the economic loss due to the misspecification of eligibility for drought disaster assistance and insurance that is evaluated in a specific drought policy.

14.3 Measuring the Incremental Value of Information of Earth Observation

The microeconomics approach to estimating VOI (described in Chapter 10) depends on the mean and spread of uncertainty surrounding a decision (Macauley 2006). It is defined as the economic gain that results from making better decisions, with less uncertainty from additional information, and depends on (a) the reduction in uncertainty for the decision-maker that is provided by the additional information and (b) what is at stake as an outcome of the decision (Bernknopf et al. 2016, in press).

Studies about the valuation of Global Earth Observation System (GEOS) information have focused primarily on potential benefits of GEOS information (Williamson et al. 2002; Macauley 2006; Macauley and Diner 2007). Potential societal benefits from Moderate-Resolution Land Imagery (MRLI) include cost savings in natural resource allocation, environmental regulation, and reduced damage to public goods (Kalluri et al. 2003; Isik et al. 2005; Macauley and Diner 2007). A few examples have attempted to quantify the benefits of information from GEOS in monetary values (Bouma et al. 2009; Macauley et al. 2010; Macauley and Laxminarayan 2010). For example, Macauley et al. (2010) developed an expenditure-based VOI estimation model to derive a value for Landsat data from the economic value of accurately estimating forest carbon offsets. The case studies described in this chapter are focused on specific applications of the value in use for two types of EO—MRLI (Landsat) and gravity field measurements (GRACE). Analysis involves a comparison of the economic benefits that a decision-maker is

* The Landsat Program is a series of Earth-Observing satellite missions jointly managed by NASA and the U.S. Geological Survey (http://landsat.usgs.gov/what_is_landsat.php; accessed November 17, 2016).

able to obtain in a scenario with the EO data relative to a baseline without the EO data. The comparison has three parts:

1. Development of a quantitative representation of a decision without EO and a representation of how this information is improved when EO is available.
2. Application of a decision-making model to predict the choices that a decision-maker could make based on the baseline and the improved information.
3. Estimation of the VOI, as in any benefit–cost analysis (see Chapter 10), is the difference between the economic benefits that result from a decision made with EO and the ones that result from a decision made without it.

In the examples, it is assumed that the EO is available as open-access data from the public sector. Furthermore, it is assumed that the decision-maker usually has some information that provides support for subjective probabilities of the outcome of a decision. That is, the decision-maker or his support staff developing recommendations utilizes the expected value and standard deviation of a probability distribution as the only information required in the decision.

14.4 Value of Information of Moderate-Resolution Land Imagery or Agricultural Land Management to Reduce the Potential for Groundwater Contamination

14.4.1 Introduction

In this case study, the EO data are applied in a hypothetical land use adaptation policy to reduce the impact of agrochemical groundwater contamination in the Midwest United States. Recent U.S. Energy Policy has mandated increases in the use of biofuels for energy consumption. The U.S. Energy Policy Act of 2005 and the Energy Independence and the Energy Security Act of 2007 legislated biofuels supply requirement, including subsidies for farmers to increase the production of corn and other energy feedstocks, to reduce dependence on fossil fuels.

The case study is about how an increase in corn production (used as a feedstock in biofuel production) can change the quality of the groundwater where nitrogen is applied to crops nearby private and public drinking water wells. In certain soils and surficial geology, some of the nitrogen will leach into the soil and migrate into an aquifer. Once in the soil and depending on the surficial geology, the nitrogen may convert to nitrate compounds that can react with other chemicals to form carcinogenic compounds (Forney et al. 2012). The resulting nitrate accumulation in the groundwater has the potential to exceed the U.S. Environmental Protection Agency's (USEPA) health standard for drinking water, which cannot exceed 10.0 mg/L.

14.4.2 Landsat Imagery to Land Use Information

The Landsat archive was used to locate agricultural production from 2000 to 2010 for estimating the amount of nitrogen that could leach into the soil and to a subsurface aquifer. The EO was transformed from satellite imagery to geospatial information by classifying the data into crop type in a rectangular grid. The resulting classifications of land use were coupled with a statistical groundwater vulnerability model to determine the risk of future groundwater contamination. Landsat, the Moderate-Resolution Imaging Spectroradiometer (MODIS), and the Advanced Wide Field Sensor (AWiFS) archives were used in a spatiotemporal analysis of the impact of nitrates on groundwater resources (Forney et al. 2012).* The archive is critical because different crops leach more or less nitrogen and can be linked to groundwater pollution that accumulates from nonpoint sources over time. Both the parcel level and regional risks are related to the quality of information about crop production, variable production inputs, farm management practices, and parcel characteristics. Crop production is the amount of each crop produced on a parcel. EO provides excellent spatiotemporal information for environmental regulatory decisions, because the data for the study period provided the population of land uses. Forney et al. (2012) provided a summary of the accuracy of transformation from data to information for the study period.

The case study was an application of the Production Function Approach (see Chapter 5 for an explanation of the approach) that was described in Forney et al. (2012). The analytical challenge was to measure the incremental economic value of the EO to assess the impacts of nonpoint-source pollution from farm activities in northeastern Iowa (outlined in Figure 14.1). As background for the empirical analysis of the VOI, the economic model in Equation 14.1 was developed to solve the production and water quality interdependence problem for producers and regulators. In the model, economic agents used spatiotemporal information from markets and natural systems to aid in maximizing agricultural production and not decreasing groundwater quality. The State of Iowa was chosen because of the amount of corn produced for food and biofuel and the use of groundwater in private and municipal drinking water wells.

