Published in final edited form as:
Weather Clim Soc. 2018 January ; 10(1): 187–203. doi:10.1175/WCAS-D-16-0044.1.

The Value of Remotely Sensed Information: The Case of GRACE-Enhanced Drought Severity Index

Richard Bernknopf[†,*], **David Brookshire**[†], **Yusuke Kuwayama**[††], **Molly Macauley**[††], **Matthew Rodell**[‡], **Alexandra Thompson**[††], **Peter Vail**[††], and **Benjamin Zaitchik**[‡‡]

[†]Department of Economics, University of New Mexico, Albuquerque, New Mexico 87131, United States

[††]Resources for the Future, Washington, District of Columbia 20036, United States

[‡]NASA Goddard Space Flight Center, Greenbelt, Maryland 20771, United States

[‡‡]Department of Earth and Planetary Sciences, Johns Hopkins University, Baltimore, Maryland 21218, United States

Abstract

A decision framework is developed for quantifying the economic value of information (VOI) from the Gravity Recovery and Climate Experiment (GRACE) satellite mission for drought monitoring, with a focus on the potential contributions of groundwater storage and soil moisture measurements from the GRACE Data Assimilation (GRACE-DA) System. The study consists of: (a) the development of a conceptual framework to evaluate the socioeconomic value of GRACE-DA as a contributing source of information to drought monitoring; (b) structured listening sessions to understand the needs of stakeholders who are affected by drought monitoring; (c) econometric analysis based on the conceptual framework that characterizes the contribution of GRACE-DA to the US Drought Monitor (USDM) in capturing the effects of drought on the agricultural sector; and (d) a demonstration of how the improved characterization of drought conditions may influence decisions made in a real-world drought disaster assistance program. Results show that GRACE-DA has the potential to lower the uncertainty associated with our understanding of drought, and that this improved understanding has the potential to change policy decisions that lead to tangible societal benefits.

Keywords

Drought; GRACE; Groundwater; Soil moisture; Value of information

1. Introduction

Droughts are some of the costliest natural disasters in the United States. Average annual losses that are attributable to drought nationwide are estimated to be in the range of $6 to $8 billion (FEMA 1995). The drought in California, which imposed a cost of US$ 2.7 billion on

[*]Corresponding author. Department of Economics, University of New Mexico, 1915 Roma Avenue NE, Albuquerque, NM 87131. Tel: (650) 935-2330. rbern@unm.edu.

the state in 2015 (Howitt et al. 2015), serves as a reminder of the losses that these disasters can impose on economic sectors. Current federal, state, and municipal policies seek to provide assistance to minimize the economic and environmental impacts of droughts. However, identifying the optimal allocation of these financial resources is complicated because droughts impose societal costs unevenly across the landscape and over time. For this reason, it is desirable for decision makers in drought management to have the best possible understanding of the location, timing, and severity of droughts.

Decision makers often rely on a template or model that monitors current drought conditions to inform management actions. In the United States, many government programs that allocate resources for drought assistance utilize the US Drought Monitor (USDM). The USDM is an expert-based risk map that provides information about the severity of droughts across the country on a weekly basis[1] and is used to inform major drought management decisions. These maps are used to determine farmer eligibility for federal drought assistance programs and issue drought emergency declarations. However, the USDM represents the actual state of the environment in a simplified manner. In other words, a USDM severity categorization for a given location in a given week is estimated with a mean and variance, and the size of the variance can affect the expected socioeconomic benefits of management decisions. For example, a large variance in USDM categorizations can result in potentially costly misclassifications to receive government program assistance. Modifications to the USDM that reduce the uncertainty associated with an estimate of current drought conditions can lead to improved societal outcomes in the form of reduced economic losses due to drought.

Studies have argued that the USDM could describe drought conditions more comprehensively and more objectively if additional soil moisture and groundwater information were incorporated into the map (Houborg et al. 2012). In this paper, a multi-method framework is developed for quantifying the economic value of information (VOI) derived from the National Aeronautics and Space Administration's (NASA) Gravity Recovery and Climate Experiment (GRACE) satellite mission for drought monitoring. We evaluate the potential contribution of groundwater storage and soil moisture measurements from the GRACE Data Assimilation (GRACE-DA) System to the USDM. The analysis consists of four main components. First, a statistical decision framework is presented that utilizes a Bayesian updating procedure to establish the informativeness of a particular combination of scientific data and indicators that are organized into an information structure for a specific decision (Lawrence 1999). This framework demonstrates analytically that the value of information from GRACE-DA increases if incorporation of this information into the USDM can increase the correlation between the USDM drought category assigned to a location and the actual drought intensity in that location. Second, we conducted structured listening sessions to understand the needs of stakeholders who are affected by drought monitoring. Third, an econometric analysis is performed to test whether there are significant statistical improvements in the prediction of county drought impacts if models include GRACE-DA explanatory variables. We use these models to predict the effect of drought on

[1]The USDM map for any given week can be accessed at http://droughtmonitor.unl.edu/.

the agricultural sector and test whether models that include GRACE-DA information exhibit better measures of goodness of fit compared to models that do not include GRACE-DA information. Fourth, we demonstrate how the improved characterization of drought effects afforded by GRACE-DA information may influence decisions made in a real-world drought disaster assistance program. Our example addresses the US Department of Agriculture's Livestock Assistance Grant Program (LAGP), a state block fund designed to recover forage production losses resulting from the 2006 summer drought.

2. Bayesian decision framework

The Bayesian decision framework described in this section formalizes how GRACE-DA drought indicators can be employed to analyze decisions in the agricultural sector. Bayesian models previously have been applied to decisions in the agricultural sector in a variety of ways. Examples include: Bradford and Kelejian (1977) employed a two-period Bayesian statistical model to evaluate the effect of the quality of information on decisions associated with weather forecasts for an agricultural harvest. Crean et al. (2014) applied state-contingent production theory in a Bayesian model to assess the value of seasonal climate forecasts for long-term farm planning. Bayesian models have also been employed in regulatory analyses. Bernknopf et al. (2001) demonstrate the VOI of applying regional scale nonpoint source groundwater vulnerability assessments for pesticide use, crop yield, and groundwater treatment regulations.

2.1. Decision model

The value of the GRACE-based information depends on (a) what is at stake as an outcome of the decision and (b) how uncertain is the decision maker's information. Estimation of the economic impact requires an explanation of how the decision maker's information changes as a result of the acquisition of new information and a way to quantify that value. Figure 1 illustrates how the Bayesian decision approach can be applied in the context of a drought disaster assistance program. The influence diagram includes: (1) a random variable of the possible states of the environment S, (2) a decision represented as a management action A, (3) an expected payoff associated with a specific combination of a state of the environment and an action $\pi(s, a)$, and (4) and a random variable of the state of the environment observations D.

Both S and D are uncertain quantities and are probability densities that are denoted by oval nodes in Figure 1. These probabilities are characterized in the next section. A management action shown as a rectangular node in Figure 1 is a decision and when combined with the conditional probability $p(S|D)$, yields a probabilistic payoff, which the decision maker maximizes at the expected value. The payoff shown as a hexagonal node in Figure 1 is an outcome of an action A that results from a decision and an information structure. For a given decision problem, information structures can provide different qualities of information that will lead to potentially different expected payoffs that can be ranked (Laffont 1989). A USDM information structure has greater informativeness if the correlation coefficient increases between S and D with the addition of GRACE-DA indicators (Lawrence 1999).

