Chapter 10
Estimating the Benefits of Land Imagery in Environmental Applications: A Case Study in Nonpoint Source Pollution of Groundwater

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Abstract Moderate-resolution land imagery (MRLI) is crucial to a more complete assessment of the cumulative, landscape-level effect of agricultural land use and land cover on environmental quality. If this improved assessment yields a net social benefit, then that benefit reflects the value of information (VOI) from MRLI. Environmental quality and the capacity to provide ecosystem services evolve because of human actions, changing natural conditions, and their interaction with natural physical processes. The human actions, in turn, are constrained and redirected by many institutions and regulations such as agricultural, energy, and environmental policies. We present a general framework for bringing together sociologic, biologic, physical, hydrologic, and geologic processes at meaningful scales to interpret environmental implications of MRLI applications. We set out a specific application using MRLI observations to identify crop planting patterns and thus estimate surface management activities that influence groundwater resources over a regional landscape. We tailor the application to the characteristics of nonpoint source groundwater pollution hazards in Iowa to illustrate a general framework in a land use-hydrologic-economic system. In the example, MRLI VOI derives from reducing the risk of both losses to agricultural production and damage to human health and other consequences of contaminated groundwater.

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R. Laxminarayan and M.K. Macauley (eds.), *The Value of Information: Methodological Frontiers and New Applications in Environment and Health*,
DOI 10.1007/978-94-007-4839-2_10,

Keywords Integrated assessment • Landsat • Moderate-resolution land imagery • Remote sensing • Nonpoint source pollution • Value of information • Agricultural production • Land use and land cover • Joint production • Nitrate • Groundwater contamination • Hydrogeology • Ecosystem service • Environmental regulation • Agricultural policy • Renewable fuel standard • Ethanol • Economic loss • Risk

10.1 Introduction

Moderate-resolution land imagery[1] (MRLI) accrues benefits to society at large by providing a spatiotemporal land use and land cover (LULC) signal that can be linked to ground-based, land management activities and their effects on human and natural ecosystems. In this chapter, we develop a general framework for estimating the value of MRLI in an application to public policy issues related to agricultural production and its effects on ecosystem services.[2] An interdisciplinary analytical framework for making decisions is developed using the intrinsic heterogeneity of regional land characteristics (e.g. land cover transitions, soil characteristics, geomorphology, temperature, geology, transport and biochemical processes, and climatic regime), and external inputs (e.g., irrigation, nutrient application, crop management) to land parcels to produce corn and soy crops.

The societal benefits from MRLI information–that is, the value of information (VOI)–is the incremental value (i.e. cost savings) to public sector decision making (i.e. government regulation). Cost savings arise from avoiding costly errors in administering regulations for sustaining ecosystem services (e.g. groundwater contamination and compliance with the Clean Water Act). MRLI sensors and their data archives provide LULC information at a derived error rate in detecting farm land use that can be used as inputs to a probabilistic estimate of adverse change to an ecosystem service. For example, MRLI can provide a cumulative, multi-temporal accounting of crops that have differential effects on groundwater quality, which can be used to forecast critical levels of nitrate (NO_3^-) concentration in an aquifer. The data can inform decisions to regulate land use for mitigating a potentially irreversible loss of groundwater resources.

User surveys suggest that MRLI is used for decision making in land-use planning and management, water resources management, ecological forecasting, emergency and disaster management, national and homeland security, coastal zone

[1] Moderate resolution land imagery is defined in the spatial domain as having a pixel resolution between 30 and 250 meters.

[2] Ecosystem services are defined as the production of goods (such as timber, seafood, and industrial raw materials), life support processes (such as pollination, water purification, and climate regulations), life fulfilling conditions (such as beauty, cultural inspiration, and serenity), and preservation of future options of resource (such as biodiversity and genetic conservation for future use) (Daily 1997). In this particular case study, only the good of groundwater quality is considered.

management, and transportation management and infrastructure planning (Miller et al. 2011). Nelson et al. (2007) reviewed applications of Landsat—an MRLI sensor—in the agriculture sector, broadly defined to include production agriculture, water resources management, rangeland management, forestry, and environmental management. Early studies by Earth Satellite Corporation (1974) and ECON Inc. (1974) identified potential operational benefits of Landsat, in which both studies contained projections anticipating that agricultural applications would provide a significant share of the total benefit of the imagery. Results reported by Earth Satellite Corporation were $158 million[3] to $414 million for agricultural applications and those reported by ECON, Inc. (1974) would be in the range of $3.8 billion to $25.8 billion for agricultural applications. In both studies, the benefits from remotely sensed data were estimated by assuming that it resulted in improvements in production forecasts.

Other studies about the valuation of Global Earth Observation System (GEOS) information focused primarily on potential benefits of GEOS information (Macauley 2006, 2007; Williamson et al. 2002; Kalluri et al. 2003; Isik et al. 2005). Potential societal benefits from MRLI include cost savings in natural resource allocation, environmental regulation and reduced damage to public goods (Macauley 2007). Only a few studies have attempted to quantify the benefits of information from GEOS in monetary values (Macauley 2010; Bouma et al. 2009). Macauley (2010) developed an expenditure-based VOI estimation model to derive a value for Landsat data from the economic value of accurate estimates for forest carbon offsets. The study considers the scenario where a new hyperspectral sensor added to the platform can change the derived value of Landsat data for the period 2022–2026. This information is combined with climate policy scenarios and related to economic data about forest sequestration projected for the same time period. Bouma et al. (2009) used the stated-preference method to estimate the economic benefits of satellite-based information to be $2.68 million annually for managing water quality in the North Sea. Nelson et al. (2007) also reviewed the use of Landsat by the Risk Management Agency (RMA). This agency, as part of the United States Department of Agriculture (USDA), is responsible for monitoring compliance with the terms of the federal crop insurance program and assessing whether fraud has been committed. In testimony before Congress in 2006, USDA estimated the agency's return-on-investment in 2005 alone was 458 times the cost, based on $34.4 million in restitution and forfeiture and a $75,000 USDA image archive subscription fee. The Farm Security and Rural Investment Act of 2002 authorizes the secretary of Agriculture to issue rules the secretary considers necessary to ensure producers' compliance with programs that help farmers manage market risk and safeguard environmentally sensitive land. Some other, non-monetized uses of Landsat imagery are to approximate the extent and temporal dynamics of natural disasters such as flooding, hail storms and forest fires. Evaluation of cost

[3] All dollar values in this chapter are deflated to the 2009 price level.

savings attributed to each of the MRLI applications described above provides a limited indication of the partial VOI of MRLI.

This chapter is part of a larger study being conducted by the U.S. Geological Survey (USGS) to identify operational applications of Landsat data that have a quantifiable economic value. This chapter describes the development of a conceptual economic model that links remote sensing to physical processes. In the first section, the components of an integrated assessment approach (IAA) (Antle and Just 1991) that support the general framework are described. These components include profit maximization by producers, revealed preference for social risk, and cost effectiveness of regulation. The general framework is applied to a regional environmental externality problem. The next section contains an application of the economic model for agricultural production, nutrient loading, and the effects to an ecosystem service. This type of application expresses benefits as value-in-use, bequest, option, and existence values that result from the integration of remotely sensed observations and natural science process models and data. MRLI information is used to observe and help document the effect of agricultural production on ecosystem services to avoid costly errors in administering regulations to sustain those services. Satellite imagery is especially useful at the regional scale because it captures the temporal change of the population of land activities better than conventional methods of spatial and temporal sampling of representative locations (Wilkie and Finn 1996). Furthermore, MRLI observation and long-term datasets (archives) provide increased accuracy and precision for modeling biophysical processes such as LULC change related to groundwater dynamics, thereby improving the targeted response of decision makers and regulators as they seek to manage and maintain ecosystem services of the resources (groundwater quality). The example highlights the intersection—and potential conflict—of policies that encourage biofuels from corn production and incentivize reduced agricultural production via USDA conservation programs, and provisions of the Safe Drinking Water Act of 1974 (P.L. 107–377, 2002, amended). Depending on the quality of information available to decision makers, these policy and management tools may be employed more or less effectively. In other words, the greater sources of nonpoint source pollution can be more specifically addressed while locations that do not contribute to the nitrate loading and pollution of a given well could be less strictly regulated.

The model estimates the joint output of agricultural production and groundwater pollution as an example. On one hand, the model is used to estimate the economic value of agricultural production while minimizing the risk of a loss in groundwater quality. On the other hand, the model estimates the increased cost to producers from either increased input costs or reduced fertilizer application. The joint output model is followed by a loss estimation procedure that is used as the basis for comparing the value of sensor data sets. The example assumes the regulator needs to be cautious (reduce or eliminate fertilizer application for corn production) to avoid the loss of groundwater resources due to nonpoint source contamination (Lichtenberg 1991). The regulator's decision involves the implementation of regulation(s) in anticipation of a natural resource failure to avoid more costly alternatives later. The cost effectiveness of the MRLI is demonstrated when decisions are made less costly to society with the imagery rather than without it. Although the example presented here is preliminary, it is representative of the types of applications that are possible with MRLI. Finally, we summarize the model and express the need for empirical testing of the framework. At the time of the writing of this chapter, a pilot analysis is underway to evaluate the framework in Iowa.

10.2 Conceptual Framework

The conceptual framework for valuing MRLI is developed in an IAA within the context of agricultural, energy, and environmental policies. In the IAA, we combine two levels of decision making in an adaptation of the Antle and Just (1991) integrated framework (Fig. 10.1). The first level is the farmer and the second is the regional decision maker or regulator. The economic model is based on a farmer's choice among competing land uses in a geographic region (Antle and Valdivia 2006; Antle and McGuckin 1993; Antle and Just 1991). The upper part of

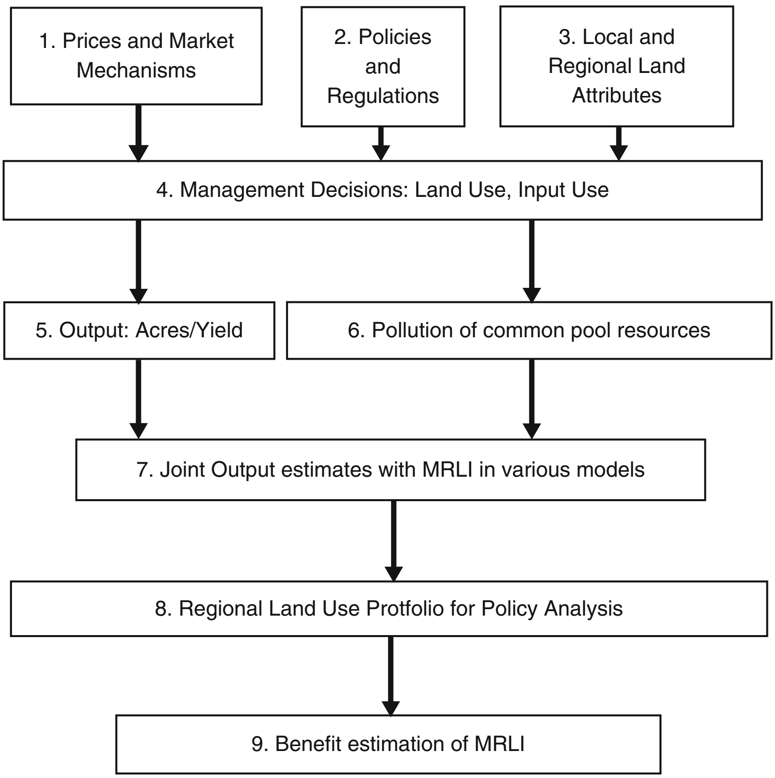

Fig. 10.1 Conceptual framework for integrated assessment approach (Adapted from Antle and Just 1991)

Fig. 10.1, boxes 1–6, relates to decisions by individual producers that result in a joint output of economic production and pollution. The lower part of figure, boxes 7 and 8, contains the observations of MRLI over multiple years and crop rotations to estimate temporal regional-scale production, the accumulation of agricultural inputs on the environment, and the risks to the decision maker. Box 9 of Fig. 10.1 integrates all previous boxes into a risk assessment associated with agricultural, energy, and environmental policies and the desirability of regulation.