The study area outlined in red in Figure 14.1 includes the following:

- 5.4 million hectares in 35 counties in Northeast Iowa. A great majority of cropland in the region produces corn and soybeans.
- The region covers 603 watersheds (subbasins), with a median of 7910 hydrologic response units. Hydrologic response units are areas within a watershed that respond similarly to a given input, such as nitrogen.

* During the period 2006–2008, the Landsat sensor delivered MRLI that contained stripes that were not acceptable for use in the USDA Cropland Data Layer (CDL). The images that were used in the CDL were provided by AWiFS/MODIS. However, there was a reduction in the resolution and quality of the images for classification of land use.

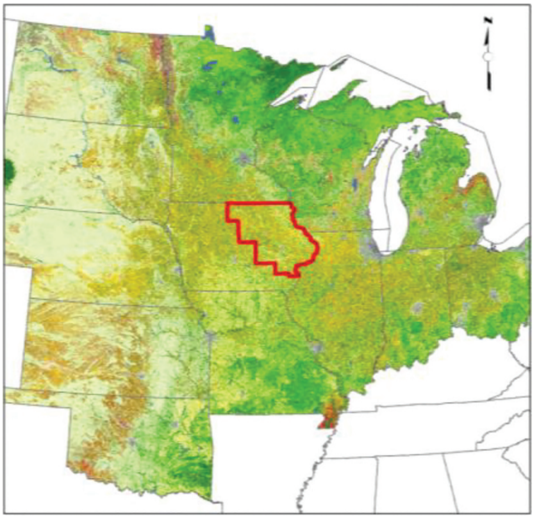

FIGURE 14.1
Iowa study area. (From Forney, W. et al., An economic value of remote-sensing information—Application to agricultural production and maintaining groundwater quality, Professional Paper 1796, Reston, VA, U.S. Geological Survey, 2012. With permission.)

- The USDA Cropland Data Layer that is based on the corn and soybean production estimates for 2001–2010 provided by the EO data.
- The environmental impact of the relative distribution of corn and soybeans is a result of the amount of nitrogen applied, which is typically 114 lb/acre for corn and is 3 lb/acre for soybeans.
- Water quality was sampled from 32,000 wells, ranging from just below the surface to 1220 meters.
- 80% of Iowa drinking water is from groundwater.

14.4.3 Integrated Assessment Model

Miller et al. (2011) identified agriculture and environmental science in the federal sector as a large application of MRLI and, in particular, Landsat. Biofuel production from corn ethanol and other sources was incentivized, but the increase in renewable fuel production could not occur independently of constraining public health policies such as the Federal Clean Water Act of 1972 and Safe Drinking Water Act of 1974, state water quality codes, and groundwater protection acts. The U.S. Environmental Protection Agency (EPA) established the threshold Maximum Contamination Level (MCL) at 10 milligrams per liter (mg/L) nitrate (measured as nitrogen) for safe drinking water. Drinking water exceeding the MCL of nitrate causes human health impacts such as methemoglobinemia, which is also known as *blue baby syndrome* in infants. Nitrate is not a carcinogenic compound; however, it reacts with other chemicals to form carcinogenic compounds, such as nitrosamines and nitrosamides, that are associated with multiple different types of cancers (Mirvish 1995; Weyer et al. 2001; Ward et al. 2005). Hence, there is a physical interdependence of agrochemical application to enhance production and the impact that the chemicals have on groundwater quality.

There are adaptation and mitigation approaches to reduce the amount of nitrate that accumulates in the groundwater that can be implemented. Mitigation approaches to the problem are to impose command and control regulations or to tax farmers to limit nitrogen application. Alternatively, an adaptation policy would be to reallocate regional land use to preserve the drinking water quality of groundwater resources. To address any of these approaches to this issue in a decision framework, an integrated natural–economics science model would be useful. Here, MRLI is used in a policy analysis to evaluate land use adaptation decisions by the individual farmer and regulators (Forney et al. 2012).

The MRLI data relate agricultural production, environmental pollution, and the joint production of agricultural products (corn and soybeans) and groundwater contaminants (nitrates) (Bernknopf et al. 2012). Analysis was possible by adapting an integrated assessment approach (IAA) from Antle and Just (1991). A production decision produces the joint output of a marketable agricultural commodity (Antle and McGuckin 1993) and a nonmarket service of groundwater quality. Decisions at regional scale involve land uses and their impact on ecosystem services.

Archival and current MRLI observations of regional crop production and rotation can be linked to the current level and future accumulation of nitrates in the groundwater. Farmers and regulators can adapt to the environmental risk by using MRLI to inform a potential reallocation of regional land use to preserve the groundwater resources. The economic value of the MRLI is derived using Equation 14.1, in which both the farmer and the regulator seek to maximize agricultural production for any given location within the region, while avoiding an increase in groundwater pollution from those agricultural nitrogen sources.