The comparison of the information structures provides an incremental economic value of the change in the quality of the input to a decision (Qian et al 2009, Gossner 2000).

The following two sections formally describe how incremental VOI can be generated by adding GRACE-DA indicators to the USDM.

2.2. Probabilities for the Bayesian approach

The Bayesian approach is a way to evaluate whether a decision maker's probability density over an outcome of interest will change as a result of new information (Lawrence 1999). Prior to receiving new information, the decision maker's belief regarding the probability of occurrence is referred to as the decision maker's *prior belief* regarding the probability density. Upon receipt of new information, the decision maker makes an observation that provides an improvement in the prediction of the outcome of interest. This expected outcome is referred to as the decision maker's *posterior belief* regarding the probability of occurrence.

Let the continuous random variable $S_{i,t}$ represent the intensity of drought in county i in week t. The decision maker is uncertain about the value of $S_{i,t}$, but has beliefs about this value. For simplicity, suppose the decision maker considers $S_{i,t}$ to be normally distributed with mean $\mu_{S_{i,t}}$ and variance $\sigma^2_{S_{i,t}}$. The decision maker also expects to obtain information from the USDM, which will assign a drought category $d_{i,t}$ to county i in week t. Based on the USDM information from previous weeks, $D_{i,t}$ is assumed to be continuous and normally distributed with mean $\mu_{D_{i,t}}$ and variance $\sigma^2_{D_{i,t}}$.

The decision maker believes that $S_{i,t}$ and $D_{i,t}$ are correlated. Following Lawrence (1999), the decision maker's beliefs are estimated as a bivariate normal distribution:

$$\left(S_{i,t}, D_{i,t}\right) \sim BN\left(\mu_{S_{i,t}}, \sigma^2_{S_{i,t}}; \mu_{D_{i,t}}, \sigma^2_{D_{i,t}}; \rho\right), \quad (1)$$

where ρ is the correlation coefficient between the two variables.

Now, suppose that the decision maker observes that the USDM has assigned drought category $d_{i,t}$ to county i in week t. The distribution of $S_{i,t}$, conditional on observing $D_{i,t} = d_{i,t}$, is given by:

$$\left(S_{i,t} \middle| D_{i,t} = d_{i,t}\right) \sim N\left(\mu_{S_{i,t}} + \rho\frac{\sigma^2_{S_{i,t}}}{\sigma^2_{D_{i,t}}}(d_{i,t} - \mu_{D_{i,t}}), (1-\rho^2)\sigma^2_{S_{i,t}}\right). \quad (2)$$

This is the decision maker's posterior probability distribution, where the conditional posterior mean is equal to:

$$\mathbb{E}\left[S_{i,t}\middle|D_{i,t}=d_{i,t}\right]=\mu_{S_{i,t}}+\rho\frac{\sigma^2_{S_{i,t}}}{\sigma^2_{D_{i,t}}}\left(d_{i,t}-\mu_{D_{i,t}}\right), \quad (3)$$

and the conditional posterior variance is equal to:

$$Var\left[S_{i,t}\middle|D_{i,t}=d_{i,t}\right]=(1-\rho^2)\sigma^2_{S_{i,t}}. \quad (4)$$

Equation 4 shows that the conditional posterior variance is decreasing in the correlation coefficient ρ. This relationship implies that any change in the USDM that increases ρ, i.e. the correlation between the USDM drought category assigned to a county and the actual drought intensity in that county, can reduce the variance that the decision maker faces. It follows that if we are able to show that the incorporation of GRACE-DA in a statistical model of drought is able to produce a new set of drought categories $D^G_{i,t}$ (GRACE-DA categorical variables) that correlate better with $S_{i,t}$, the posterior variance is smaller than the variance associated with current USDM drought categories $D_{i,t}$.

2.3. Payoff and VOI

The contributions of an increase in the correlation between USDM drought categorizations and actual drought intensity on value for the decision maker is characterized through a payoff function. The most effective decision is to use the expected value (first moment) of a probability distribution of payoffs (Berger 1985). Deviation away from the expected value in either direction is a loss that can be represented as the variance (second moment) of a probability distribution (Freixas and Kihlstrom 1984). The symmetric loss associated with an increase in the deviation from the expected value increases as the square of the error for USDM drought severity classification. There is a greater penalty or economic impact derived from the decision as the variance of the probability distribution becomes larger. To represent the impact of the misclassification, we apply a quadratic loss function in the eligibility selection decision. Suppose that the risk neutral decision maker's payoff associated with an action $A_{i,t}$ for county i in week t can be represented as being quadratic in the level of the action and the intensity of drought $S_{i,t}$:

$$\pi\left(S_{i,t}, A_{i,t}\right)=\omega_1+\omega_2 S_{i,t}+\omega_3 A_{i,t}+\omega_4 S_{i,t}A_{i,t}+\omega_5 S^2_{i,t}-\omega_6 A^2_{i,t}, \quad (5)$$

where ω_6 >0. In the context of using the USDM to make decisions about drought assistance, $A_{i,t}$ could signify the amount of drought assistance allocated to county i in week t, while the payoff $\pi(S_{i,t}, A_{i,t})$ could represent the value of losses in the agricultural sector that were avoided given that a county experienced a drought of intensity $S_{i,t}$ and received drought assistance in the amount of $A_{i,t}$.[2] Derivation of the first-order condition shows that the optimal prior choice is $A^*_{i,t} = \frac{\omega_3 + \omega_4 \mu_{S_{i,t}}}{2\omega_6}$, while the optimal conditional choice is $A^*_{i,t}\Big|D_{i,t} = d_{i,t} = \frac{\omega_3 + \omega_4 \mathbb{E}\left[S_{i,t}\middle|D_{i,t} = d_{i,t}\right]}{2\omega_6}$. Given the quadratic payoff function in Equation 5, the decision rule is linear in the expectation of $S_{i,t}$. Substituting the optimal decision rules into the payoff function yields the value of the prior and conditional decisions:

$$\max_{A_{i,t}} \mathbb{E}\left[\pi\left(S_{i,t}, A_{i,t}\right)\right] = \kappa_1 \left[\mathbb{E}\left[S_{i,t}\middle|D_{i,t} = d_{i,t}\right]\right]^2 + \kappa_2 \mathbb{E}\left[S^2_{i,t}\middle|D_{i,t} = d_{i,t}\right] + \kappa_3 \mathbb{E}\left[S_{i,t}\middle|D_{i,t} = d_{i,t}\right] + \kappa_4 \qquad (6)$$

where κ_1, κ_2, κ_3, and κ_4 are constants. It can be shown that the value of information is (Lawrence 1999):

$$VOI = \kappa_1 \left\{\left[\mathbb{E}\left[S_{i,t}\middle|D_{i,t} = d_{i,t}\right]\right]^2 - \mu^2_{S_{i,t}}\right\} = \kappa_1 \left\{\sigma^2_{S_{i,t}} - Var\left[S_{i,t}\middle|D_{i,t} = d_{i,t}\right]\right\}. \qquad (7)$$

Because $Var\left[S_{i,t}\middle|D_{i,t} = d_{i,t}\right] = (1 - \rho^2)\sigma^2_{S_{i,t}}\ if \left(S_{i,t}, D_{i,t}\right)$ has a bivariate normal distribution, it follows that:

$$VOI = \kappa_1 \left\{\rho^2 \sigma^2_{S_{i,t}}\right\}. \qquad (8)$$

As a result, the VOI is proportional to the variance of drought and the square of the correlation coefficient. Thus, the value of information increases with ρ^2.