The IAA incorporates two conceptual vectors, "Scale" and "Time," that are critical to consider for the analytical approach (Hong et al. 2007). Input variables are distributed spatially across the region and vary according to land characteristics and external factors that affect a given parcel. It is important to note that a parcel could include many fields, and farming operations could include multiple parcels.

Depending on the crop, its price elasticity, tendency for substitution, and the size and structure of the market, price data (Fig. 10.1, box 1) fluctuate from year to year and within a given year (*The Financials* 2010), whereas pollution (Fig. 10.1, box 6) potentially has a spatial and temporal cumulative effect on the resource over a number of years.

Environmental impacts of agricultural activities are controlled under several regulatory frameworks,[4] **R**, (Fig. 10.1, box 2). The degree to which these federal and state environmental and agricultural policies, regulations, and statutes apply depends on the particular farm and location of its fields (Fig. 10.1, box 3). Some locations, such as riparian corridors, will likely have more beneficial uses for a wider range of regulations (e.g. under the Clean Water Act, Endangered Species Act, and Safe Drinking Water Act). Others, such as highly permeable soils that allow surface water to infiltrate into the groundwater aquifer system, are likely to have fewer beneficial uses if the range of regulations is narrowed (e.g. under the Groundwater Protection Act, and total maximum daily loads, TMDLs). For those that do apply, the temporal interval that influences the decisions of an agricultural producer is assumed to be yearly, while the effect on natural resources is assumed to be monthly to seasonal. That said the creation, alteration, monitoring and enforcement of these regulations occur over longer time scales, which are assumed

[4] Regulatory frameworks include Farm Bill provisions, the USDA Conservation Programs, environmental policy, and energy policy. The Farm Bill legislation began in 1933. The Farm Bill is responsible for influencing many activities related to the decisions facing a farmer including crop insurance, credit programs and direct and counter-cyclical payment contracts. The Farm Bill also governs the USDA's Conservation Programs that provide voluntary, yet binding, cost-share programs. Depending on the contract and the program mechanism, the USDA's cost-sharing programs (Figure 10.1, box 2) have a duration of anywhere from three to thirty years. In addition to the agricultural programs, farmers in states such as Iowa face federal and state environmental policies and regulations such as the Federal Clean Water Act, Endangered Species Act, National Environmental Policy Act, Safe Drinking Water Act, 1990 Clean Air Act Amendments, Food Quality Protection Act of 1996; and the State Air Quality Code, Water Quality Codes, Groundwater Protection Act, Contaminated Sites (pesticides and fertilizers) Code, Pesticide Act of Iowa, Agrichemical Remediation Act, Agricultural Drainage Wells Code, Soil Conservation Districts Laws, Fishing and Game Hunting laws, Endangered Plants and Wildlife laws, Farmland Preservation Statutes, and Manure Management Plans and Tile Lines (Figure 10.1, box 2).

to be exogenous drivers of the producers behavioral changes and management decisions (Fig. 10.1, box 4).

As for energy policy, although the first energy policy that influenced ethanol production was the 1978 Federal Tax Credit, two more recent bills are of greater significance. The Energy Policy Act of 2005 set the renewable fuel standard (RFS) to increase ethanol levels from 4.0 billion to 7.5 billion gallons per year by 2012. In 2007, the Energy Independence and Security Act (P. L. 110–140) increased the RFS levels to require the use of at least 36 billion gallons of biofuel by 2022, 15 billion gallons being corn ethanol and the remainder being cellulosic ethanol (such as perennial grasses, biomass and municipal solid waste) and other advanced biofuels (Fig. 10.1, box 2). Spatially, their influence on the IAA is at the farm scale. As posited in this conceptual framework, the goals for ethanol production and the influence of the RFS on decision making of the producer will be across all their fields in response to expectations of higher corn prices.

Natural resource damage arises from agrichemical pollution and other effects of agricultural production, which range across many biogeochemical patterns and processes (Fig. 10.1, boxes 3 and 6). Some of the more salient ones are erosion and sedimentation, surface and groundwater nutrient loading and pesticide pollution, greenhouse gas fluxes, habitat and native vegetation loss, wetland dewatering and conversion, reductions in biodiversity, and take of at-risk or listed species (Fig. 10.1, box 6). For implementation of the IAA, essential considerations are: (1) the number of natural resource processes, pollutant loadings and their associated effects on ecosystem services (Fig. 10.1, box 6); (2) the degree of original modeling (or easily—adaptable existing models) to incorporate and adequately characterize the biophysical processes of the system related to the particular ecosystem services (Fig. 10.1, box 7); and (3) the temporal and spatial consistency of all the modeling components and their data availability. For our initial example in this study, we focus on groundwater pollution from agricultural nonpoint source pollution.

An economic model is developed for efficient allocation of resources from a regulator's perspective. Producers are expected to behave as profit maximizers under given regulatory constraints. A probabilistic estimate of pollution is based on a spatiotemporal agricultural production portfolio, which can be derived from a Cobb-Douglas production function. A forecast of the time to exceed a regulatory standard for resource consumption is made after the risk of contamination is determined. Whether and how much to regulate then depends on the regulator's risk preference.

10.2.1 Economic Model

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**:

$$\max_{\mathbf{R}} \mathbf{PQ}$$
$$s.t. \quad risks \leq \boldsymbol{\alpha}$$

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 (here groundwater). Both the plot level and regional risks are related to the quality of information about crop production (**q**), variable inputs (**v**), farm management practices (**z**) and plot characteristics (**e**). The crop production **q** is the amount of each crop produced on a plot. It is a function of **v, z** and **e**.

In terms of **v,** by making decisions to maximize the production from their fields (Fig. 10.1, box 5), producers apply fixed and variable inputs such as irrigation, fertilizer, soil amendment, and pesticides (North Dakota State University 1997). These decisions and the rates and durations of application are made at certain times of the year, generally assumed to be within a given growing season. For example, during certain periods of the crop's growth cycle, fertilizer is applied to facilitate plant growth or insecticides are applied to limit the invasion of parasitic insects. The application of these two products, however, may not occur at the same time. This can hold true for other **v** used in production.

In terms of **z**, the methods for production, farm management practices are tempered by the biophysical characteristics of a given location. The method options available to farmers include weed and insect management techniques such as integrated pest management, seed selection (genetically engineered products, seed collected from previous years, and hybrid seed), crop rotation, tillage and biomass practices, mechanized- or hand- labor efforts, and others (Fig. 10.1, box 4) (North Dakota State University 1997).

In terms of **e**, properties of the plot that play crucial roles in the production of corn and potential damage to ecosystem goods are soil characteristics and variation in precipitation and temperature (Fig. 10.1, box 3). Physical and chemical properties of soils govern the quantity of agricultural inputs available to production as well as their fate and transport into groundwater resources. Additionally, rainfall intensity and duration and the use of irrigation are important factors in the fate and transport of inputs. These factors help explain crop yield in addition to resource pollution dynamics.

Next we describe more extensively and formulate models for each of the components that constitute the inputs needed for the regulator's maximization problem in Eq. (10.1).

10.2.2 Producer Behavior

The objective function and constrained risk in Eq. (10.1) depend on the behavior of the producer. That producer's behavior is one of profit maximization. **Q** is the aggregation of producer outputs **q** at the plot level and risk is a function of plot conditions $\mathbf{e}$ accumulating because of the actions of the producer. Given $\mathbf{R}$ the producers seek to maximize profit on each plot:

$$\begin{aligned}
&\max_{\{\mathbf{q}_t,\mathbf{v}_t,\mathbf{z}_t\}} \sum_{t=t_0}^{\infty} d^t \pi\left(\mathbf{q}_t, \mathbf{v}_t, \mathbf{z}_t, \mathbf{P}(\mathbf{R})_t, \mathbf{W}(\mathbf{R})_t, \mathbf{e}_t\right) \\
&s.t. \quad \mathbf{e}_{t+1} = \mathbf{e}_t + \Delta\mathbf{e}(\mathbf{q}_t, \mathbf{v}_t, \mathbf{z}_t) \\
&\qquad \mathbf{R}_t^{q\min} \le \mathbf{q}_t \le \mathbf{R}_t^{q\max} \\
&\qquad \mathbf{R}_t^{v\min} \le \mathbf{v}_t \le \mathbf{R}_t^{v\max} \\
&\qquad \mathbf{R}_t^{z\min} \le \mathbf{z}_t \le \mathbf{R}_t^{z\max}
\end{aligned} \tag{10.2}$$

Discounting is by factor d, π is the annual profit function, $\mathbf{W}$ is input costs vector and $\mathbf{R}$ is explicitly shown as minimum and maximum regulatory constraints on the decision variables and subsidies applied to the prices and costs the producer faces. Current choice variables affect the future by changing the properties of the plot by the function $\Delta e(\cdot)$. Time, t, is discrete corresponding to planting decisions made each annual growing season. In terms of aggregating the estimation of joint output and conducting statistical analyses for regional policy analysis, we assume an annual basis is appropriate (Fig. 10.1, box 8). Although many of the financial outlays for corn production practices, their pollution consequences, related biophysical phenomena, and environmental science measurements occur at finer time periods, the bottom line for a farmer is the amount of money she ends up with at the end of the year from the choices she has made during the prior year and in years past (Lence and Hayes 1995).

10.2.3 Revealed Preference for Social Risk

The regulator solves Eq. (10.1) acting as if $\boldsymbol{\alpha}$ is given, but this acceptable risk is also the result of an optimization process at the higher level of authority of the policy maker. A probability of exceeding regulatory standard, $\boldsymbol{\alpha}(\mathbf{R})$, is associated with policies $\mathbf{R}$. The expected present discounted value of the policies to society, $\pi^s(\mathbf{R}, \boldsymbol{\alpha}(\mathbf{R}))$, can be optimized by choosing $\mathbf{R}^*$ from possible policies $\boldsymbol{\Gamma}$:

$$\max_{\mathbf{R}\in\Gamma} \pi^s(\mathbf{R}, \alpha(\mathbf{R})) \tag{10.3}$$

The choices of policy makers reveal social preferences.[5] To the extent that π^s and $\boldsymbol{\Gamma}$ are stable, $\boldsymbol{\alpha}^* = \boldsymbol{\alpha}(\mathbf{R}^*)$ is also stable. We can infer $\boldsymbol{\alpha}^*$ from observed

[5] Others have used observed government actions to reveal social preferences. McFadden (1975) inferred the revealed value of indirect costs and benefits to highway route selectors and Ross (1984) shows how revealed preference can be applied to infer the implied social weights of regulators. We aren't using reveled preference to infer values, but rather to infer the optimal constraints implied by those values.

regulatory outcomes. This inferred $\boldsymbol{\alpha}^*$ is the risk constraint to which regulators have conformed, and we assume it is a reasonable risk constraint for the future to apply to marginal alterations of policy or to the case of improved information structure.