The regional model incorporates both the producers' (an individual's perspective) and the regulators' (a regional perspective) priorities in accommodating the overall decision-making process. The regional economic model is based on an individual producer's objective to maximize profit, while constraining risks of a marketable crop in Equation 14.1. Given the regulations R, producers seek to maximize profit on each plot of land. The IAA developed for the case study was used to determine an efficient allocation of resources from a regulator's perspective (Bernknopf et al. 2012). As part of this approach, agricultural producers are expected to behave as profit maximizers under given regulatory constraints. Depending on the regulator's objectives and risk preference, a decision to regulate is made. Thus, regulators seek to maximize the value of agricultural output, while limiting the risk of resource damage. Given prevailing crop prices **P**, they choose regulations **R**:

$$\begin{aligned} &\max_{R} PQ \\ &s.t. \quad \text{risks} \le \alpha \end{aligned} \tag{14.1}$$

where **P** represents prices of relevant crops, **Q** represents aggregate production of those crops, and **α** represents the probability of exceeding a regulatory standard that causes damage to a resource, namely groundwater. Based on the economic model in Equation 14.1, a probabilistic estimate of cumulative pollution was predicted for an agricultural production portfolio. A forecast of the time to exceed a regulatory standard for resource consumption is calculated in a statistical survival function after the risk of contamination is determined. A statistical survival function uses a cumulative nitrate estimate to provide a conditional probability of exceeding a concentration level that represents a threshold of nitrate contamination that adversely affects humans. Survival (1—failure) analysis (Kalbfleisch and Prentice 1980; Lancaster 1990; Kleinbaum 1996) is applied by the regulator for a probability of exceedance α of a given economic loss. It is assumed that good regulatory policy reduces or eliminates the adverse health effects of nitrates on humans.

The case for the use of EO is made by linking land use information from the satellite archive with agricultural, geospatial, and hydrogeologic models. The MRLI archive is used to classify agricultural land into corn, soybean, or other crops. This baseline land use is linked to Iowa nitrogen application rates for acreage of each crop in a county.* A cumulative nitrate index was developed to accumulate the amount of nitrate that was migrating toward a drinking water well in a statistical regression analysis. Figure 14.2 represents the spatiotemporal history over a 10-year period of the zone of capture for a particular well overlaid on a land use map for one of the years of the production period. Depending on the crop planted in a specific year, the model is applied to obtain groundwater vulnerability from nitrogen application in a 10-year encapsulation for a particular drinking water well of a capture zone (shown as black polygons emanating backward in time from the well). Drinking water quality survivability is estimated in subbasins of the region retrospectively for 10 years and then projected for the next 10 years, as shown in Figure 14.3. Based on this risk map, the regulator can make decisions to avoid exceeding the USEPA drinking water quality standard for the period ending in 2020. Since this study was undertaken, the Hruby et al (2015) conducted a survey of Iowa groundwater and an evaluation of public wells' vulnerability to contaminants. The analysis

* Iowa State University 2007; http://www.ipm.iastate.edu/ipm/icm/2007/2-12/nitrogen.html; accessed November 17, 2016).

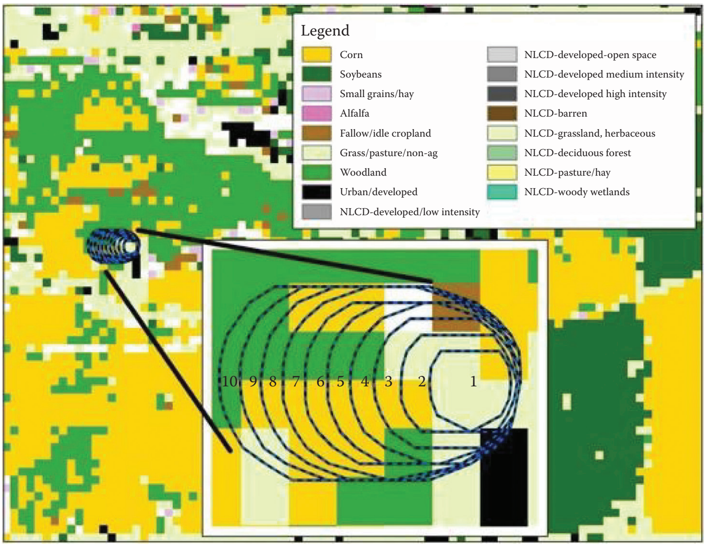

FIGURE 14.2
Well capture zone results on USDA Cropland data layer. Source: (From Forney, W. et al., An economic value of remote-sensing information—Application to agricultural production and maintaining groundwater quality, Professional Paper 1796, Reston, VA, U.S. Geological Survey, 2012.)

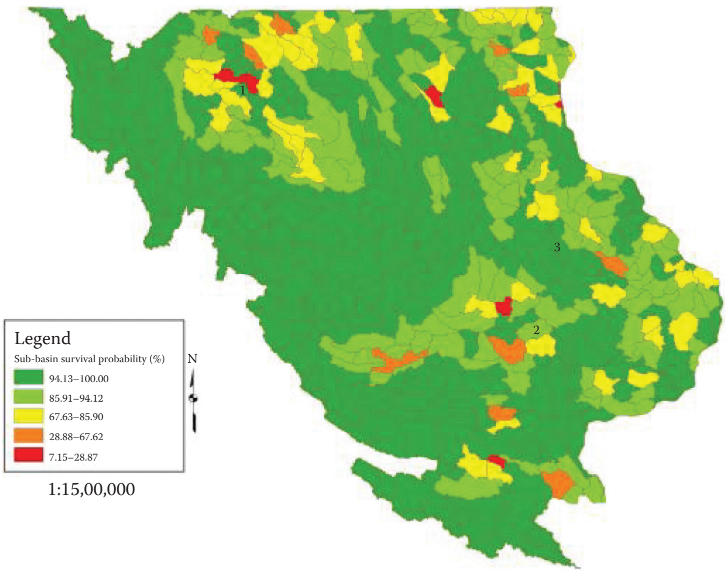

FIGURE 14.3
Groundwater failure and sub-basin probability of survival. Source: (From Forney, W. et al., An economic value of remote-sensing information—Application to agricultural production and maintaining groundwater quality, Professional Paper 1796, Reston, VA, U.S. Geological Survey, 2012.)

for nitrate + nitrite was detected in 26% of the wells sampled in the state, and 3% of these samples exceeded the MCL of 10 mg/L (Hruby et al. 2015).