3. Application background

3.1. The US Drought Monitor

The USDM classification scheme identifies general drought areas, labelling 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 for a USDM map are the result of a well-documented process (Svoboda et al. 2002) conducted by

[2]Payoffs (π) might be influenced by drought assistance allocations ($A_{i,t}$) in several ways. For example, drought assistance may allow agricultural producers to undertake mitigation actions that reduce the impact of drought on crop or livestock output. Drought assistance funds may also be used directly to enhance farm revenues, which in some cases may prevent higher debt or bankruptcy on the part of the producer.

climatologists from the National Oceanic and Atmospheric Administration (NOAA), the US Department of Agriculture (USDA), and the National Drought Mitigation Center (NDMC).

In addition to reviewing literature describing the USDM (Svoboda et al. 2002), a series of structured listening sessions were conducted with USDM authors to better understand how drought severity categorizations are assigned and to what extent GRACE-DA information influence these categorizations. The right portion of the information flow diagram in Figure 2 depicts the process by which USDM authors, who take turns serving as the lead author each week, evaluate a suite of objective inputs. One set of inputs is summarized in an explicitly weighted combination of inputs known as the Objective Blend of Drought Indicators. USDM authors also refer to higher-resolution information including field observations. In addition to these objective inputs, the authors deliberate with local experts to assess drought conditions. This regional and local expert input and dialogue allow for identification of localized and severe droughts experienced by communities. During the listening sessions, we found that most USDM authors are aware of GRACE-DA and some use it as a data source for verification purposes. The USDM relies on both conventional water supply metrics with long archives and remotely sensed data as inputs, which are transformed into categorizations or indicators that are simple enough for practical use.

The USDM is used as a screening instrument by various USDA programs to determine who is eligible for financial assistance during and after a drought disaster. An example of the application of the USDM for a specific drought decision is stated in the USDA Agricultural Act of 2014 for the LAGP. To be eligible, a county must have experienced exceptional (USDM category D4) or extreme (USDM category D3) drought during March 7, 2006 to August 31, 2006.

The USDM information structure that supports eligibility decisions can contain a variety of different indicators that vary over space and time. Using Equation 8, alternative versions of the inputs to the USDM can be indexed by their relative informativeness. By being able to index various combinations of indicators and other input data, it is possible to rank alternative information structures according to their VOI. A case can be made for a county level application of reducing the societal cost of drought severity misclassification by adding GRACE-DA variables to the USDM.

The VOI of GRACE observations consists of the gains that result from reducing the uncertainty in decisions that are based on incremental information. In this context, information from GRACE-DA could improve the correlation between the message (i.e., the USDM drought severity category) and the outcome (i.e., eligibility for government assistance or insurance), leading to a more cost-effective allocation of assistance funds.

3.2. The GRACE-DA System

The GRACE satellites are sensitive to variations in water stored at all levels above and within the land (Rodell and Famiglietti 2001). Through a series of processes that include removal of the atmospheric and oceanic influences and elimination of correlated errors, scientists are able to use GRACE’s precise observations of gravitational effects on the orbits of its two satellites to produce monthly maps of terrestrial water storage anomalies (deviations from the long term mean) (Swenson and Wahr 2006; Landerer and Swenson 2012). However, the coarse spatial (>150,000 km^2) and temporal (monthly) resolutions of the maps limit their direct applicability for drought monitoring, and the vertically integrated nature of the measurements does not allow for distinction between anomalies related to snow, surface water, soil moisture, or groundwater (Li et al. 2012; Houborg et al. 2012). The left portion of Figure 2 highlights relevant data sources and the steps required to turn low resolution GRACE terrestrial water storage anomaly data into useful drought indicators as an additional informational component of the USDM (Houborg et al. 2012). In order to increase resolution, disaggregate the measurement vertically, and eliminate the time lag associated with GRACE data releases, NASA scientists developed GRACE-DA (Zaitchik et al. 2008). GRACE-DA uses ensemble Kalman smoother type data assimilation to integrate GRACE data with ground- and space-based meteorological inputs (e.g., precipitation, solar radiation, etc.) within a Catchment Land Surface Model (Koster et al. 2000).

The GRACE-DA system produces estimates of soil moisture and groundwater storage variations that are used to generate probabilistic drought indicators. These indicators are defined relative to the baseline cumulative distribution function of wetness conditions during 1948–2009 as simulated by the Catchment model. Three indicators are produced: (1) a surface soil moisture percentile, based on soil moisture anomalies in the top two centimeters of the column, (2) a root zone soil moisture percentile, based on the top 100 centimeters, and (3) a groundwater percentile, based on storage below the root zone. GRACE-DA drought indicators are provided to the NDMC in the form of maps and datasets to be consistent with the USDM. The horizontal resolution of the GRACE-DA drought indicators was approximately 25 km at the time of this study, although it has recently been improved to 12 km. The products are produced and distributed in time to support production of the official, weekly USDM drought maps.

4. Econometric analysis

The Bayesian decision framework in Section 2 provides the foundation for empirical estimation of the correlation between the USDM drought severity categories and the true state of drought. However, identifying the size of this correlation is difficult because there is no objective source of information on the “true” state of drought that can be compared to USDM drought severity categorizations. One way to overcome this challenge is to examine the statistical relationship between the USDM drought categorizations and observed data in the agricultural sector that is likely to be affected. In the following econometric analysis, we use farm income and crop yield data as proxies for the “true” state of drought.

Drought can affect agricultural income in several ways. For example, drought can adversely affect crop conditions and yields, thereby reducing farm revenues. Drought also can increase on-farm production costs by increasing the amount of irrigation water that must be applied or increasing the use of inputs that can substitute for water, such as labor and fertilizer. On the other hand, drought may increase net farm income if agricultural markets respond to reduced supply with higher crop or livestock prices, or if the drought triggers additional government or crop insurance payments to farmers and ranchers. Because of these various impacts of drought on the agricultural sector, one would expect a statistical analysis to show that a drought indicator is correlated with farm income, even if the analysis is unable to identify the exact mechanism that generates the correlation.

The econometric models are specified to estimate the marginal effect of drought, while accounting for the fact that some of the determinants of the outcome (including some dimensions of drought) cannot be observed. The degree to which these unobserved determinants affect the ability of an individual or organization to use the observed data to predict the economic outcome is quantified by the standard errors associated with each of the models. As a result, the addition of GRACE-DA information to these models can reduce standard errors. This reduction in error can be interpreted as an improvement in our understanding of the impacts of drought.

4.1. Data

The econometric analysis employs data from the USDM and GRACE-DA as key explanatory variables. The NDMC maintains weekly USDM drought designation data, which is archived online back to the year 2000 in the form of county-level statistics.[3] The University of Nebraska-Lincoln maintains weekly GRACE-DA spatial data online; Tagged Image File Format (TIFF) images of these spatial data are available for every week between August 2002 and September 2014.[4]

The USDM and GRACE-DA county data were merged, resulting in a dataset with drought designations by the USDM and the three GRACE-DA indicators for every county in the continental United States, for every week between 2002 and 2014. We then assigned a single drought category to each county-week observation by taking the highest drought category. For example, if 10 percent of a county is classified as D4 and the remainder is classified in a lower category in a given week, category D4 is assigned to that county-week observation. Then, for each county, the total number of weeks in each year that the county was assigned to each drought category under the USDM and the three GRACE-DA indicators is calculated.