The risk constraint matrix, $\boldsymbol{\alpha}$, consists of the acceptable risk level for multiple resources (designated by the subscript) at multiple thresholds of failure (designated by the superscript):

$$\alpha = \begin{bmatrix} \alpha_1^{T1} & \alpha_1^{T2} & \cdots \\ \alpha_2^{T1} & \alpha_2^{T2} & \cdots \\ \vdots & \vdots & \ddots \end{bmatrix} \tag{10.4}$$

For example, the subscript 1 in Eq. (10.4) could designate nitrate pollution in unconstrained deep aquifers and the superscript T1 could designate threshold 10 mg/l, such that $\alpha_1{}^{T1}$ is the probability that nitrate pollution in an unconstrained deep aquifer will exceed 10 mg/l.

The conditional probability of exceeding the natural resource quality standard $\boldsymbol{\alpha}$ is derived from a cumulative probability distribution, which is a function of properties of a land plot that affect the regional groundwater resources and hydrogeologic processes of the aquifer.

10.2.4 Cost Effective Regulation with MRLI

The regulations described above with the additional information from MRLI ($\boldsymbol{\omega}(1)$) would be $\mathbf{R}^*(\boldsymbol{\omega}(1), \boldsymbol{\alpha})$ and without additional information ($\boldsymbol{\omega}(0)$) would be $\mathbf{R}^*(\boldsymbol{\omega}(0), \boldsymbol{\alpha})$ 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 $\mathbf{Q}^*_{\mathbf{R}(\boldsymbol{\omega}(1),\, \boldsymbol{\alpha})}$ with the information than without $\mathbf{Q}^*_{\mathbf{R}(\boldsymbol{\omega}(0),\, \boldsymbol{\alpha})}$ at the same resource risk level. Therefore, the VOI to the regulator is stated explicitly as:

$$VOI_{\boldsymbol{\omega}(1)} = \mathbf{P}\left[\mathbf{Q}^*_{\mathbf{R}(\boldsymbol{\omega}(1),\boldsymbol{\alpha})} - \mathbf{Q}^*_{\mathbf{R}(\boldsymbol{\omega}(0),\boldsymbol{\alpha})}\right] \tag{10.5}$$

The application of the conceptual framework involves the use of the Landsat MRLI archive to estimate the joint outputs of agricultural production and pollution. Specific crop rotations are evaluated in a dynamic model that includes spatially explicit inputs in four dimensions: latitude, longitude, depth in the hydro-geologic system, and time. Our model characterizes relevant biogeochemical processes from the land surface through geologic strata to groundwater well extraction and quantifies the effect on farm income and potential damage to private and public well water supplies resulting from repeated applications of nitrogenous fertilizer (nitrogen) over the past several decades. As observed by MRLI, the pattern of the joint output of crops and pollution from the portfolio of land uses creates information to analyze locations by screening them on the basis of different criteria and to estimate an expected return on investment from farming practices in a socially-relevant context, namely their pollution and effects on common pool resources. Note that this approach is a close approximation of an alternative value of information based on the policy maker's optimization problem (Eq. (10.3)). Equation (10.5) will yield a lower VOI than this alternative, given diminishing returns of crop production, however this alternative approach would rely on a detailed understanding of the value of groundwater protection that is difficult to accurately observe.

10.3 Application

As a demonstration of the IAA, we forecast the risk of exceeding a regulatory standard for groundwater pollution in Iowa. As mentioned before, earlier studies on the application of MRLI show significant use in the agricultural sector. MRLI provides a time series of LULC signals that are linked to levels of inputs in crop production and their potential consequences to natural resources. In predominantly agricultural states such as Iowa, where approximately 80 % of the population depends on groundwater for drinking water, regulation of nitrate contamination associated with agricultural production is an issue of serious concern. Therefore, application of the conceptual framework to agricultural production and its effects on the ecosystem service of groundwater quality is selected.

10.3.1 Agricultural Production and Its Ecosystem Service Effects

Farmers may overuse or underuse fertilizers, especially nitrogenous fertilizers (Mortensen and Beattie 2005). The improper choice of fertilizer application rate can be costly to the farmer in terms of lower yields as a result of excessive vegetative growth, susceptibility to storm and insect damage, and poorer crop quality (Brady and Weil 2002) as well as higher fertilizer cost. We model producers' fertilizer application decision (1) as part of the dynamic optimization of profit. This decision hinges on the uncertainty faced by producers about the growing season's weather conditions. Given the policies and market conditions they face, producers might address uncertainty by choosing to err on the side of under- or over-application (Sheriff 2005). Fertilizer runoff and leaching-often a result of over fertilization and lack of uptake by vegetation-into streams or groundwater is an unintended consequence that can cause ecological and environmental damage (Martinez and Albiac 2006). Groundwater pollution occurs as a result of the interaction of several factors at the land surface including fertilizer application and its interaction with the soils and hydrogeology below the surface. Furthermore, under-fertilization limits yields. Both overuse and underuse are a misallocation of resources. Although it is assumed that a farmer must meet all the requirements of the laws and that the ecological structure and function of some locations provide multiple benefits and ecosystem services, a catastrophic social loss of clean groundwater is risked when over-application of nitrogenous fertilizer is widespread and persistent (Heal 1991). A regulator's informed intervention could help internalize externalities and reduce the losses associated with a misallocation of resources.

We apply a simple production function to model crop yield with a response plateau beyond which the marginal product is zero (Hall 1998). Further, we assume that corn producers operate at constant returns to scale and display diminishing marginal productivity (Livanis et al. 2009). We apply the production function (Eq. (10.6)) to many parcels in a regional-scale analysis, so the response function must be representative of the physical processes while being tractable region-wide. A Cobb-Douglas production model with a plateau meets both criteria (Mortensen and Beattie 2005):

$$\begin{aligned} q &= \zeta_0 \prod_{i=2}^{n_e} e_i^{\zeta_i^e} \prod_{i=1}^{n_z} z_i^{\zeta_i^z} (\zeta_1 + v_1 + e_1)^{\zeta_i^e} \text{ for } (v_1 + e_1) < NIT^{\max} \\ &= \zeta_0 \prod_{i=2}^{n_e} e_i^{\zeta_i^e} \prod_{i=1}^{n_z} z_i^{\zeta_i^z} (\zeta_1 + NIT^{\max})^{\zeta_i^e} \textit{ otherwise} \end{aligned} \tag{10.6}$$

where q is one element of $\boldsymbol{q}$—production in tons per hectare of a crop, v_1 is the nitrogenous fertilizer application rate, z_i is one of the n_z relevant elements of $\mathbf{z}$ (e.g. no till, irrigation), e_i is one of the n_e relevant elements of $\mathbf{e}$ (e.g. e_1 is residual nitrogen, and other e_i include moisture content, slope, soil type, and depth to water), and $NIT^{\max}$ is the amount of nitrogen beyond which marginal production is 0. The profit-maximizing behavior of individual farmers will neglect the overall welfare of the region. Here we hypothesize that a mismatch of parcel characteristics and crop production can lead to an increased likelihood of exceeding the regional regulatory standard for nitrate concentration in groundwater.

In this problem, given the land characteristics and the particular crop that the farmer is trying to grow, we assume there is a continuum of land parcel types, and an associated optimal application of land uses, fertilizer and irrigation and other inputs as costs of production. The combination of individual production decisions and observation of the producers at regional scale provides a mechanism to evaluate pollution issues at both intensive and extensive agricultural margins over time. Decisions at the intensive margin include management decisions such as chemical application rates for a given unit of land (Antle and McGuckin 1993; Antle and Just 1991). These types of decisions are usually short run input decisions including how much nitrogenous fertilizer should be applied during a specific growing season. Decisions at the extensive margin determine what land is used for production versus other purposes (e. g., USDA conservation programs), and thus determine the environmental characteristics of land in and out of production. These decisions entail long-run concerns such as crop rotations over different growing seasons. Thus, some parcels of land ought to be used in a different way (e.g. marginally productive lands close to streams ought to be in a USDA conservation program) and the parcels of land in a given LULC assignment can be mismanaged (i.e. fertilizers can be over applied). Both of these problems increase the magnitude of the pollution problem. The magnitude of the problem is a function of the history of use j. Depending on such characteristics as application rates, watershed size and connectivity, slope position, nitrate mobility, dispersion and travel times, aquifer and well depth, and groundwater age, the history of use can influence the groundwater pollution levels on the order of years, decades or centuries (Tomer and Burkart 2003; Meals et al. 2010).

Evaluation of the accumulation of regional environmental effects begins with application of a multi-period, spatial model of agricultural production for corn-soybean crop rotations (Lambert et al. 2006), where the land use and crop rotations are observed using MRLI. The first part of the model is the agricultural production and response function in Eq. (10.6). The planting pattern dictated by Eq. (10.6) will—in steady state—reduce either to some rotation pattern between corn and soybean or to fallow (i.e., in forage, conservation program, or non-agricultural use) We should also note that, to a relatively minor extent in our study area, the choice is sometimes to grow crops other that corn and soybeans. The choice to plant a crop in a given season depends on relative prices of the crops and costs of inputs. The decision to produce corn during a particular rotation means that a specific quantity of nitrogen is applied and if the decision is to produce soybeans, a different quantity of nitrogen (if any at all) will be applied (Lambert et al. 2006). Fallow land requires no nitrogen, but later planting of the site will affect retained nitrogen.

The longest ongoing studies of corn-soybean sequencing in the northern Corn Belt (Lauer et al. 1997) indicate that in a typical rotation, the production of corn is 13 % higher than with continuous corn and soybean production is 10 % higher than with continuous soybean. Transitioning from fallow, first year corn is 15 % more productive, but no improvement is apparent for second-, third-, or later-year corn crops, compared to simply growing corn continuously. Soybean production is 18, 8, and 3 % more productive for first-, second-, and third-year crops, respectively, compared to continuous soybean, and no improvement is found after the third consecutive year of soybean planting. These data average results from specific experimental plots and indicate the crops' typical production trends over time; the exact effect of a rotation cycle for a given crop's production depend on the particular site's characteristics, rotation history, and other management practices.