Currently, the Iowa Department of Natural Resources maintains a statewide source-water protection areas map of susceptible community water supplies. The determination of susceptibility identifies certain aquifers that are better protected than others, based on the cumulative confining layer thickness above the aquifer (http://www.iowadnr.gov/Environmental-Protection/Water-Quality/Source-Water-Protection). Although the State of Iowa has concerns about the groundwater, the issue of nitrate contamination has not been eliminated.

14.4.4 Results

The EO data provides an input to the decision to adapt agricultural land use to maximize the value of agricultural production and preserve potable groundwater resources. The VOI is calculated as the net present value of the benefits of the MRLI. The net present value of the information is the discounted monetized difference of the benefits of land use reallocation and water quality that can be attributed to the MRLI. Maximum estimated VOI for EO is an annualized \$858 million ± \$197 million per year (in 2010) and has a net present value of \$38.1 billion ± \$8.8 billion for northeastern Iowa (the equations for these monetary values are contained in the appendix to this part of Chapter 14). The VOI is a hypothetical estimate and most likely unattainable. More realistically, if it were possible to identify a 1% improvement by reallocating land use with EO, the VOI would be an annualized \$43.0 million per year (in 2010) and has a net present value of \$1.91 billion for northeastern Iowa.

14.4.5 Summary

The policy assessment was about an adaptation of land use to consider the economic impact of reallocating land for agricultural production, based on the future availability of potable groundwater in northeastern Iowa. Estimation of a dynamic nitrogen loading and transport model allowed the determination of the cumulative impact of nitrates in groundwater at specified distances from specific sites (wells) for 35 Iowa counties and two aquifers. Over a 10-year period, groundwater wells' probability of survival is so low that these wells could be threatened by nitrate contamination. These wells should be monitored, and exceedance of the nitrate standard should be avoided. Based on this statistical prediction, a statistical survivor function was specified and estimated to forecast the probability of preserving drinking water quality in a private or municipal well. The probability is used by a regulatory agency for further evaluation of the water quality status relative to the chemical standard. The impact of incorporating EO was to demonstrate that it could be used to provide a stewardship type of land management by reallocating production of corn and soybeans to avoid the negative effects of nitrate on groundwater quality.

14.5 Estimate the Value of Information of the NASA Gravity Recovery and Climate Experiment (GRACE) Satellite Mission

14.5.1 Introduction

In this case study, a retrospective analysis* of USDA drought mitigation decision-making provides the context for evaluating the VOI of GRACE (Bernknopf et al. 2016). Drought-related decisions arise because the Secretary of Agriculture has the responsibility to declare a natural disaster that is due to severe and prolonged drought and to mitigate the financial impact of lost agricultural production. Specifically, the U.S. Agricultural Act of 2014 legislated payments to eligible livestock producers due to drought through the Livestock Forage Disaster Program. The USDA also promulgated regulations that assigned the Secretarial Disaster Designation Process (7 CFR Part 759) to the USDA Farm Service Agency. The process provides for emergency loans to eligible producers suffering losses due to drought. These USDA responsibilities necessitate the use of the U.S. Drought Monitor (USDM) to determine farmer eligibility for financial assistance. In addition, the USDM is used to inform several major drought management decisions, including eligibility for federal drought assistance programs and drought emergency declarations by state agencies.

Many government programs that allocate resources for drought assistance employ the USDM. The USDM utilizes a classification scheme that identifies general drought areas, labeling droughts by intensity, with Category D1 being the least intense and Category D4 being the most intense. Category D0 is used to indicate drought watch areas. The categorizations in any given USDM map are the result of a well-documented process (Svoboda et al. 2002) conducted by climatologists from the National Oceanic and Atmospheric Administration (NOAA), the USDA, and the National Drought Mitigation Center (NDMC).

The USDM is an ensemble of drought indicators and is a simplified version of the actual state of the environment (Bernknopf et al. 2015). Primary inputs for the USDM include the Palmer Drought Severity Index, NOAA Climate Prediction Center Soil Moisture Model percentiles, the U.S. Geological Survey (USGS) daily streamflow percentiles, precipitation data, NOAA National Climate Center Standardized Precipitation Index percentage of normal precipitation, and remotely sensed satellite vegetation health indices. Supplemental information includes evaporation-related indicators, reservoir, lake, and groundwater levels; field observations of soil moisture; Western Regional Climate Center Western Drought; Snow Telemetry; and GRACE products. The expert-based map weekly communicates the severity of droughts by county

* A retrospective study relates the outcome to risk and preventive factors present before start of the study (https://www.reference.com/world-view/difference-between-prospective-retrospective-studies-91a9e31f66eb4a55).

in the United States. A given USDM categorization can be estimated with an expected severity category and variance based on deliberations among the authors and variations in the physical indicators. The size of the variance can, in turn, affect the expected socioeconomic outcomes of management decisions that are made based on these categorizations. For example, high variance in USDM categorizations can result in misclassifications of eligibility for drought assistance. A modification to the USDM that can reduce the variance associated with a drought category can lead to reduced social losses.