Farm income data were obtained from the Bureau of US Economic Analysis (BEA) for each county and year covered by the drought indicator data. The economic indicator of interest in the analysis is the sum of realized net income and the value of inventory change. Realized net income consists of total cash receipts and other income for farms, minus total production expenses. The value of inventory change is the value of the net change in farm inventories of livestock and crops that are held for sale during a calendar year. As a result, we obtain an estimate of farm proprietors' income for a given year that includes farm income from production during that year only, and not that of previous years. Inventories are an important factor to control for in an analysis of the impacts of drought on farm income since inventories contain value of production generated in previous years for which current drought status does not apply. BEA data on farm income are annual and were available until 2013; thus, the final panel data set covers the 2002 to 2013 period.

---

[3]This archive can be accessed at http://droughtmonitor.unl.edu/MapsAndData/GISData.aspx.

[4]The GRACE-DA drought indicator data are described in Section 2.2. The spatial data can be accessed at http://seca.unl.edu/web_archive/nasa/GRACE.

Corn yield data were obtained from the USDA's National Agricultural Statistics Service. While farm income data are available for every county in every year during the 2002 to 2013 period, yield data are not available for every county-year. Yield observations are missing when counties do not experience corn production, have a sufficiently small number of producers such that information is not disclosed for privacy reasons, or are simply not surveyed.

One important implication of the choice for an agricultural indicator is the relationship between a drought severity signal and agriculture production is subject to many biophysical and behavioral processes in addition to impacts on crop and livestock conditions. As a result, the correlations capture the potentially countervailing effects of on-farm drought management and adaptation, including changes in irrigation practices, crop choice, and seed type choice, as well as policy-driven effects on farm income such as payments from drought relief programs and crop insurance. Therefore, the correlations identified below should not be interpreted as only representing the direct impact of drought on crop and livestock conditions, rather it is the impact of drought on farm income given all the adjustments that are available to farmers and ranchers.

4.2. Model estimation

Our econometric approach enables the comparison of the degree of correlation between different sets of drought indicators and realized net farm income. Estimation of realized net farm income in a county in a specific year involves USDM indicators only as explanatory variables:

$$FarmY_{it} = \alpha + \beta_0 USDM_{D0wks_{it}} + \cdots + \beta_4 USDM_{D4wks_{it}} + \lambda_t + \varphi_i + \varepsilon_{it}. \quad (9)$$

In Equation 9, $FarmY_{it}$ represents realized net farm income plus the value of inventory change or corn yield in county i in year t, depending on the specification. $USDM\_D0wks_{it}$ represents the number of weeks in year t that county i was designated as being in drought category D0, $USDM\_D1wks_{it}$ represents the number of weeks in year t that county i was designated as being in drought category D1, etc. Equation 9 includes a set of year dummies, 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. Finally, county fixed effects are included, represented by φ_i, which allows us to obtain unbiased parameter estimates in the presence of unobserved, county-specific characteristics that do not vary over time.

In a similar equation, USDM and GRACE-DA indicators are combined to estimate the effect of additional parameters. First, groundwater storage indicators are added as explanatory variables:

$$FarmY_{it} = \alpha + \beta_0 USDM_{D0wks_{it}} + \cdots + \beta_4 USDM_{D4wks_{it}} + \beta_5 GRACE_{GW_{D0wks_{it}}} + \cdots + \beta_9 GRACE_{GW_{D4wks_{it}}} + \lambda_t + \varphi_i + \varepsilon_{it}, \quad (10)$$

where $GRACE\_GW\_D0wks_{it}$ represents the number of weeks in year t that county i was designated as being in drought category D0 by the GRACE groundwater indicator, $GRACE\_GW\_D1wks_{it}$ represents the number of weeks in year t that county i was designated as being in drought category D1 by the GRACE groundwater indicator, etc. We then repeat the estimation of Equation 10 by replacing the GRACE-DA groundwater storage indicators with the GRACE-DA surface and root zone soil moisture indicators to quantify the correlation of these indicators with net farm income independently. Next, versions of Equation 10 were estimated with two of the three GRACE-DA indicators as explanatory variables. This involves three additional regressions (i.e. one including GRACE-DA groundwater storage and surface soil moisture, one including GRACE-DA groundwater storage and root zone soil moisture, and one including GRACE-DA surface soil moisture and root zone soil moisture). Finally, a version of Equation 10 includes all three GRACE-DA indicators. In total, this procedure involves seven regressions. Use of linear specifications for statistical analysis of panel data is standard practice in the economics literature (Greene 2011).

Equation 9 and all versions of Equation 10 are estimated using robust standard errors clustered at the county level to account for any heteroskedasticity in the data. When farm income is the dependent variable, each model is estimated for all counties in the lower 48 states to obtain goodness-of-fit measures that apply to the nation as a whole. For corn yield, each model is estimated for the subset of counties for which yield data are available. In addition, we explore whether GRACE-DA affects the goodness of fit differentially across six regions, the Northeast, Southeast, Midwest, South, High Plains, and West.[5]

4.3. Goodness-of-fit for comparing information structures

Table 1 presents results from estimation of Equations 9 and 10, where we only present coefficient estimates for a specification of Equation 10 that includes all three GRACE indicators. The results illustrate how the magnitude of the coefficient estimates associated with the USDM variables change substantially when GRACE indicators are also included as variables in the regression. In addition to identifying differences in the coefficient estimates arising from estimation of Equations 9 and 10, we compare the goodness of fit of the two models by calculating three statistics and performing one statistical test. The three statistics are:

1. Adjusted R-squared;
2. Akaike Information Criterion (AIC); and

[5]States were aggregated into these regions based on the convention used by the USDM. Colorado and Wyoming, which are double-counted in USDM maps as being in both the West and High Plains regions, were both placed in the High Plains region for this study.

NASA Author Manuscript

NASA Author Manuscript

3. Bayesian Information Criterion (BIC).

Adjusted R-squared is a variant of the commonly used R-squared statistic. For a particular regression, the adjusted R-squared is equal to the percentage of the variation in net farm income or corn yield explained by the drought indicators included as explanatory variables. The adjusted R-squared accounts for the fact that R-squared automatically increases when extra explanatory variables are added to a model, and is thus more suitable when comparing the explanatory power of regression models that contain different numbers of predictors. An adjusted R-squared is necessary since the regressions that include GRACE-DA indicators have a larger number of predictors than the one that only includes USDM indicators. The AIC and BIC are alternative measures to aid model selection, with the BIC imposing a heavier penalty on model complexity. Taken together, improvements in these three statistics for models that include GRACE-DA variables suggest that their inclusion in a model improves the goodness of fit between drought, net farm income, and crop yields. F tests were conducted to estimate the joint significance of the GRACE-DA variables in those regressions that included them as predictors. Joint significance of the GRACE-DA variables suggests that their inclusion in models of drought, farm income, and crop yields is statistically appropriate.