The producer re-calculates the dynamic optimization in Eq. (10.2) with all available information at time $t = t_0$ when preparations for the next planting are made. The producer knows site characteristics, past planting on the site, cost of inputs, and expectations for the price of the alternative crops this season and future costs and prices. At that time, the producer chooses the next crop to plant that maximizes the profit for the current season plus the discounted expected profit from all future seasons (that also depend on the current choice). This choice is a transition from the past planting to the next. Because of uncertainty about each producer's knowledge and expectations, this transition is a probabilistic transition from the crop of one season to the crop for the next. The state of the crop planting at time t is represented by $\boldsymbol{\delta}_t$:

$$\boldsymbol{\delta}_t = \begin{bmatrix} \delta_{1,1,t} & \delta_{1,2,t} & \delta_{1,3,t} & \delta_{1,4,t} \\ \delta_{2,1,t} & \delta_{2,2,t} & \delta_{2,3,t} & \delta_{2,4,t} \\ \delta_{3,1,t} & \delta_{3,2,t} & \delta_{3,3,t} & \delta_{3,4,t} \end{bmatrix} \tag{10.7}$$

where $\delta_{j,\,l,\,t} = 1$ for land use j at time t for the lth consecutive year and 0 otherwise,$\delta_{j,\,4\,,t} = 1$ if land use j is planted at time t for the fourth or higher consecutive year and 0 otherwise.

The crop choice is mutually exclusive; therefore:

$$\sum_j \sum_l \delta_{j,l,t} = 1 \tag{10.8}$$

The state of the crop planting can transition to either the first year of another crop or the next year of the same crop. The probability $\boldsymbol{\gamma}$ describes the probability that $\boldsymbol{\delta}_t$ will transition to some $\boldsymbol{\delta}_{t+1}$. The transition probability from the lth year of crop j to the $l1$th year of crop $j1$ is $\gamma_{j,l}^{j1,l1}(\mathbf{z}_t, \mathbf{P}_t, \mathbf{W}_t, \mathbf{e}_t)$. Thus, given each possible crop state, we have a discrete choice of three possible outcomes that depend on prices and characteristics known at time t. For first-year corn in the prior year, the next crop state could be second-year corn with probability $\gamma_{1,1}^{1,2}$ or first-year soybean with probability $\gamma_{1,1}^{2,1}$, or first-year other with probability $\gamma_{1,1}^{3,1}$. But, for first-year corn all other transitions are not possible, e.g. the crop state could not be third-year soybean next season or fourth-year other, so those transition probabilities are by definition zero. We relate the transition probabilities to known factors using a multinomial logit:

$$\begin{aligned} \text{In}\left(\frac{\gamma_{1,1}^{1,2}}{1-\gamma_{1,1}^{1,2}-\gamma_{1,1}^{2,1}}\right) &= {}_{1,1}^{1,2}\beta_0 + {}_{1,1}^{1,2}\beta_1 p_1 + {}_{1,1}^{1,2}\beta_2 p_2 + {}_{1,1}^{1,2}\beta_3 p_3 + {}_{1,1}^{1,2}\beta_4 w_1 \\ &\quad + {}_{1,1}^{1,2}\beta_5 w_2 + {}_{1,1}^{1,2}\beta_6 w_2 z_1 + {}_{1,1}^{1,2}\boldsymbol{\upbeta}^e \mathbf{e} + \varepsilon_{1,1}^{2,1} \end{aligned} \tag{10.9}$$

$$\begin{aligned} \text{In}\left(\frac{\gamma_{1,1}^{2,1}}{1-\gamma_{1,1}^{1,2}-\gamma_{1,1}^{2,1}}\right) &= {}_{1,1}^{2,1}\beta_0 + {}_{1,1}^{2,1}\beta_1 p_1 + {}_{1,1}^{2,1}\beta_2 p_2 + {}_{1,1}^{2,1}\beta_3 p_3 + {}_{1,1}^{2,1}\beta_4 w_1 \\ &\quad + {}_{1,1}^{2,1}\beta_5 w_2 + {}_{1,1}^{2,1}\beta_6 w_2 z_1 + {}_{1,1}^{2,1}\boldsymbol{\upbeta}^e \mathbf{e} + \varepsilon_{1,1}^{2,1} \end{aligned} \tag{10.10}$$

$$\gamma_{1,1}^{3,1} = 1 - \gamma_{1,1}^{1,2} - \gamma_{1,1}^{2,1} \tag{10.11}$$

where p_1 is the real price of corn, p_2 is the real price of soybean, p_3 is the real subsidy per hectare for conservation program lands, w_1 is the real cost of nitrogenous fertilizer, and w_2 is the real cost of diesel fuel for operations including irrigation. Similar equations apply to the transition from every other crop state.

10.3.2 Loss Estimation

A societal choice involves decisions at regional scale and has an overarching effect on a variety of individual land-owners and firms. Over long periods of time, production of corn, its associated pollution, and its cumulative environmental effects at regional scale can cause substantial changes to groundwater. The policy issue is whether this ecosystem service becomes stressed and could be compromised, or even lost, because of changes in the land use pattern. The social risk is the under- or over-regulation pertaining to groundwater contamination. However, the true state of contamination in space and time at the regional scale is unknown and can be only estimated with uncertainty. Thus, there is a need for a probabilistic model of groundwater vulnerability.

A probabilistic estimate of where and when to regulate the crop producers in a region can be based on the relevant circumstances above the groundwater over t years or by way of a health standard, both of which can be assembled into the vector α in Eq. (10.4). Thus, for our analysis we assume there exists some conditional probability distribution of an adverse environmental effect in a region from land use j that is known to the regulator (Nelson and Winter 1964) and consists of three elements (Philips 1988): (1) the set of possible states of the environment $\{D_k\}$ that a nonpoint source groundwater contamination incident of resource damage type for all $j, j \in J$ land uses involved in the transition to state k, $k \in K$, possible states of concentration; (2) an observation about land use j with information ω from a specific type of MRLI; and (3) the conditional probability that a time series of land uses was observed, suggesting that a particular state of the environment will prevail in the future.

Like the production function in Eq. (10.6), the probability of a particular level of groundwater resource damage attributed to a land use at any one point in time in Eq. (10.12) is related to the intensity of crop production $\mathbf{q}$, the variable inputs $\mathbf{v}$, the methods $\mathbf{z}$, and the properties of the plot $\mathbf{e}$:

$$p_k = f(\mathbf{q}, \mathbf{v}, \mathbf{z}, \mathbf{e}) \tag{10.12}$$

p_k depends on nitrogenous fertilizer related activities on the soil surface and other nitrogen sources (e. g., atmospheric deposition, land use and cropland type, population density, and manure management), management practices including irrigation and tillage, properties of the soil in the plot, temperature and precipitation, movement of nitrate (converted from nitrogenous fertilizer) to aquifers (depending on soil biological, chemical, and physical properties and the presence of clay), movement and conductivity of the lithology (depending on characteristics of sub-surface geology such as hydraulic conductivity and bedrock such as limestone), denitrification of accumulated nitrate in aquifers (presence or absence of denitrification facilitating layers in the soil and at depth), texture of aquifers (especially unconsolidated sand and gravel), and drainage and recharge rate of and well extraction from the groundwater system (Nolan and Hitt 2006; Nolan et al. 1997, 2002; Canter 1997).

The contamination problem is one of a rate of accumulation of long-term nitrogen application in crop production. Near-surface, soil nitrogen-cycling processes such as fixation, mineralization, immobilization, nitrification, denitrification and plant uptake are often costly and difficult to measure accurately and precisely (Nolan et al. 2010). That said, a model focusing on the near-surface soil processes is:

$$e_{1,t+1} = e_{1t} + v_{1t} - le_t - \eta_t - u_t \tag{10.13}$$

where v_{1t} is the quantity of nitrogen applied as fertilizer e_{1t} is the nitrogen stock in the soil, and le_t is the quantity of nitrogen that has leached from the soil. Of the remaining variables u_t is the amount of nitrogen uptake by land use j, and η_t is the nitrogen volatilization. Nitrogen uptake and volatilization are a proportion of yield $(u_t = \upsilon q_t)$ and fertilization $(u_t = \tau v_{1t})$, respectively, where τ is the volatilization rate into the air, υ is the nitrogen uptake rate by plants, and t is the number of time periods of observation by MRLI.

The nitrate leached le_t, is the principal component of nitrogen applied that accumulates in groundwater over the period of time. Nitrogen fertilizer leached in the form of nitrate le_t is explained by:

$$le_t = f\{Y, NIT, PPT, TEM, Si, LM\} \tag{10.14}$$

Where variables are the amount of fertilizer applied (*NIT*), residual nitrogen in soil, nitrogen uptake by crops, properties of soil (*Si*, i.e. soil texture, and hydrologic group), soil temperature (*TEM*), water inputs (*PPT*, i.e. irrigation/precipitation), water table height, and land management practices (*LM*).

The quantity of leached nitrate in a given year depends upon the activities and properties of an area contributing its pollution in the given year. That area is hereafter termed as the catchment zone of a well. Earlier research on groundwater pollution defined its catchment zone as a circular area around a well. For example, Nolan (2002) used a circular area with diameter 500 m to model nitrate contamination in groundwater in given period. One of the ways to determine catchment zone would be to use an analytical element method (AEM). The AEM is capable of determining catchment zones for number of time periods using hydrogeologic properties such as aquifer base elevation, aquifer thickness, porosity and hydraulic conductivity of the geologic layers, flow gradient, and net extraction from wells. The quantity of nitrate contributed to a well by certain land use within a catchment zone for each year is used in estimating the amount of nitrate accumulated over a period of time.

Suppose a decision must be made in each t about whether to regulate nitrogen use at the land surface because of an increase in the concentration of nitrate in well water. Does the decision maker wait until the groundwater in a well is contaminated when sampled or does she anticipate the exceedance of the nitrate standard and intervene, through regulation, before a contamination incident occurs? We assert that a point in time exists when the regulator will have estimated that the probability of exceeding the standard at some point in the future will be great enough to take action to mitigate an adverse effect in the present.

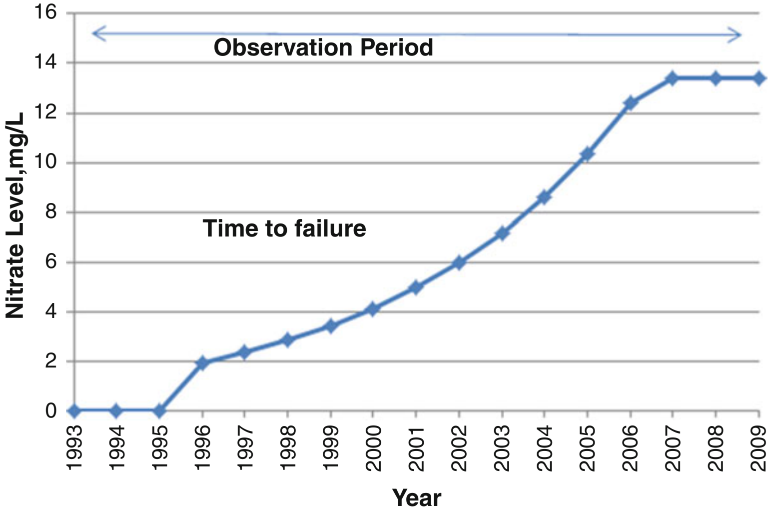

Fig. 10.2 Hypothetical illustration of cumulative nitrate indicator (CNI_t) of nitrate level

To capture the dynamic nature of the nitrate contamination problem, we introduce the cumulative nitrate indicator (CNI) shown in Fig. 10.2. Cumulative nitrate pollution in a well can be modeled with a difference equation (Yadav 1997). Equation (10.15) is the difference between the accumulated nitrates in the previous time period since time period i plus the addition of nitrate to the pool in the year the nitrogenous fertilizer was applied:

$$CNI_t = CNI_{t-1} + (\Delta NO_3)_t \tag{10.15}$$

where CNI_t is the value of the cumulative nitrate indicator in year t, $CNI_t - 1$ is the value of the cumulative nitrate indicator in year $t - 1$, and (ΔNO_3) is the nitrate concentration change over the course of 1 year.