Once the weekly USDM map is posted on the Internet by the USDA, it is applied as a screening instrument in agricultural regions to determine eligibility for financial assistance to farmers. Because, in some cases, the USDM is the sole criterion for disaster assistance eligibility, it is imperative that the USDM be accurate for cost-effective risk communication. The objective of the USDA is to identify counties that are classified as being in severe and exceptional drought to reduce agricultural losses. A drought severity misclassification is defined as an incorrect determination that the USDM selected a county to be in an exceptional or severe drought when it is not actually in either of those drought severity categories or a county that is actually in an exceptional or severe drought, which is not identified as being in those categories (Bernknopf et al. 2015).

14.5.2 GRACE Products for USDM Drought Severity Classification

The GRACE satellites measure variations in water stored at and below the land surface. The spatial (>150,000 km^2) and temporal (monthly) resolutions of GRACE limit its direct applicability for drought monitoring. The GRACE Data Assimilation (GRACE-DA) ensemble model was developed, which integrates GRACE data with other ground- and space-based meteorological observations (precipitation, solar radiation, and so on) (Zaitchik et al. 2008; Houborg et al. 2012). The GRACE-DA model provides soil moisture and groundwater storage variations that are used to generate drought indicators, based on the cumulative distribution function of wetness conditions during 1948–2009. The three indicators are information produced as a surface soil moisture percentile, based on soil moisture anomalies in the top two centimeters of the column; a root zone soil moisture percentile, based on the top 100 centimeters; and a groundwater percentile, based on storage below the root zone. The surface soil moisture drought indicator is expected to vary rapidly in response to weather events, and the groundwater drought indicator is sensitive to meteorological conditions over longer time periods. The GRACE-DA drought indicators are provided as maps and raster datasets, with a resolution of approximately 25 km^2. The products are provided weekly to support production of the official USDM drought maps. In the case study, the GRACE-DA drought indicators are incorporated into the USDM as a core dataset rather than as supplementary data to demonstrate that they can provide improved inputs to determine the eligibility for drought disaster financial assistance.

14.5.3 Application of the Bayesian Decision Method

The objective of the analysis was to demonstrate how GRACE drought indicators could add value to the USDM. The GRACE products have a complementary role to datasets included in the USDM for soil moisture and other point data. The GRACE drought indicators have been used as supplementary input in the process of making the weekly USDM. The case study was to evaluate whether GRACE information can improve the correlation between incomes of farmers and drought severity classifications from the USDM (Bernknopf et al. 2016).

The analysis is an application of the Bayesian decision theory* and principles to assess the value added of the three GRACE drought indicators. The Bayesian model is used to evaluate if the GRACE drought indicators enhance the risk communication capability of the USDM and assist in improving regional economic outcomes. Specifically, it was designed to assess whether the GRACE data would improve the USDM classification of U.S. counties for the presence and severity of drought conditions (Bernknopf et al. 2016). The model assumes that the decision-maker seeks the best information as input for allocating farm relief during a drought disaster. Consequently, if additional information were made available that provides an improvement in the relationship between the signal, the USDM drought severity category, and the outcome, eligibility for government assistance or insurance, the decision maker would incorporate the enhanced information into the decision.

The Bayesian decision model requires two steps (Bernknopf et al. 2016). The first step is the description of how the decision-maker's information changes with the acquisition of new information. That is, how the Decision-maker's probability density over an outcome of interest changes as a result of the new information. Before receiving new information, the decision-maker's belief regarding the probability of occurrence is referred to as the decision-maker's prior belief of probability density. On receipt of new information, the decision-maker observes a value for which the new observations provide an improvement in the prediction of the outcome. This expected outcome is referred to as the decision-maker's posterior belief regarding the probability of occurrence. The second step in the Bayesian decision model is to quantify the VOI by describing how the decision-maker's updated beliefs affect decisions and how these changes in the decisions affect the economic outcome relative to that which would have occurred had the decision-maker made the decisions based on prior beliefs.

* Bayesian decision theory refers to a decision theory, which is informed by Bayesian probability. It is a statistical system that tries to quantify the trade-off between various decisions, making use of probabilities and costs. An agent operating under such a decision theory uses the concepts of Bayesian statistics to estimate the expected value of its actions and update its expectations based on new information (https://wiki.lesswrong.com/wiki/Bayesian_decision_theory; accessed November 14, 2016).

14.5.4 Risk Assessment

In the Bayesian model, it is assumed that the decision-maker's decision is represented by the mean and standard deviation of a probability distribution (Sinn 1983). Further, in this example, it is assumed that two normal distributions are used in the eligibility decision (Bernknopf et al. 2016). The first normal distribution represents the intensity of drought in a county i during a particular week t, $S_{i,t}$. The decision-maker is uncertain about this value but has beliefs about it. The decision-maker believes that $S_{i,t}$ is a random variable that is normally distributed with mean $\mu_{S_{i,t}}$ and variance $\sigma^2_{S_{i,t}}$. The second distribution is the information from the USDM, which assigns a drought category to a county during a particular week. Based on USDM information from previous weeks, the decision-maker knows that the drought severity category is normally distributed. The decision-maker believes that $S_{i,t}$ and the drought severity category are correlated; that is, they have a statistical relationship that can be represented by a bivariate normal distribution. The bivariate normal distribution is the distribution for two jointly normal random variables* when their correlation coefficient is ρ.