Tables 2 and 3 list the outcomes for the three goodness-of-fit tests and the p-values associated with the F test for joint significance of the GRACE-DA indicators. The statistic is highlighted in bold font for the combination of UMDM and GRACE-DA variables that yields a better goodness of fit than all other combinations. With only a few exceptions, the econometric models indicate an improvement in the prediction of the impact of drought on farm income and corn yield by adding GRACE-DA drought indicators as supplemental information to the USDM drought severity categories. When considering all counties in the lower 48 states, the adjusted R-squared statistic improves by 13.1 percent for farm income and 2.5 percent for corn yield when going from a model with USDM indicators only to one in which all three GRACE-DA indicators are added. This improvement varies by region, from 3.3 percent in the Midwest to 38.9 percent in the South for farm income, and from 1.0 percent in the Northeast to 30.0 percent in the West for corn yield. Generally, the best goodness of fit is achieved in models in which one or more GRACE-DA indicators are present in addition to the USDM indicators. This is particularly true for the High Plains, Midwest, and South. Results for the Northeast, Southeast, and West are more mixed. The results of the F tests lead to a similar conclusion.

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. In order to address this issue, we calculated the prediction of the error component from the estimation of Equations 9 and 10. These prediction errors (residuals) represent the difference between the actual farm income and crop yield values that occurred during the sample period and the farm income and crop yield values that are predicted by the two models. For farm income, the prediction errors are already expressed in terms of dollars, so they provide a more intuitive sense of the difference in the accuracy of the models. For corn yields, we calculate a dollar representation of the residuals by multiplying predicted corn yields with observed corn acreage and prices, thus obtaining values for revenue from corn production.

Table 4 provides the number of county-year observations for all lower 48 states that are associated with different prediction error sizes for the model with USDM indicators only and the model with all three GRACE-DA indicators added. For farm income, there are 36,624 county observations during the period of the analysis with prediction errors that ranged from $4 to as much as $121M. For corn yields, there are 21,079 county observations with prediction errors that ranged from $0 to $133M. The counts comparison shows that adding GRACE-DA variables to the model alters the distribution of prediction errors. For both farm income and corn yields, the impact of this change in the distribution with GRACE-DA was to reduce the number of prediction errors in the larger ranges of, which are replaced by errors in the smaller ranges. The magnitude of the errors that are avoided by the addition of GRACE-DA indicators is economically significant given the fact that mean net farm income in our dataset is only $21.3M. Furthermore, reducing the frequency of large errors is important for decision makers because larger errors are likely to be associated with societal costs that are proportionately larger than those associated with small errors.

There is a social loss from wrongly categorizing county drought severity, which to the decision maker is measured as the uncertainty (variance) of the probability function and increases with the magnitude of the misclassification. The social loss is due to the limitation in accuracy of drought severity with the data inputs that make up the USDM. In the next section, we illustrate how this reduction in the magnitude of errors can translate to meaningful changes in a policymaking setting.

5. Policy implications and Discussion

Because many drought assistance programs seek to direct a finite amount of disaster funds to the regions that are most affected by drought during the most susceptible periods, having access to a drought indicator (or set of drought indicators) that correlates well with agricultural outcomes would generate significant societal value. The LAGP made $50 million available to states with eligible counties. To be eligible, a county must have experienced exceptional (USDM category D4) or extreme (USDM category D3) drought during March 7, 2006 to August 31, 2006. To evaluate how decision-making might be affected by incorporating GRACE-DA into the USDM, we developed county eligibility schedules under both datasets.

Results of this evaluation are presented in Figure 3. The three maps on the top row show counties that were deemed eligible for assistance based on USDM status but for which GRACE-DA indicators for groundwater storage, surface soil moisture, and root zone soil moisture (respectively) did not indicate any drought status. Maps in the lower row show counties that were deemed ineligible for assistance based on USDM status but for which GRACE-DA indicated either extreme drought (D3) or exceptional drought (D4). Counties that were deemed eligible for assistance under the USDM but had no indications of drought according to the GRACE-DA groundwater indicator were clustered near the Ogallala Aquifer. Counties that were not in drought according to the USDM but were in D3 or D4 status under the three GRACE-DA indicators were clustered in the Pacific Northwest, Nevada, Utah, Michigan, and New England. These counties would have been the most likely to switch eligibility status had GRACE-DA information influenced the production of the

NASA Author Manuscript

NASA Author Manuscript

USDM in 2006, highlighting the practical implications of harnessing the remotely sensed data.

In order to get a sense of the magnitude of the potential changes in assistance allocation, we replicated the allocation approach that USDA outlines in their LAGP program fact sheet,[6] using GRACE and USDM drought indicators to determine eligibility, using the same time period (7 March 2006 – 31 August 2006) and severity levels (D3 or D4). Once eligibility is determined using all relevant indicators, the funding allocation was estimated based on the number of adult beef cattle and sheep in eligible counties in each state, using USDA data. Keeping total funding constant at $50 million, the allocation that would have occurred had eligibility been determined using the GRACE-DA indicators is calculated.

Basing the allocation decision entirely on GRACE-DA indicators would have increased program allocation to a large number of states and reduced allocations to a small number of states, most notably Oklahoma, South Dakota, and Texas. If GRACE-DA had a greater influence on the program's eligibility decision, up to $16 million of the $50 million distributed by the LAGP would have been allocated to different states than what they actually were. One obvious 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. It is also possible that policymakers may wish to make allocations based on vulnerability considerations that the USDM is able to capture but that are not captured by GRACE-DA or by farm income or crop yield data. However, the simulations are illustrative in that they show the counties that would most likely have switched eligibility status had GRACE-DA been further incorporated into eligibility decisions, as well as provide an upper bound on the financial implications of alternative allocations under the LAGP.

The USDM is an important tool that is used by private and public sectors decision makers for drought management. Because, in some cases, it is the sole criterion for a community's eligibility for disaster assistance, it is imperative that the USDM be as accurate as possible for cost effective drought policy. In this paper, a Bayesian framework is developed for quantifying the VOI of GRACE-DA soil moisture and groundwater indicators for drought monitoring, including the development of a conceptual decision model, an econometric analysis to characterize the contribution of GRACE-DA to the USDM in capturing the effects of drought on the agricultural sector, and hypothetical simulations of a real-world drought assistance policy. GRACE-DA has the potential to lower the uncertainty associated with our understanding of drought, and that this improved understanding has the potential to change policy decisions that lead to tangible societal benefits.

Although we explored the policy relevance of our findings by examining how GRACE-DA data may have changed county eligibility for drought assistance under the LAGP program, we are unable to quantify the actual VOI in this application because we do not have access to data on county-level allocations of aid funds. Such data would have allowed the estimation of the effect of drought assistance on local agricultural outcomes. Future research

[6]The LAGP Fact Sheet is available at https://www.fsa.usda.gov/Internet/FSA_File/live_a_grant_prog06.pdf.

may be able to directly estimate the VOI of GRACE-DA for drought monitoring by explicitly modeling the socioeconomic outcomes associated with different drought management actions.

Acknowledgments

The authors wish to thank Sara Pesko for excellent research assistance, and Bradley Doorn and Mark Svoboda for valuable comments and suggestions. This project was completed with financial support from the National Aeronautics and Space Administration, NNX09A01G. We dedicate this paper to Dr. Molly Macauley for her leadership in space economics who died unexpectedly in 2016.