The nitrate concentration change in a year depends upon the surficial activities and weather variables in previous years and the soil characteristics, and characteristics of the geology underneath. The *CNI* provides the foundation for estimating the probability of exceedance of the regulatory standard. The *CNI* captures the spatially and temporally cumulative exposure of the aquifer to nitrate contamination while accounting for nitrate degradation during transport to the aquifer. The *CNI* can be expressed as:

$$CNI_t = CNI_{t-1} + \beta^0 \mathbf{e}_t^0 + \sum_{g \in G} c^g \left(\mathbf{q}_{t-g}, \mathbf{v}_{t-g}, \mathbf{z}_{t-g}, \mathbf{e}_{t-g} \right) \tag{10.16}$$

where $\boldsymbol{\beta}$ represents the coefficients for explanatory variables, g designates the groundwater catchment zone that affects the well bottom, g years after a surface activity by the function $c^g\left(\mathbf{q}_{t-g}, \mathbf{v}_{t-g}, \mathbf{z}_{t-g}, \mathbf{e}_{t-g},\right)$. Note that g is both a label that designates the catchment zone and a parameter—the average travel time from the zone to the well bottom. G is the set of groundwater zones identified for a well or potential well and some recovery is possible depending on the properties of the well bottom, $\boldsymbol{e}^{0}{}_{t}$.

The CNI_t, because it is calibrated to use all available information to estimate groundwater nitrate concentration, also brings together all information needed to assess the likelihood that contamination standards will be exceeded. Nitrate accumulation is determined by fertilizer application and other nitrogen sources, leaching of deposited nitrogen, and its transportation to groundwater strata. Transportation of leached nitrate to an aquifer depends on the travel time through geologic layers underneath the soil surface to the aquifer and sinks. There is a lag time in surface water infiltration through the hydrogeologic system, which depends on factors such as the thickness and infiltration rates of the unsaturated zone (Oakes 1982). Estimation of travel time to an aquifer must include the variability of the surficial geology and its hydraulic conductivity, dispersion, advection, permeability and oxidation zones, pump and rates of extraction, and the age and recharge rate of the ground water system (Canter 1997; Marsily 1986; Bear 1979).The CNI_t is an input to the conditional probability of exceeding a concentration level k, threshold of nitrate contamination that adversely affects humans. A survival ($1-$ failure, F) analysis (Kleinbaum 1996; Lancaster 1990; Kalbfleisch and Prentice 1980) is applied by the regulator using α.[6] The exceedance probability of a given loss is the combination of the loss L and the exceedance probability α. The first step is to estimate the instantaneous potential per unit time for a contamination event to occur as the hazard rate of transitioning from an uncontaminated state to a contaminated state of the groundwater. The nitrate concentration hazard function is the instantaneous rate of leaving the current state to destination k per unit time period at t:

$$h(t) = \sum_{k=1}^{k} h_k(t) \tag{10.17}$$

where
$h_k(t)dt = \Pr\left(\text{departure to state } k \text{ in the short interval } (t, t+dt), \text{given survival to } t\right.$

$$h_k(t) = \lim_{dt \to 0} \frac{\Pr(t \leq T \leq t + dt, D_k = 1 | T \geq t)}{dt} = \frac{p_k f_k(t)}{\bar{F}(t)} \tag{10.18}$$

where T is the duration time of staying in state k, D_k is a set of K dummy variables with a value of 1 if state k is entered and 0 otherwise, $p_k = \Pr(\text{when departure occurs to destination } k)$ and can be estimated with a rank-ordered or

[6] It is assumed that good regulatory policy reduces or eliminates the adverse health effects of nitrates on humans.

mixed logit statistical regression estimated with the variables in Eq. (10.12), $\bar{F}(t)h_k(t)dt = p_k f_k(t)dt$,

$$\begin{aligned}\bar{F}(t)h_k(t)dt &= \Pr(\text{survival to } t) \times \Pr(\text{departure to } k \text{ in } (t, t+dt))|\text{given survival to } t \\ &= \Pr(\text{departure to } k \text{ in } t, t+dt) \qquad , \text{ and}\end{aligned}$$

$$\begin{aligned}\bar{F}(t) &= \sum_{k=1}^{K} p_k \bar{F}_k(t),\ \bar{F}_k(t) \\ &= \Pr(\text{survival to } t, \text{ given that when departure occurs it is to } k)\end{aligned}$$

The specific model used in the application is the Weibull proportional intensities hazard function (Lancaster 1990):

$$h_k(t) = a\exp\left\{x_k'\beta_k\right\}t^{a-1} \tag{10.19}$$

and

$$\alpha = \bar{F}(t) = \exp\left\{-t^a \sum_{k=1}^{K} \exp\{\mathbf{x}_k'\beta_k; CNI_t\}\right\} \tag{10.20}$$

Where $\mathbf{x}'\beta_k$ here are explanatory covariates, $\bar{F}(t)$ is a cumulative distribution function that is the survivor function (Lancaster 1990) and is synonymous with the exceedance probability α, a is the Weibull parameter, and $p_k f_k(t)$ is the probability of an event that is defined as the nitrate concentration level in a number of wells in a region that exceeds a maximum contamination level (MCL) for specific health effects as a result of land use j. The greater the number of wells exceeding MCL, the more damaging the event—or loss L—is to the regulator. There are two components to estimating the loss, L: the size and extent of the natural resource damage to the ground water and the lost economic benefits of agricultural production for the area causing the natural resource damage, L_i.

Regulation of agricultural production requires the estimation of the economic loss associated with a loss event L_i, $i = 0, \ldots, I$, possible events that cause a given amount of resource damage. The economic loss is the cost to producers of regulating nitrogenous fertilizer application at the intensive margin as a tax on fertilizer inputs or as a standard limiting use, and/or at the extensive margin as an incentive to reduce the amount of crop acreage (e.g., the USDA Conservation Reserve Program). This calculation applies in our region of interest above the social risk threshold. By definition, the optimal loss is the loss in agricultural production in this region. The optimal loss will be the value of the resource at risk below the risk threshold. However, because the decision affects the producer and the public differently, there is an asymmetry of loss in the decision. See the appendix for a description of a Bayesian decision approach to the problem. Here we

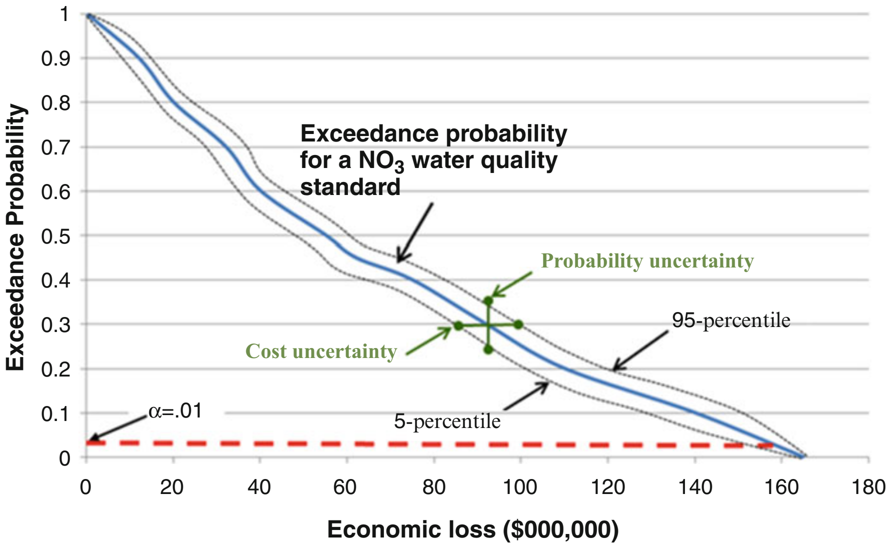

Fig. 10.3 Hypothetical exceedance probability curve for nitrate water quality standard threshold

estimate the economic loss associated with the regulatory constraint in Eq. (10.3). The loss to the producers L_i is the economic loss from event i:

$$L_i = \mathbf{P}(\mathbf{Q}(\mathbf{R}^*) - \mathbf{Q}) \tag{10.21}$$

Combining the survivor function in Eq. (10.20) with the expected loss in Eqs. (10.21) and (10.22), yields an estimate of the exceedance probability of a given economic loss $\alpha(L_i)$ (see Grossi and Kunreuther 2005, for an application of a survivor function to catastrophe modeling that is termed a probability of exceedance) is based on nitrate health standards. The exceedance probability for a given level of loss from event i is:

$$\alpha(L_i) = \Pr(L > L_i) \tag{10.22}$$

The risk to the decision maker of a groundwater resource failure can now be determined. To conduct a risk analysis we set a tolerance level at a specific exceedance probability for a regulatory standard (i.e. nitrate concentration in groundwater). The risk tolerance level for $\alpha = 0.01$ is shown in Fig. 10.3. The dashed line shows for that exceedance probability an economic loss (cost to the producers) if the health standard is exceeded. The vertical axis represents the exceedance probability and the horizontal axis is the economic cost due to the regulation associated with an estimated amount of natural resource damage.

Alternatively, we can construct a marginal groundwater protection supply curve based on the marginal loss in production. This creates a more direct—and less difficult to appropriately apply—measure of the value of the protected resource.

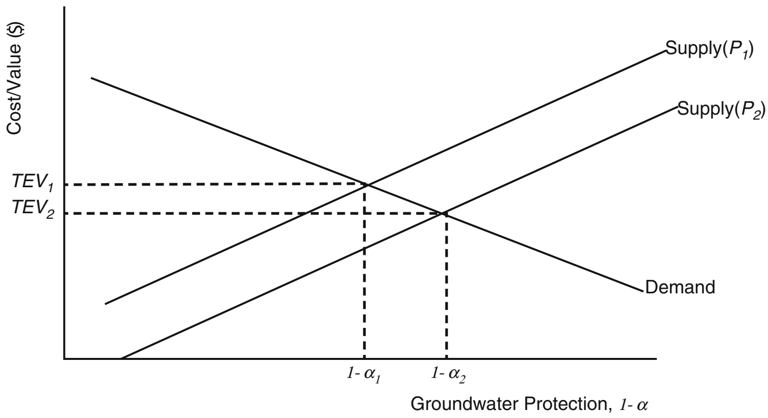

Fig. 10.4 Supply and demand for groundwater protection

This supply curve shifts as crop prices change from, say, $\boldsymbol{P_1}$ to $\boldsymbol{P_2}$ (Fig. 10.4). At the observed levels of groundwater protection, α_1 and α_2, the marginal cost of this protection level equals the marginal value of the groundwater protected, TEV_1 and TEV_2. From the observed history of variation in crop prices and the corresponding variation in groundwater protection, we can estimate a demand curve for groundwater protection that aggregates all of the values of the resource, for total economic value.