In the model, the decision-maker observes that the USDM has assigned a drought category to county i for week t and updates the prior belief about the intensity of the drought (Bernknopf et al. 2016). The distribution of $S_{i,t}$ is conditional on observing the USDM severity category assignment to form the posterior distribution. If the correlation ρ, increases between a drought category assigned to a county by the USDM and the actual drought intensity in that county, there will be a reduction in the posterior distribution variance. It follows that the incorporation of GRACE products that provide a new set of drought indicators correlates better with drought intensity, and the decision-maker will face an uncertainty that is smaller than the current USDM drought categories without GRACE.

14.5.5 Risk Management and Value of Information

For VOI to be positive, the correlation must increase between the two distributions. The payoff of increased correlation to the decision-maker is represented by a change in the value of the losses to the agricultural sector that were avoided, given that a county experienced a drought of intensity $S_{i,t}$ and received drought assistance. Measurement of the relationship between the decision-maker's actions and the payoff to the decision-maker of undertaking those actions to assess the VOI is required. A decision-maker who makes an optimal decision based on the payoff function and believes that

* https://www.probabilitycourse.com/chapter5/5_3_2_bivariate_normal_dist.php, accessed November 15, 2016.

the distribution of $S_{i,t}$ and the drought severity category are bivariate normal will derive the following VOI:

$$\text{VOI} = \kappa_1 \left\{ \rho^2 \sigma^2_{S_{i,t}} \right\} \tag{14.2}$$

where κ_1 is a constant. Value of information is proportional to the variance of drought and the square of the correlation coefficient. Thus, VOI increases with ρ^2.

The USDM information structure is the combination of input data that supports drought assistance eligibility decisions. Each variation in the input information can contain a variety of different indicators, depending on the location of county *i* in week *t*. Using Equation 14.2, alternative versions of the USDM can be indexed according to their relative informativeness (Lawrence 1999). By being able to index the various combinations of indicators and other input data, it is possible to rank the alternative choices for application to the eligibility decision, according to their VOI.

14.5.6 Econometric Analysis

Ranking alternative USDM information structures is an empirical evaluation. An econometric analysis was conducted to estimate the value added by including GRACE drought indicators to the USDM. The econometric model was used to estimate the correlation between incomes of farmers and the USDM with and without the contribution of GRACE drought indicators (Bernknopf et al. 2016). The econometric model uses observed data to estimate the incremental economic effect of drought on agricultural incomes, while accounting for the fact that some of the determinants of the outcome (including some dimensions of drought) cannot be observed.

The econometric analysis in Equation 14.3 employs data for the lower 48 U.S. states from the USDM and GRACE drought indicators as key explanatory variables. County-year panel data[*] are based on USDM maps from the National Drought Mitigation Center's website and GRACE data provided by the University of Nebraska–Lincoln. To evaluate the relationships between these drought signals and realized economic agricultural outputs, farm income data of the U.S. Bureau of Economic Analysis were collected for each county and each year that is covered by the USDM and GRACE data (Bernknopf et al. 2016). The main agricultural economic indicator of interest is realized as net income plus the value of inventory

[*] Panel data is a dataset in which the behaviors of entities are observed across time (https://www.princeton.edu/~otorres/Panel101.pdf; accessed November 16, 2016).

change. The dataset covers the period from 2002 to 2013. The econometric model is as follows:

$$
\begin{aligned}
FarmY_{it} = {} & a + \beta_0 USDM\_D0wks_{it} + \cdots + \beta_4 USDM\_D4wks_{it} \\
& + \beta_5 GRACE\_sfsm\_D0wks_{it} \cdots \beta_9 GRACE\_sfsm\_D4wks_{it} \\
& + \beta_{10} GRACE\_rtzm\_D0wks_{it} \cdots \beta_{14} GRACE\_rtzm\_D4wks_{it} \\
& + \beta_{15} GRACE\_GW\_D0wks_{it} \cdots \beta_{19} GRACE\_GW\_D0wks_{it} + \lambda_t + \varphi_i + \varepsilon_{it}
\end{aligned}
\tag{14.3}
$$

where $FarmY_{it}$ represents realized net farm income in county i in year t, $USDM\_D0wks_{it}$ represents the number of weeks in year t that county i was designated as being in drought category $D0$, $USDM\_D4wks_{it}$ represents the number of weeks in year t that county i was designated as being in drought category $D4$, $GRACE\_sfsm\_D0wks_{it}$ represents the number of weeks in year t that county i was designated as being in drought category $D0$ by the GRACE surface soil moisture indicator, $GRACE\_sfsm\_D4wks_{it}$ represents the number of weeks in year t that county i was designated as being in drought category $D4$ by the GRACE surface soil moisture indicator, $GRACE\_rtzm\_D0wks_{it}$ represents the number of weeks in year t that county i was designated as being in drought category $D0$ by the GRACE root zone moisture indicator, $GRACE\_rtzm\_D4wks_{it}$ represents the number of weeks in year t that county i was designated as being in drought category $D4$ by the GRACE root zone moisture indicator, $GRACE\_GW\_D0wks_{it}$ represents the number of weeks in year t that county i was designated as being in drought category $D0$ by the GRACE groundwater indicator, and $GRACE\_GW\_D4wks_{it}$ represents the number of weeks in year t that county i was designated as being in drought category $D1$ by the GRACE groundwater indicator. The remaining variables are as follows: λ_t, which controls for unobserved, time-varying determinants of farm income that are equivalent for all counties; these effects can include changes in crop or livestock prices at the national level or changes in the availability of modern seed varieties and other improved agricultural production technologies; φ_I, which represents county fixed effects, for obtaining unbiased parameter estimates in the presence of unobserved, county-specific characteristics that do not vary over time; and ε_{it}, which is an error term. All categories of drought severity are present in each regression equation. The alternative combinations of the USDM and GRACE indicators, regressions, and statistical inferences can be found in Bernknopf et al. (2015).