References

Berger, J. Statistical Decision Theory and Decision Analysis. 2. Springer-Verlag; 1985. p. 617

Bernknopf, R., Dinitz, L., Loague, K. An Interdisciplinary Assessment of Regional-Scale Nonpoint Source Groundwater Vulnerability: Theory and Application; USGS Professional Paper 1645. -2001.p. 27[Available online at http://pubs.usgs.gov/pp/pp1645/pp1645.pdf.]

Bradford DF, Kelejian HH. The value of information for crop forecasting in a market system: Some theoretical issues. Rev Econ Stud. 1977; 44(3):519–531.

Crean J, Parton K, Mullen J, Hayman P. Valuing seasonal climate forecasts in a state-contingent manner. Aust J AgrR Resour Ec. 2014; 59(1):61–77. DOI: 10.1111/1467-8489.12041

Economou T, Stephenson DB, Rougier JC, Neal RA, Mylne KR. On the use of Bayesian decision theory for issuing natural hazard warnings. Proc R Soc A. 2016; 472:20160295. http://dx.doi.org/10.1098/rspa.2016.0295. [PubMed: 27843399]

Freixas, X., Kihlstrom, R. Risk aversion and information demand, Chapter 5. In: Boyer, M., Kihlstrom, RE., editors. Bayesian Models in Economic Theory. North-Holland: 1984. p. 317p

FEMA (Federal Emergency Management Agency). National Mitigation Strategy: Partnerships for Building Safer Communities. -1995.p. 44[Available online at http://fas.org/irp/agency/dhs/fema/mitigation.pdf]

Gossner O. Comparison of Information Structures. Games and Economic Behavior. 2000; 30:44–63. DOI: 10.1006/game.1998.0706

Greene, W. Econometric Analysis. Pearson; 2011. p. 1232

Houborg R, Rodell M, Li B, Reichle R, Zaitchik B. Drought indicators based on model-assimilated Gravity Recovery and Climate Experiment (GRACE) terrestrial water storage observations. Water Resources Res. 2012; 48(7):1–17. DOI: 10.1029/2011WR011291

Howitt, R., MacEwan, D., Medellín-Azuara, J., Lund, J., Sumner, D. Economic Analysis of the 2015 Drought for California Agriculture. 2015. p. 16[Available online at https://watershed.ucdavis.edu/files/biblio/Final_Drought%20Report_08182015_Full_Report_WithAppendices.pdf]

Koster RD, Suarez MJ, Ducharne A, Stieglitz M, Kumar P. A catchment-based approach to modeling land surface processes in a general circulation model. 1. Model structure. J Geophys Res. 2000; 105(D20):24809–24822. doi:0.1029/2000JD900327.

Laffont, J-J. The Economics of Uncertainty and Information. MIT Press; 1989. p. 289

Landerer F, Swenson S. Accuracy of scaled GRACE terrestrial water storage estimates. Water Resour Res. 2012; 48:4.doi: 10.1029/2011WR011453

Lawrence, D. The Economic Value of Information. Springer-Verlag; 1999. p. 393

Lence SH, Hayes DJ. Parameter-based decision making under estimation risk: An application to futures trading. J Financ. 1994; 49(1):345–357. DOI: 10.2307/2329149

Li B, Rodell M, Zaitchik BF, Reichle RH, Koster RD, van Dam TM. Assimilation of GRACE terrestrial water storage into a land surface model: Evaluation and potential value for drought monitoring in western and central Europe. J Hydrol. 2012; 446:103–115. DOI: 10.1016/j.jhydrol.2012.04.035

Qian C, Chen J, Nakagawa T. Comparison of Two Information Structures with Noise and Its Application to Bayes Decision Analysis. Quality Technology &Quantitative Management. 2009; 6(1):1–10. http://dx.doi.org/10.1080/16843703.2009.11673180.

Rodell M, Famiglietti JS. An analysis of terrestrial water storage variations in Illinois with implications for the Gravity Recovery and Climate Experiment (GRACE). Wat Resour Res. 2001; 37:1327–1340. DOI: 10.1029/2000WR900306

Svoboda M, LeComte D, Hayes M, Heim R, Gleason K, Angel J, Rippey B, Tinker R, Palecki M, Stooksbury D, Miskus D, Stephens S. The Drought Monitor. B Amer Meteor Soc. 2002; 83(8): 1181–1190. DOI: 10.1175/1520-0477(2002)083<1181:TDM>2.3.CO;2

Swenson S, Wahr J. Post processing removal of correlated errors in GRACE data. Geophys Res Lett. 2006; 33:8.doi: 10.1029/2005GL025285

Zaitchik B, Rodell M, Reichle R. Assimilation of GRACE terrestrial water storage into a land surface model: Results for the Mississippi River Basin. J Hydrometeor. 2008; 9(3):535–548. DOI: 10.1175/2007JHM951.1

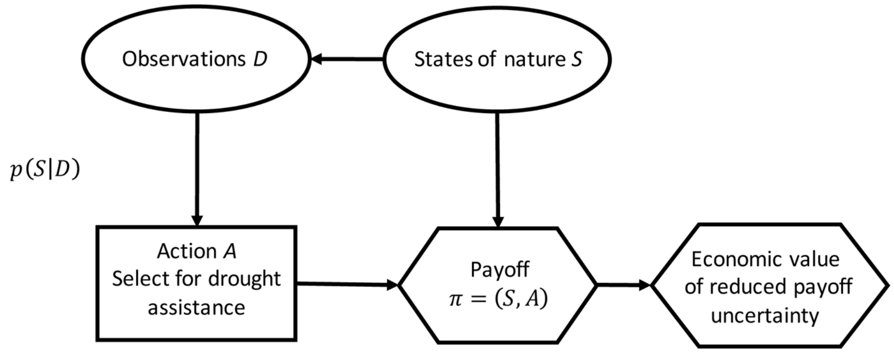

Figure 1.

Influence diagram describing the decision problem of issuing financial assistance. Oval nodes indicate uncertain quantities, rectangular node relates to decisions and hexagonal nodes relate to outcomes (adapted from Economou et al 2016).

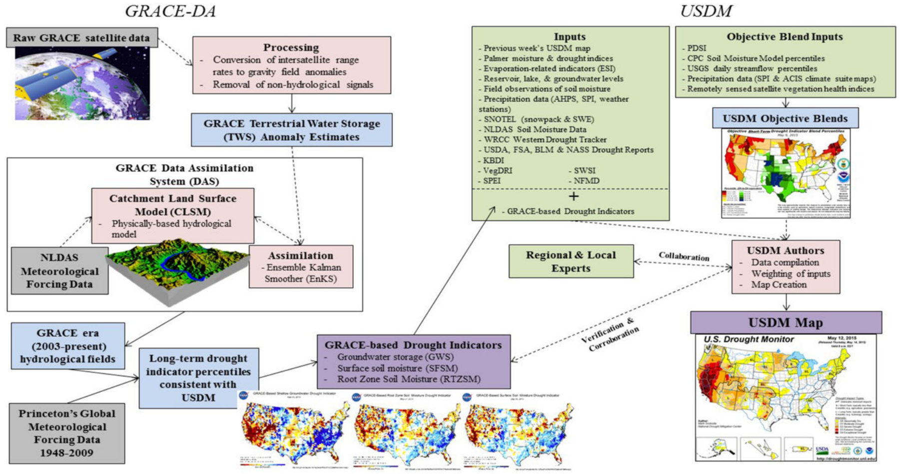

Figure 2.