10.3.3 VOI: Comparison of Sensor Data Sets

Implementation of the IAA assumes that individual producers use prior information about markets, prior production, and regulations to decide whether to plant corn or do something else with the land. MRLI is used to observe those decisions. Thus, a policy could either target specific sensitive parcels of land, or, more likely, adjust general rules or incentives that change the pattern of planting and fertilizer application across the region's landscape. The estimates are based on the characteristics and derived classification products of each distinct sensor carried on a specific satellite platform and their imagery archives. For the National Aeronautics and Space Administration's (NASA) and the USGS's Landsat program, a 38-year archival history of observations exists while the Indian Space Research Organization's Advance Wide Field Sensor (AWiFS) has a 5-year history. The sensors' attributes and their expected cost savings can be compared.

The sensor and resolution characteristics of each type of MRLI provide data at a given error rate (i.e. typical remote sensing user and producer accuracy assessments) in detecting the land use practices of individual farmers that is central to the VOI determination. Calculation of VOI involves a two-phase analysis: (1) estimate VOI derived from remotely sensed land imaging versus traditional sampling methods[7] and (2) estimate VOI derived from a satellite sensor aboard Landsat versus another sensor on a different satellite (e. g., AWiFS). The VOI is the incremental cost savings in an application to demonstrate an economic return to the investment in the imagery. The $VOI_{\boldsymbol{\omega}(1)}$ is the benefit B possible given information from some source $\boldsymbol{\omega}(1)$ minus the information available without that source $\boldsymbol{\omega}(0)$:

$$VOI_{\boldsymbol{\omega}(1)} = B_{\boldsymbol{\omega}(1)} - B_{\boldsymbol{\omega}(0)} \tag{10.23}$$

Alternatively stated, the difference between the predicted loss of value of production as a result of more stringent regulation pertaining to prevent groundwater resources loss using $\boldsymbol{\omega}(1)$ and $\boldsymbol{\omega}(0)$ is the proxy for VOI. Thus, some important VOI questions follow: which information source ($\boldsymbol{\omega}$), is more accurate and comprehensive? Which MRLI source has fewer errors of commission and omission? Does the estimation error affect the decision? How does an information archive improve prediction of resource loss from stock pollutants? Because an MRLI archive is critical for estimating the historical use of the land and its associated legacy of effects on common pool resources, does the temporal extent of the archive make any difference? Can MRLI sensors from different satellites like Landsat and AWiFS be coupled to improve the LULC classification probability distribution and associated estimates?

To summarize aspects of the previous sections and to frame the following example, the model is implemented using the following steps:

1. Identify an operational use of remotely sensed data that has a quantifiable economic value and policy relevance, in this case, the effects of land use practices on groundwater quality. Highlight the intersection of policies that encourage biofuels from corn production, incentivize a reduction of agricultural production for protecting resources via USDA conservation programs, and conflict with provisions of the Safe Drinking Water Act.
2. Apply Landsat or other MRLI to monitor changes in LULC that affect ecosystem functions, goods and services to estimate how the use of MRLI data brings tangible economic benefits to users.
3. Use annual MRLI observations as the basis for estimating crop yields and nutrient loading into the soil. Estimate the joint outputs of agricultural production and pollution. Couple observed land uses over time with water quality test

[7] Traditional sampling methods have included the following trajectory over time: prior to 1945, crop area estimates were not consistently available; from 1954 to 1978, area sampling frames with aerial photography were determined and field-surveys conducted; from 1978 to 1999, Landsat supplemented aerial photography for sampling stratification, but field surveys still included regression estimators for major crop acreages, harvest by region, state and county as well as livestock numbers, economic variables and farm demographics; from 2000 to present, the remotely sensed and classified Cropland Data Layer provides wall-to-wall crop types and areas, yet it still requires the June Agricultural Survey to collect ~11,000 field-based samples nation-wide (Hale et al. 1999; Lubowski et al. 2005).

data at different depths in a statistical survivor analysis. Use the conditional probability of exceeding a nitrate regulatory standard as the threshold for regulating agricultural production.

4. Measure the economic consequences for farm income and potential effects on private and public well water supplies resulting from repeated nitrogen usage.

10.4 Example

Groundwater has both market and nonmarket values. These include use values that are sometimes partially paid for, such as drinking water and irrigation supply, and non-market use values such as wetlands and spring water sources for in-stream flow. Groundwater also has non-use values that are related to quality, such as option value (Weisbrod 1964), and existence value (Krutilla 1967). The nonmarket value can be estimated using revealed-preference methods such as travel cost and hedonic pricing, or stated-preference methods such as contingent valuation and conjoint analysis. The overall purpose of the various techniques is to determine the willingness to pay (WTP), in this case WTP for protecting groundwater quality. WTP estimated using contingent valuation ranges from \$57.37 to greater than \$1434.37 per household per year (Crutch-field et al. 1997; Poe 1999). Jordan and Elnagheeb (1993) used a contingent valuation payment card to estimate WTP specifically for nitrates reduction at \$204.89 per household per year for public wells, and \$237.17 for private wells. Poe and Bishop (1999) estimated WTP for a one-unit improvement in nitrate contamination at \$136.64 per household per year in a study conducted in Wisconsin, and in Delaware it was estimated at \$150.79 by Sparco (1995). Loomis et al. (2009) used conjoint analysis to estimate WTP for reducing health risks in infants by reducing nitrate in drinking water using actual and hypothetical markets. WTP estimates for reduction in risk of shock, brain damage and mortality in infants was \$2, \$3.70 and \$9.43, respectively, in actual markets, and \$14, \$26, and \$66, respectively, in hypothetical markets, indicating bias in the hypothetical situation. Contingent valuation and conjoint analysis also can be used to value groundwater protection. The range in values here, however, suggests that the application of these methods contains variability in outcomes, and uncertainty about the correct, absolute value.

Complete and correct aggregation of all the use and non-use, market and non-market values of clean groundwater to a total economic value demand curve[8] is fraught with uncertainty and methodological difficulties. Care is needed to avoid (1) double accounting of some values contributing to more than one component value and (2) omission of unidentified, yet significant, values. Furthermore, as

[8] We will express demand as the as the schedule for the price, *TEV*, that society is willing to pay to ensure groundwater will be protected with certainty $1 - \alpha$. Thus, *TEV* is dollar value of marginally increasing $1 - \alpha$.

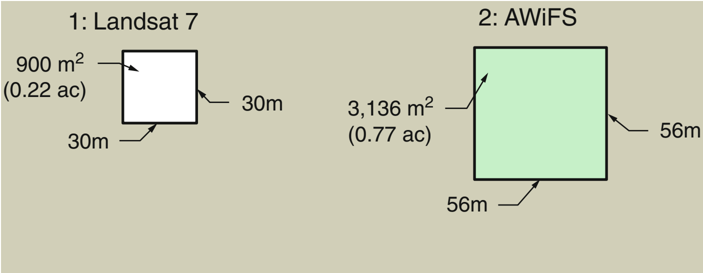

Fig. 10.5 Spatial characteristics of two MRLI sensors. The thermal band (10.6) has a resolution of 60 m, and the panchromatic band (10.8) has a resolution of 15 m (Note: Representations of spatial sensor resolutions are to relative scale)

suggested above, the accuracy of the component values is limited by the valuation techniques used.

In the example, MRLI is used to observe (screen) the land uses of a population of land parcels in Iowa that vary in their biophysical, ownership, and location characteristics. The land parcels are assigned a land use j, (j = corn, soybeans, other agriculture, or developed). An observation is processed for locations across a landscape relevant to a groundwater resource that results in a label for that land parcel; this label assigns a land use j for all land associated with a groundwater resource. Using spatial autocorrelation of well nitrate measurements can determine the possible spatial extent, lag distance, and direction of the influence that other well nitrate observations may have on a particular well, which can relate to the delineation of the catchment zone. After receiving the land-use signal and updating the exceedance probability for the regulatory standard, the regulator makes the decision to either regulate or not regulate the use of nitrogen given the crop rotation pattern covering the groundwater recharge area.

10.4.1 Data

Two primary sensors are compared in the example: Landsat 7 Enhanced Thematic Mapper plus ETM + = ($\boldsymbol{\omega}(1)$), and AWiFS = ($\boldsymbol{\omega}(0)$). Some basic characteristics of the two sensors are detailed in Fig. 10.5. The return intervals and number of bands for the two sensors are as follows:

1. Landsat 7: 16 days,[9] 8 bands (3 visible, 2 short-wave infrared, 1 thermal infrared, 1 mid-wave infrared, and 1 panchromatic).
2. AWiFS: 5 days, 4 bands (3 visible, 1 short-wave infrared).

[9] Please note, with Landsat 5 and 7 operating concurrently with polar-opposite orbits, the revisit rate is 8 days.

Among other factors, the ability of sensors to detect ground features accurately is a function of pixel size, spectral signatures, band combinations, frequency of overflights, cloud cover, and image processing, classification, and analysis techniques. Assumptions about the scale of certain features important to the integrated assessment (e. g., field, parcel, farm, census block, ZIP code, county) are implicit to the scale to which a sensor can resolve. For example, a typical center-pivot irrigation system on a large, factory farm can cover 128 acres, an area resolvable by both sensors. Some family and organic farms, however, are much smaller and may be only one field on a portion of a parcel. These scales may be resolvable only by AWiFS or Landsat, just Landsat, or not by MRLI at all. Furthermore, the return intervals of the different sensors, especially when considered in conjunction with the potential for cloud cover, can create an incentive or disincentive for using one sensor over another. This is further complicated by the number of bands and potential band combinations available from each sensor for classification purposes.

Returning to the economic model with the MRLI capabilities and sensor characteristics in mind, $\boldsymbol{\omega}(1)$ is the information with continuing Landsat data from the 38 year history of Landsat. $\boldsymbol{\omega}(0)$ is the data available if Landsat were discontinued and includes the best available alternative data, which we presume to be from the AWiFS remote-sensing platform. $\boldsymbol{\omega}(0)$ includes the Landsat historical archive, but these archival data are less compatible with the AWiFS data so calibrating risk models and assessing the cumulative condition of the sites will be compromised. $\boldsymbol{\omega}(1)$ includes the continuation of spatially—explicit LULC data derived from Landsat observations, specifically whether the land is used to grow corn, soybeans, or other cover types, or is developed. The primary difference in the information structure and availability between $\boldsymbol{\omega}(1)$ and $\boldsymbol{\omega}(0)$ is that no new Landsat observations are available.

10.4.1.1 MRLI Observation and Classification

Figure 10.6 displays a time series of MRLI observations and classification of LULC from 2000 to 2008. The land is classified each year according to what the sensor detects, the ability of the classifier, and the availability of ancillary data. The 9 years of observations depicted in Fig. 10.6 indicate that: (1) crop rotations, although persistent, are not perfectly repetitive as evidenced by the field outlined in blue; (2) apparent differences exist in the resolution of ground features in the earlier years with Landsat relative to the later years with AWiFS; and (3) the area that is neither corn nor soybean is consistent over time but less prevalent with AWiFS. Each of these points leads to a different amount of actual and modeled nitrogen use. For example, with year-over-year blanket coverage of the area, there is less chance of missing disruptions to the crop rotation patterns and the associated changes in nitrogen application than compared to traditional sampling techniques.