The analysis results shown in Table 14.1 reveal that the USDM, with and without GRACE, exhibits a low correlation between realized net farm income and drought severity categories. However, standard measures of statistical inference with big datasets may not be useful, and other measures are necessary (Varian 2014). The econometric analysis in this example used statistical information criteria metrics to test whether adding GRACE drought indicators showed an improvement relative to the current USDM (Bernknopf et al. 2016).

TABLE 14.1

Statistics and F-Tests for Assessing the Goodness of Fit of Net Farm Income Models with and without GRACE-DA Indicators for the Lower 48 States (N = 36,624)

	No GRACE Indicators	Root Zone Soil Moisture Only	Surface Soil Moisture Only	Groundwater Only	Root Zone and Surface Soil Moisture	Root Zone Soil Moisture and Groundwater	Surface Soil Moisture and Groundwater	All GRACE Indicators
Adjusted R squared	0.0808	0.0817	0.0819	0.0838	0.0826	0.0845	0.0840	**0.0850**
Akaike information criterion	851,268	851,236	851,228	851,152	851,207	851,131	851,150	**851,117**
Bayesian information criterion	851,404	851,415	851,406	**851,331**	851,428	851,352	851,371	851,381
p-Values for F-test (all coefficients for GRACE variables = 0)	N/A	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Source: Bernknopf, R. et al., The value of remotely sensed information: The case of GRACE-enhanced drought severity index, Working Paper, Department of Economics, University of New Mexico, 2016.

Bold type represents the most preferred value for the goodness of fit statistic and information criterion.

Models are compared in Table 14.1 by calculating four statistics that are used to describe the goodness of fit: adjusted R-squared assumes that larger values are preferred, whereas the Akaike information criterion and the Bayesian information criterion assume that smaller values are preferred. Improvements in these statistics for models that include the GRACE drought indicators suggested that their inclusion in a model describing the relationship between drought and farm income improves the goodness of fit of the model. In addition, an F-test for the joint significance of the GRACE variables showed that their inclusion in models of drought and farm income is statistically warranted and that an improvement occurred in the prediction of the impact of drought on farm income. Adding GRACE-DA information to the USDM indicators in certain regions improved the prediction of losses in farm income in the presence of drought. The statistics and F-test generally show that the best goodness of fit is achieved in models in which all three GRACE drought indicators are present, in addition to the USDM indicators. This is true for all the lower 48 U.S. states as well as regionally for the Midwest and South. On the other hand, the cases in which the model is based on current USDM indicators in the Northeast, Southeast, and West regions have the best goodness of fit for the Bayesian information criterion, which heavily favors model simplicity.

Expressing improvements in goodness of fit in terms of statistics and information criteria can make it difficult to assess whether the improvements are economically significant. To compare the impact of the prediction of the error for models that included USDM drought indicators only and models that included both USDM and GRACE drought indicators, the economic value of misclassification for eligibility was estimated. The analysis demonstrated that the societal cost of misclassifying farmer eligibility for financial assistance is reduced by about \$13.3 billion for 2002–2013 or about \$1.1 billion per year with the addition of GRACE drought indicators to the USDM (Bernknopf et al. 2016).

14.5.7 A Policy Implication: Application to the Eligibility for the Livestock Assistance Grant Program

The USDA Livestock Assistance Grant Program is a state-by-state block fund for recovering forage production losses due to a 2006 summer drought. The U.S. Congress allocated \$50 million for eligible counties. A county is eligible if it has experienced exceptional drought or extreme drought in the period from March 7, 2006, to August 31, 2006. Eligible counties would have been affected if more GRACE product information were taken into account (Bernknopf et al. 2016). To evaluate and contrast how decision-making might be affected, GRACE-DA drought indicators were compared with the USDM to identify where eligibility decisions overlapped and those counties where the decisions were different.

About $16 million of the $50 million distributed would have been allocated to different states. Counties that had significant differences in drought status between the USDM and the GRACE drought indicators would have been the most likely to switch eligibility status, had the GRACE information influenced the production of the USDM in 2006. Counties that were deemed eligible for assistance under the USDM (severe and exceptional drought) but had no indications of drought according to the GRACE groundwater indicators were clustered near the Ogallala Aquifer in the Midwest United States. Counties that were not in drought according to the USDM but were with the three GRACE drought indicators were clustered in the Pacific Northwest, Nevada, Utah, Michigan, and New England. Understanding the location of these counties is important, because these are the counties that are most likely to have received aid when it was not necessary or not received aid when it was indeed very necessary.