Information flow diagram form GRACE-DA and the U.S. Drought Monitor weekly mapping process

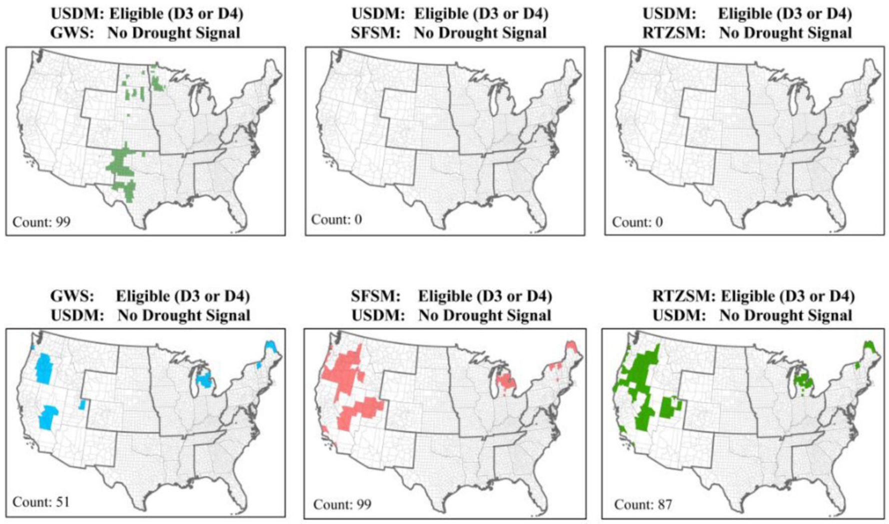

Figure 3.
Comparison of county eligibility for the Livestock Assistance Grant Program (2006) using USDM and GRACE DAS indicators. Maps in the top row show counties that were deemed eligible for assistance based on USDM status but GRACE DAS indicators for groundwater storage, surface soil moisture, and root zone soil moisture (respectively) did not indicate any drought status. Maps in the lower row show counties that were deemed ineligible for assistance based on USDM status but GRACE DAS indicators for groundwater storage, surface soil moisture, and root zone soil moisture (respectively) indicated either extreme drought (D3) or exceptional drought (D4).

Table 1

Effects of drought on net farm income and corn yield estimated using USDM and GRACE-DA indicators

	Realized Net Income + Value of Inventory Change		Corn Yield (bushels per acre)	
	No GRACE indicators (USDM only)	All GRACE indicators	No GRACE indicators (USDM only)	All GRACE indicators
Total weeks in D0 (USDM)	22.616***	21.921***	−0.316***	−0.304***
	(5.037)	(5.889)	(0.023)	(0.024)
Total weeks in D1 (USDM)	8.905	14.767**	−0.402***	−0.386***
	(6.772)	(7.333)	(0.024)	(0.025)
Total weeks in D2 (USDM)	−18.067**	−4.858	−0.636***	−0.615***
	(8.609)	(8.577)	(0.030)	(0.032)
Total weeks in D3 (USDM)	−46.115***	−39.366***	−0.556***	−0.544***
	(5.821)	(6.590)	(0.038)	(0.040)
Total weeks in D4 (USDM)	−96.279***	−50.429***	−0.735***	−0.634***
	(8.378)	(8.656)	(0.058)	(0.061)
Total weeks in D0 (RZSM)		25.583		0.096
		(22.600)		(0.089)
Total weeks in D1 (RZSM)		74.346***		0.175
		(28.775)		(0.106)
Total weeks in D2 (RZSM)		99.579***		−0.002
		(32.986)		(0.137)
Total weeks in D3 (RZSM)		192.634***		0.095
		(37.585)		(0.165)
Total weeks in D4 (RZSM)		377.925***		1.076***
		(36.112)		(0.187)
Total weeks in D0 (SFSM)		−40.530		−0.082
		(26.020)		(0.091)
Total weeks in D1 (SFSM)		−93.538***		−0.331***
		(29.912)		(0.108)
Total weeks in D2 (SFSM)		−166.727***		0.020
		(34.478)		(0.138)
Total weeks in D3 (SFSM)		−184.068***		−0.228
		(38.299)		(0.165)
Total weeks in D4 (SFSM)		−414.534***		−1.161***
		(36.779)		(0.185)
Total weeks in D0 (GWS)		28.165***		0.007
Total weeks in D1 (GWS)		28.751***		0.123***
		(8.571)		(0.029)
Total weeks in D2 (GWS)		18.354*		0.097**
		(10.139)		(0.042)
Total weeks in D3 (GWS)		53.009***		−0.057
		(11.762)		(0.056)

NASA Author Manuscript

NASA Author Manuscript

	Realized Net Income + Value of Inventory Change		Corn Yield (bushels per acre)	
	No GRACE indicators (USDM only)	**All GRACE indicators**	**No GRACE indicators (USDM only)**	**All GRACE indicators**
Total weeks in D4 (GWS)		2.401		0.180***
		(8.123)		(0.039)
Constant	−743.947***	−752.698***	111.459***	111.221***
	(89.329)	(93.035)	(0.457)	(0.465)
R2	0.075	0.085	0.290	0.298
Adjusted-R2	0.074	0.084	0.290	0.297
RMSE	6,620	6,585	20	19
Akaike Information Criterion	748,372	747,999	185,481	185,281
Bayesian Information Criterion	748,508	748,263	185,608	185,528
N	36,624	36,624	21,109	21,109

Table 2

Statistics and F tests for assessing the goodness of fit of net farm income models with and without GRACE-DA indicators

	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
All lower 48 states (N = 36,624) (Realized Net Income + Value of Inventory Change)								
Adjusted R squared	0.075	0.075	0.075	0.075	0.083	0.077	0.077	**0.084**
Akaike Information Criterion	748,372	748,366	748,349	748,344	748,046	748,286	748,294	**747,999**
Bayesian Information Criterion	748,508	748,545	748,528	748,523	748,267	748,508	748,516	**748,263**
p-values for F-test (all coefficients for GRACE variables = 0)	N/A	0.008	<0.001	<0.001	0.000	0.000	0.000	0.000
High Plains (N = 4,848)								
Adjusted R squared	0.180	0.183	0.184	0.188	0.186	0.191	0.190	**0.194**
Akaike Information Criterion	101,627	101,609	101,605	101,582	101,597	101,565	101,573	**101,555**
Bayesian Information Criterion	101,730	101,745	101,741	**101,719**	101,766	101,734	101,742	101,756
p-values for F-test (all coefficients for GRACE variables = 0)	N/A	0.004	<0.001	<0.001	<0.001	0.000	<0.001	<0.001
Midwest (N = 10,296)								
Adjusted R squared	0.284	0.286	0.289	0.286	0.292	0.288	0.292	**0.294**
Akaike Information Criterion	212,589	212,570	212,525	212,576	212,493	212,544	212,489	**212,467**
Bayesian Information Criterion	212,705	212,722	**212,677**	212,728	212,681	212,733	212,677	212,692
p-values for F-test (all coefficients for GRACE variables = 0)	N/A	<0.001	0.000	0.019	0.000	<0.001	0.000	0.000
Northeast (N = 3,564)								
Adjusted R squared	0.096	0.098	0.099	0.097	0.101	0.098	0.099	**0.101**
Akaike Information Criterion	63,369	63,367	63,361	63,372	**63,361**	63,372	63,366	63,364
Bayesian Information Criterion	**63,468**	63,497	63,491	63,502	63,521	63,532	63,527	63,555
p-values for F-test (all coefficients for GRACE variables = 0)	N/A	0.062	0.026	0.169	0.006	0.163	0.098	0.002
South (N = 7,764)								
Adjusted R squared	0.117	0.127	0.121	0.132	0.148	0.144	0.139	**0.162**
Akaike Information Criterion	155,364	155,273	155,329	155,233	155,097	155,128	155,178	**154,970**