Next, the classified land uses are input to the agricultural production function in Eqs. (10.6), (10.7), (10.8), (10.9), (10.10), and (10.11) to estimate nitrogen use. If the

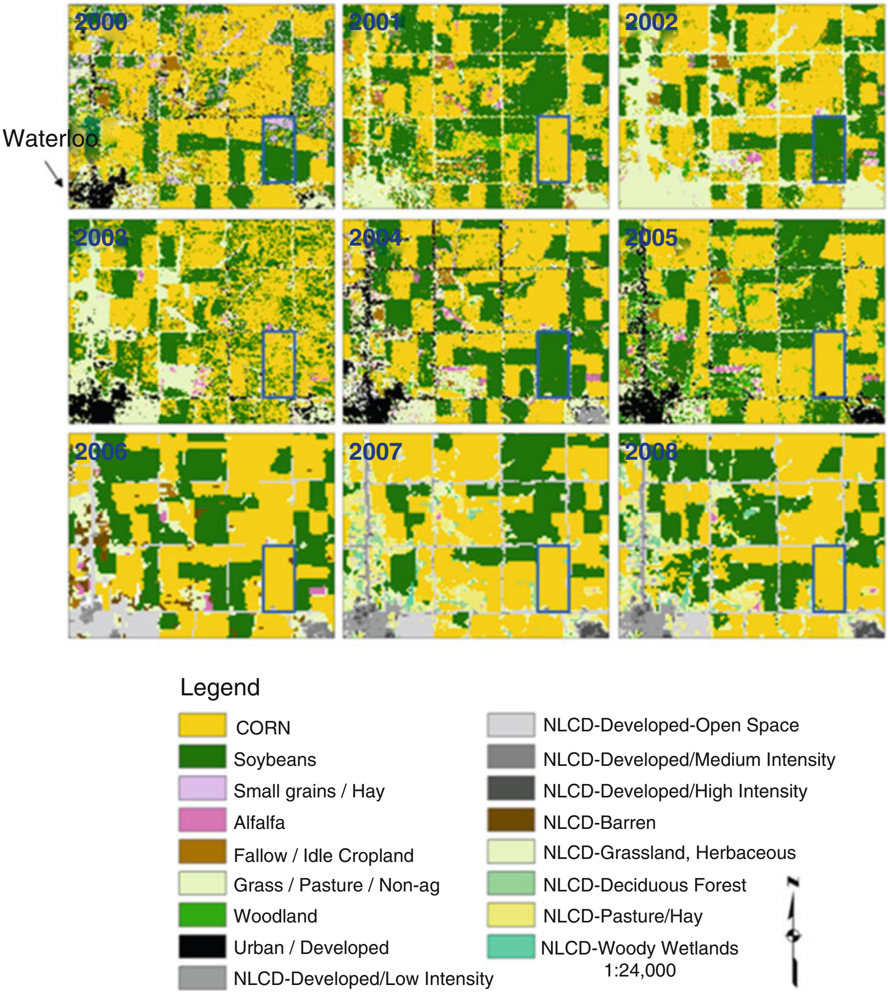

Fig. 10.6 Cropland data layer: Landsat (2000–2005) and AWiFS (2006–2008)

land has been classified as corn, based on the county and state agriculture records, we calculate the amount of nitrogen applied for a given range of yields in the area. If not corn, the amount of nitrogen for soybeans is less and for fallow it is zero.

10.4.1.2 Historical Agriculture and the Hydrogeologic System

This section provides agricultural and hydrogeologic context for the application of the conceptual framework to estimate CNI_t, α, and p_k in Iowa. Figures 10.7 and 10.8 provide historical context for the acreages and yields of corn and soy harvested in Iowa. It is interesting to note the general linear trends (with some outliers) in yield

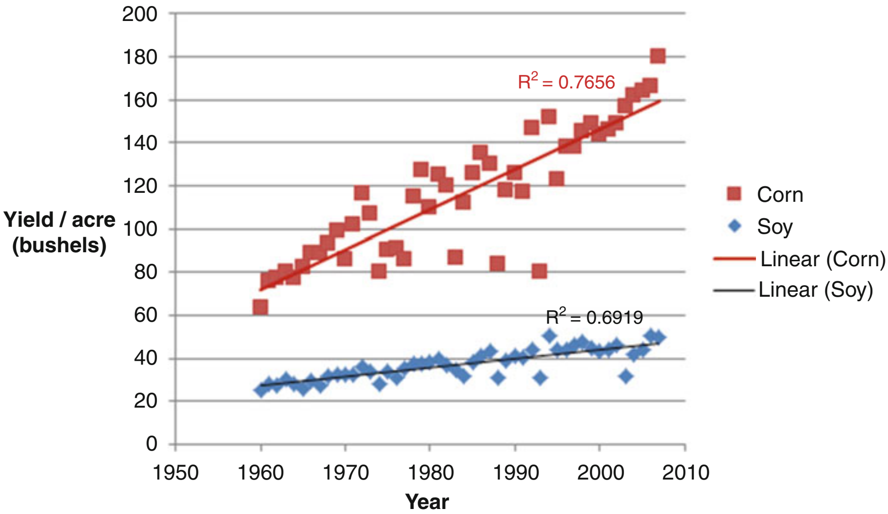

Fig. 10.7 Corn and soybean trends in yield in Iowa (Source: Iowa State University Extension Service 2010)

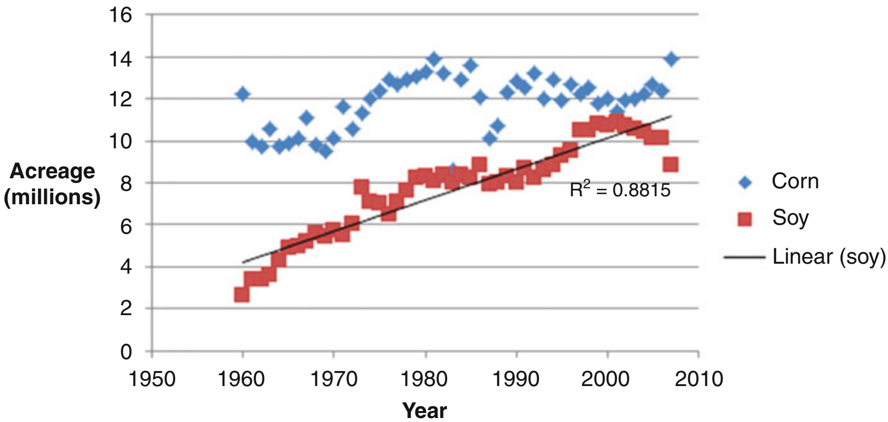

Fig. 10.8 Corn and soybean trends in acreage in Iowa (Source: Iowa State University Extension Service 2010)

per acre for corn and soybeans in Iowa from 1960 to 2007 (Fig. 10.7), which suggests that agricultural production technology and techniques became more sophisticated, industrialized, and efficient. One of the influencing agricultural production technologies is increased use of nitrogenous fertilizer, which results in an increase in nitrate concentration in groundwater. The general trends, which are less linear, for acreage in production for corn and soybeans in Iowa from 1960 to 2007 are shown in Fig. 10.8. In both Figs. 10.7 and 10.8, the R^2 values are provided

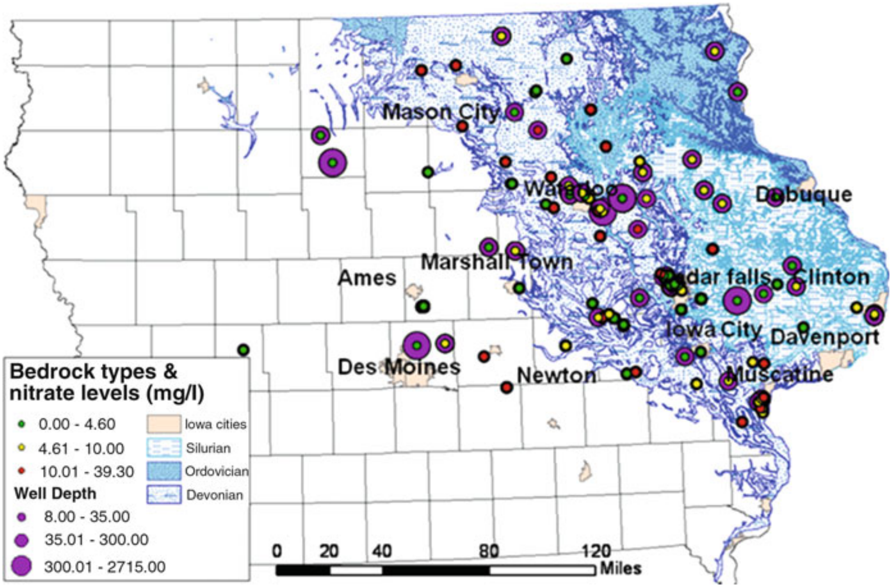

Fig. 10.9 USGS monitored sites and groundwater provinces. Approximately 20,000 Iowa Department of Natural Resources wells are monitored, but not shown

(where linearity is assumed), and the explanatory power of the variance in the trend lines are high.

In comparing the correlation of national and state trends—as well as in-state trends—in acreage, given the apparent indication that the trends are non-linear, the significance was tested with Kendall's tau and Spearman's rank tests instead of Pearson's product–moment correlation test. For corn, correlations were 0.745 and 0.880 (both p-values < 0.01), respectively, suggesting a statistically significant correlation in acreage dedicated to production over time at national and state levels. For soybeans, correlations were 0.809 and 0.928 (both p-values < 0.01), respectively, also suggesting a statically significant correlation over time in acreage dedicated to production at national and state levels. In Iowa, the correlation between corn and soybean acreage for the Kendall's tau test was not found to be significant at the p-value < 0.01 level, but the Spearman's rank test was found to be significant at that level, thereby suggesting an inconclusive result that the annual rotation patterns between crops are not necessarily regular and definitively correlated.

Turning to the groundwater resources information, well data and hydrogeologic properties of well-locations are available from the USGS and the Iowa Department of Natural Resources. Locations, depths, and nitrate levels of the USGS National Water Quality Assessment database and the groundwater provinces of northeast Iowa are shown in Fig. 10.9. The driving factors of the hydrogeologic system, depending on the hydraulic conductivity and permeability, groundwater moves at rates from a few inches a year to several feet per minute. Groundwater resources occur at various depths and in a variety of materials (Prior et al. 2003). Surficial aquifers occur in relatively loose granular sediments that lie between the land surface and deeper bedrock. The surficial aquifers and aquitards consist of alluvium (water-deposited sand and gravel), loess (wind-deposited silt) and glacial till (pebbly or sandy clay deposited by ice). Thickness of these materials ranges from 0 m in parts of northeastern Iowa to 180 m in west-central Iowa. Loess and glacial till are fine textured and have moderate to low permeability. Alluvial aquifers are unconfined. Some alluvial deposits consist of fine grained-silts and clays; others are coarse thick and extensive. If coarse and permeable materials, alluvial aquifers may have high yield and occur at depths of less than 30 m. Significant alluvial aquifers occur along the Mississippi River corridor in eastern Iowa.