14.5.8 Summary

Based on the Bayesian decision model and its application with econometric modeling techniques, GRACE-DA has the potential to lower the uncertainty associated with understanding drought severity and that this improved understanding has the potential to change policy decisions that lead to tangible societal benefits. Econometric modeling showed an improvement in the goodness of fit of statistical models that account for the impact of drought on farm income when GRACE drought indicators were added to the USDM drought severity categories to improve the prediction of losses in farm income. With the addition of the GRACE drought indicators, the number of county misclassifications decreased, thus reducing the uncertainty of the information delivered by the USDM. The outcome suggests that the improvement in classification would increase the efficiency of management decisions.

Suggestive evidence of the societal benefits to incorporate GRACE-DA into the USDM is shown in a hypothetical case study of the USDA Livestock Assistance Grant Program. The program criteria determine county eligibility for assistance, based on the USDM. Using 2006 data, counties that had significant differences in drought status between the USDM and GRACE-DA were identified. These counties would have been the most likely to switch eligibility status, had GRACE-DA information influenced the production of the USDM in 2006. One caveat regarding these hypothetical changes in eligibility is that they assume that the eligibility decisions would be made entirely based on a GRACE-DA indicator, which is unlikely to occur in practice. In reality, decision-makers will use GRACE-DA as one of the several information sources, so that not every eligibility change that was actually simulated would occur.

14.5.9 Conclusion

New EO technologies provide better information, for example, population statistics rather than sample statistics to reduce decision risk. The agricultural sector studies summarized above utilized quantitative models and analysis to value EO in specific decisions. The transformation of EO data into geospatial information in the two examples could lead to improvements in government and business operations.

The VOI case studies affirm the efficiency of the technology investment choices. The studies demonstrated that connecting the information products to operational applications provides an economic value to the EO. Results showed that (a) EO is likely to lower the uncertainty associated with the understanding of factors that affect a decision and (b) this improved understanding has the potential to change policy decisions that lead to tangible societal benefits.

The case study research included evidence, relied on multiple sources of quantitative evidence, and estimated benefits of the application. In both examples, a form of Bayesian model was used to evaluate whether the MRLI or the GRACE-DA enhances the reliability of the risk communication to the decision-maker. The economic analysis suggests that including the scientific data and subsequent geospatial information products can support decisions and programs that could have resulted in smaller economic loss. Each example case study was an evaluation of a decision within its real-life context, that is, a value in use. However, the simulations are only illustrative in that they show the possibility of positive return on investment and the potential for successful implementation of the technology.

What remains are the necessary trials for testing the geospatial information in use cases. A use case is the interaction of various stakeholders with a decision process. The objectives would be to design implementation experiments of a system from the user's and contributor's perspectives and to communicate system behavior in their terms. A use case requires communication of system requirements, how the system operates and may be used, the roles that all participants play, and the value that the customer or user will receive from the system.[*] For example, USDA decision-makers should evaluate the benefits of integrating GRACE-DA and other types of EO to improve the statistical robustness of the USDM.

[*] https://en.wikipedia.org/wiki/Use-case_analysis.

Appendix

This appendix is a brief summary of the calculations by Forney et al. (2012) for estimating the net present value for MRLI benefits.

The economic value $\mathbf{P\Delta Q}$ is the difference in the benefits, with and without MRLI, respectively, which is the *VOI*:

$$\mathrm{VOI}_{\omega(1)} = \mathrm{P}[\mathrm{Q}_{\mathrm{R}(\omega(1)\alpha)} - \mathrm{Q}_{\mathrm{R}(\omega(0)\alpha)}] \tag{14.A1}$$

where the regulations with the additional information from MRLI ($\omega(1)$) would be $\mathbf{R}(\omega(1),\boldsymbol{\alpha})$ and without additional information ($\omega(0)$) would be $\mathbf{R}(\omega(0),\boldsymbol{\alpha})$ for the probability of exceeding the regulatory standard for resource damage, $\boldsymbol{\alpha}$. The additional information may allow regulations to be better targeted, so that the crop production will be different $\mathbf{Q}_{\mathbf{R}(\omega(1),\boldsymbol{\alpha})}$ with the information than without information, $\mathbf{Q}_{\mathbf{R}(\omega(0),\boldsymbol{\alpha})}$.

The present discounted value of **PQ** is calculated by summing the quantities of corn and soybeans produced in each land unit for each year **Q**, that is multiplied by the present discounted vector of real prices **P**, that prevailed during the period of analysis. A possible combination of cropping choices across the study region is eliminated if the environmental constraint is exceeded, and among those choices not eliminated, the optimization algorithm steps through cropping choices until a maximum **PQ** is identified and annualized. The present discounted value of the difference between optimal (with MRLI and associated modeling data) and baseline (without MRLI data) is **PΔQ**. The VOI expressed as an equivalent annual income (EAI) is:

$$\mathrm{EAI} = \mathrm{P}\Delta\mathrm{Q}\frac{r(1+r)^t}{(1+r)^t - 1} \tag{14.A2}$$

where r is the discount rate. Assuming a similar flow of benefits into the indefinite future because of the continuation of the availability of MRLI, for this region, the net present value (NPV) is calculated as follows:

$$\mathrm{NPV} = \mathrm{EAI}\frac{(1+r)}{r} \tag{14.A3}$$

This net present value is an estimate of the value of using MRLI-based information for managing the corn/soybean crop patterns and groundwater resources in the study region into the indefinite future.

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