All lower 48 states (N = 36,624) (Realized Net Income + Value of Inventory Change)								
	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
Bayesian Information Criterion	155,475	155,419	155,475	155,379	155,278	155,309	155,359	**155,185**
p-values for F-test (all coefficients for GRACE variables = 0)	N/A	0.000	<0.001	0.000	0.000	0.000	0.000	0.000
Southeast (N = 6,228)								
Adjusted R squared	0.210	0.212	0.212	0.211	0.217	0.213	0.213	**0.218**
Akaike Information Criterion	113,219	113,214	113,211	113,222	113,176	113,209	113,204	**113,172**
Bayesian Information Criterion	**113,326**	113,356	113,353	113,364	113,351	113,385	113,379	113,381
p-values for F-test (all coefficients for GRACE variables = 0)	N/A	0.013	0.001	0.293	<0.001	0.001	<0.001	0.000
West(N=3,924)								
Adjusted R squared	0.036	0.040	0.040	0.039	0.041	0.042	0.041	**0.042**
Akaike Information Criterion	80,949	80,938	80,938	80,942	80,939	**80,937**	80,938	80,939
Bayesian Information Criterion	**81,050**	81,070	81,070	81,074	81,102	81,100	81,101	81,133
p-values for F-test (all coefficients for GRACE variables = 0)	N/A	<0.001	0.001	0.036	0.000	0.001	0.002	<0.001

Table 3

Statistics and F tests for assessing the goodness of fit of corn yield models with and without GRACE-DA indicators

	No GRACE indicator	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
All lower 48 states (N = 21,109) (Corn Yield (bushels per acre)								
Adjusted R squared	0.290	0.291	0.290	0.292	0.296	0.293	0.293	**0.297**
Akaike Information Criterion	185,481	185,445	185,482	185,440	185,321	185,412	185,417	**185,281**
Bayesian Information Criterion	185,608	185,612	185,649	185,607	**185,528**	185,619	185,624	185,528
p-values for F-test (all coefficients for GRACE variables = 0)	N/A	0.005	0.173	<0.001	0.000	<0.001	<0.001	0.000
High Plains (N = 3,633)								
Adjusted R squared	0.341	0.350	0.352	0.343	**0.360**	0.350	0.352	0.359
Akaike Information Criterion	31,214	31,166	31,156	31,207	**31,119**	31,171	31,162	31,127
Bayesian Information Criterion	31,313	31,296	31,286	31,337	**31,280**	31,332	31,323	31,319
p-values for F-test (all coefficients for GRACE variables = 0)	N/A	<0.001	<0.001	0.023	0.000	<0.001	<0.001	<0.001
Midwest (N = 8,812)								
Adjusted R squared	0.437	0.441	0.442	0.445	0.442	0.447	**0.448**	0.448
Akaike Information Criterion	75,533	75,475	75,466	75,420	75,463	75,391	**75,380**	75,386
Bayesian Information Criterion	75,646	75,624	75,614	75,568	75,647	75,576	**75,564**	75,605
p-values for F-test (all coefficients for GRACE variables = 0)	N/A	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Northeast (N = 1,758)								
Adjusted R squared	0.498	0.502	0.502	0.501	0.502	0.502	0.502	**0.503**
Akaike Information Criterion	14,768	**14,759**	14,760	14,761	14,764	14,762	14,763	14,766
Bayesian Information Criterion	**14,856**	14,874	14,875	14,876	14,906	14,904	14,905	14,936
p-values for F-test (all coefficients for GRACE variables = 0)	N/A	0.007	0.016	0.013	0.016	0.007	0.024	0.020
South (N = 3,192)								
Adjusted R squared	0.287	0.292	0.288	0.292	0.292	0.300	0.298	**0.301**
Akaike Information Criterion	27,681	27,663	27,681	27,663	27,667	27,634	27,643	**27,634**

All lower 48 states (N = 21,109) (Corn Yield (bushels per acre)								
	No GRACE indicator	**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**
Bayesian Information Criterion	**27,778**	27,791	27,808	27,791	27,825	27,792	27,801	27,822
p-values for F-test (all coefficients for GRACE variables = 0)	N/A	0.001	0.144	<0.001	0.010	0.000	<0.001	<0.001
Southeast (N = 3,120)								
Adjusted R squared	0.356	0.360	0.359	0.360	0.376	0.362	0.365	**0.378**
Akaike Information Criterion	27,989	27,976	27,978	27,975	27,901	27,968	27,953	**27,897**
Bayesian Information Criterion	28,086	28,103	28,105	28,102	**28,059**	28,125	28,111	28,085
p-values for F-test (all coefficients for GRACE variables = 0)	N/A	0.012	0.011	0.009	0.000	0.001	<0.001	0.000
West (N = 594)								
Adjusted R squared	0.101	0.133	0.120	0.106	**0.135**	0.130	0.115	0.131
Akaike Information Criterion	5,028	**5,011**	5,020	5,030	5,014	5,018	5,028	5,022
Bayesian Information Criterion	**5,098**	5,103	5,112	5,122	5,129	5,132	5,142	5,158
p-values for F-test (all coefficients for GRACE variables = 0)	N/A	0.005	0.094	0.261	0.010	0.009	0.289	0.028

Table 4

Distribution of the magnitudes of prediction errors for farm income models with and without GRACE-DA indicators

Magnitude of error	Number of county-year observations			
	Net farm income		Corn yield	
	USDM only	With GRACE-DA	USDM only	With GRACE-DA
≥ $131,072,000 and < $262,144,000	0	0	1	1
≥ $65,536,000 and < $131,072,000	35	36	12	15
≥ $32,768,000 and < $65,536,000	187	183	91	88
≥ $16,384,000 and < $32,768,000	864	839	363	361
≥ $8,192,000 and < $16,384,000	2,199	2,177	971	958
≥ $4,096,000 and < $8,192,000	4,675	4,687	1,986	1,965
≥ $2,048,000 and < $4,096,000	9,070	9,217	2,697	2,688
≥ $1,024,000 and < $2,048,000	8,033	8,433	2,830	2,829
≥ $512,000 and < $1,024,000	5,379	5,057	2,655	2,683
≥ $256,000 and < $512,000	2,932	2,918	2,363	2,374
≥ $128,000 and < $256,000	1,600	1,473	2,093	2,107
≥ $64,000 and < $128,000	833	790	1,682	1,714
≥ $32,000 and < $64,000	401	455	1,342	1,294
≥ $16,000 and < $32,000	205	170	864	881
≥ $8,000 and < $16,000	114	103	495	454
≥ $4,000 and < $8,000	59	37	253	268
≥ $2,000 and < $4,000	13	26	115	131
≥ $1,000 and < $2,000	11	14	75	71
≥ $0 and < $1,000	14	9	161	167