Bedrock aquifers consist of solid rock layers such as limestone, dolomite, and sandstone. The groundwater in deep aquifers in Iowa can be older than 10,000 years. Bedrock consists of sedimentary rock layers, limestone and dolomite (carbonate rocks) as well as shale, siltstone, and sandstone. Thickness ranges from 1,580 m in southwest Iowa and about 240 m in the northeast. Some of the more prominent deep aquifers are the: Dakota aquifer, Mississippian aquifer, Silurian aquifer, Devonian aquifer, and Cambrian Ordovician aquifer.

10.4.2 Comparing Loss Estimates of Two Alternative MRLIs

This section presents an example of a hypothetical application of the integrated assessment approach with alternative data sets, Landsat and AWiFS. It includes the calculation of an estimate of the economic loss associated with the regulation of the maximum contamination level standards using the remotely sensed observations as well as the difference in the estimated economic loss between them. This difference can have an important effect on the decision to regulate.

We begin by identifying the relevant decision time increment of 1 year for t and setting α for a risk tolerance level. These two components are combined to provide the estimate of the expected loss $\alpha(L_i)$. To calculate $\alpha(L_i)$, we estimate the conditional exceedance probabilities for MCL regulatory standards of 4 and 10 mg/l as specified by the U.S. Environmental Protection Agency (EPA). The current MCL of 10 mg/l is more than double that of Germany and South Africa, where the standard is 4.4 ppm (Kross et al. 1995). Other nitrate concentrations may be relevant for a parallel analysis, since only below 0.2 mg/l is the risk considered low, while above 4.8 mg/l carries known risks (Nolan and Hitt 2006). The nitrosamines and nitrosamides that result when nitrates react with organic compounds are associated with 15 types of cancers including tumors in the bladder, stomach, brain, esophagus, bone and skin, kidney, liver, lung, oral and nasal cavities, pancreas, peripheral nervous system, thyroid, trachea, acute myelocytic leukemia, and T and B cell lymphoma (Mirvish 1995).

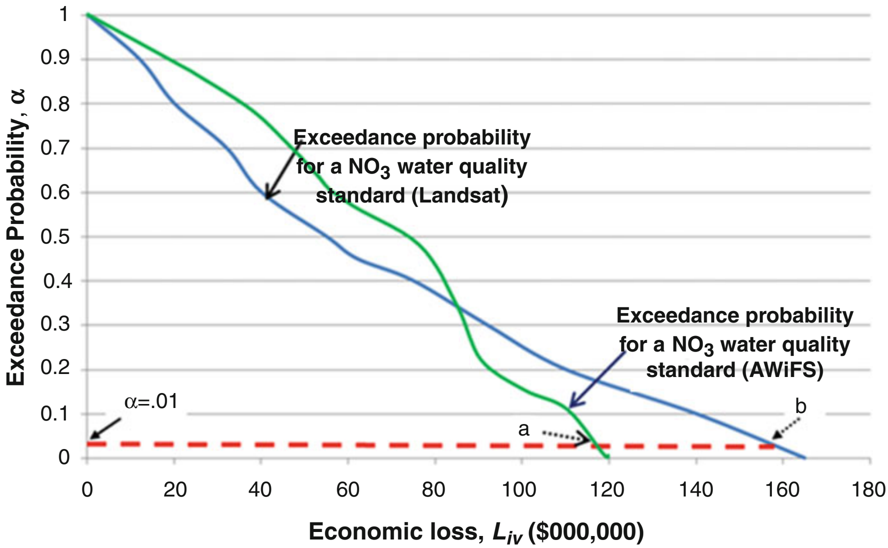

Fig. 10.10 Hypothetical exceedance probability curves for Landsat and AWiFS in northeastern Iowa

For the example, consider a hazard rate for exceeding the nitrate standard (based on the MCL analyzed in the wells sampled) in a region of Iowa of 0.05 as a result of land use j. The greater the number of wells that exceed MCL in the region, the more severe event i would be. In our hypothetical example, $(p_k) = 0.0005$ is the regional probability for an event that has an $\alpha_{\omega n} = 0.01$ averaged over the number of wells, n in the region. If regulation occurs, the economic loss, L_i, is the total loss in value of agricultural production due to the regulatory change (e.g., changing the tax on nitrogenous fertilizer).

The total production loss can cover a wide range depending on event size in a major agricultural region that is also heavily dependent on ground water resources for potable water as in Iowa. Consider the region described by Fig. 10.9. For our hypothetical severe event ($p_k = 0.0005$), the horizontal dashed line located at $\alpha = 0.01$ identifies the expected loss estimate based on each type of MRLI data. The two MRLI information types yield different loss estimates. The economic loss at $\alpha = 0.01$ could be either a little under \$120 million for Landsat (point a) or almost \$160 million for AWiFS (point b) in Fig. 10.10. Depending on which MRLI information is available, the cost of preventing the low probability, severe-contamination event is either \$160 million or \$120 million.

The VOI for this example is the estimated difference in the economic value of agricultural production lost if the MRLI information of the lower cost regulation (fewer acres in corn production) is implemented. That is, in this illustration of the method, if Landsat is available and corn production is regulated, the benefit (savings) of avoiding the loss of the groundwater is \$40 million less in income loss to the farmer than is the case with AWiFS.

10.5 Summary

In this chapter, we have assembled models from a variety of scientific disciplines into a general framework of economic decision making. The integrated assessment approach links MRLI data to models of productive land uses, emissions and environmental damage caused by the land uses and risks to natural resources to better assess the joint production of market goods and environmental degradation. The VOI for MRLI in this particular case is based on the more efficient and accurate estimation of the joint production of market and environmental (i.e. non-market) goods made possible by better information.

In our application, we link the MRLI data to agricultural production, nitrate loading and groundwater vulnerability models to estimate the joint output of agricultural production and nitrate groundwater pollution. The VOI of MRLI for this case is the increased value of agricultural production that is possible because of better-calibrated regulatory measures for the protection of groundwater. Given that this is only one case study involving estimates of a limited set of goods, the VOI of MRLI should be considered a lower bound of its overall value to society.

We illustrate the method and application with a hypothetical example in which the VOI derives from: (1) providing cost effective information on the population of land activities across space and over time to analyze a particular harm to ecosystem services, and (2) reducing the risk of a regulatory decision error in cases where groundwater pollution is a likely problem. The use of MRLI information must show an incremental cost savings or result in a new application to demonstrate an economic return.

This research provides a method to demonstrate the value of MRLI information in an operational application and to assist in estimating the cost effectiveness of investment in space-based remote sensing that informs congressional policy makers and other stakeholders about the potential environmental risks associated with specific agricultural and health policies and regulations. Empirical application of the conceptual framework would involve a two-phase analysis: first, estimate VOI derived from remotely sensed land imaging vs. traditional sampling methods, and then determine VOI derived from Landsat versus. other satellite sensors. VOI pertaining to other regulatory decisions can be similarly estimated; for example:

- In the agricultural sector, nitrogen application and surface water protection, pesticide application and protection of surface water and groundwater resources, and water quality monitoring of impaired waterways that fall under the jurisdiction of EPA's TMDLs;
- In the mineral sector, mining for coal and downstream pollution; and
- LULC changes that affect patterns and processes of landscapes such as wildlife corridors and habitat connectivity for listed species, and indices of biodiversity, ecosystem integrity, and forest health.

The value of information arises from the spatial data or temporal archive or both provided by MRLI. The framework developed in this chapter has many potential applications.

Appendix

Previous studies on the economics of information and uncertainty established that information becomes valuable when the information can be profitably employed in a decision making process by reducing the risk facing decision makers, especially when the consequences to the decision maker are uneven (Morgan and Henrion 1990). In this application where the consequences are uneven, the underlying behavior is the use of nitrate fertilizers on fields. Of critical interest to the regulator is when to intervene to control the rate of change in the groundwater quality to avoid the costly treatment of water wells. To intervene either too early or too late relative to a regulatory threshold is to affect individuals and firms, e.g., agricultural production, negatively or to contaminate either or both shallow and deep groundwater. On the other hand, to intervene too late allows a greater potential of contamination, i.e., the regulator's risk. Bayesian Decision Analysis can be applied as a regulator's decision problem involving uncertainty.

The loss function we face is asymmetric (Fig. 10.A.1) since groundwater resource damage is very costly to mitigate and thus the total economic value of diminished current and potential uses and existence of a pristine resource is large relative to the marginal loss of agricultural output. Edwards (1988) found the willingness to pay to prevent groundwater damage increased linearly with risk. The marginal risk to the groundwater increases as nitrate fertilizer application increases, we model the social loss of over application with an exponential functional form.

The modified linex loss function in Fig. 10.A.1 is adapted to the risk analysis in the hypothetical example (van Noortwijk and van Gelder):

$$L(\Delta) = -c_v \mathrm{In}(\alpha) \cdot (\lambda^* - \lambda) + \frac{d}{1-d} L_{i(j)} \alpha \left[\exp\left\{ \mathrm{In}(\alpha) \cdot \frac{\lambda^* - \lambda}{\lambda} \right\} - 1 \right] \quad (10.A.1)$$

where c_v is the additional variable cost to reduce nitrogen use, $\mathrm{In}(\alpha)$ is the q-quantile (level of risk tolerance) of the nitrate concentration distribution, and λ is the parameter of the nitrate loading distribution.

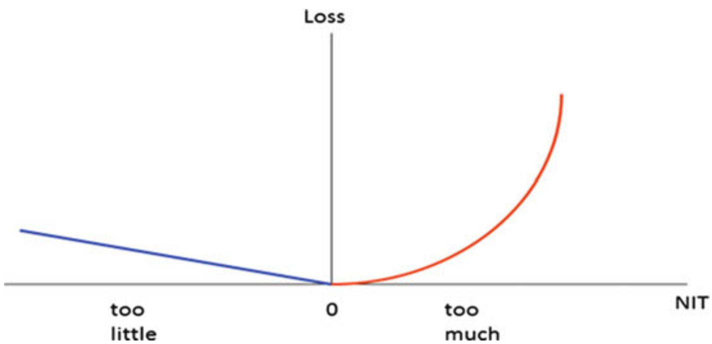

Fig. 10.A.1 Decision risk faced by regulators of societal cost of groundwater damage (*red*) vs. loss of agricultural production (*blue*). Asymmetric loss to regulator: too little NIT = crop income/profit loss; too much NIT = risk of aquifer loss

10. Commentary: Satellite Observations and Policy Improvements for Agriculture and the Environment

Catherine Shelley Norman

Bernknopf, Forney, Raunikar and Mishra (BFRM 2010) consider the value of medium-resolution land imagery (MRLI) to a regulator focused on keeping water quality risks to an acceptable level. They present a general model of the biological, physical and economic processes at work, and then outline a specific example focusing on corn and soybean rotations and the fate and transport of associated nonpoint source pollution in a nitrogen-limited region of Iowa. MRLI allows the regulator to monitor changes in land use and optimize regulations to reflect nutrient burdens on the system, economic costs, and the value of mitigation plans.

In offering a comprehensive, integrated approach to valuing the information provided by programs like Landsat, the authors' focus is on valuing the decisions that hinge on the information provided by a given set of observations. Their model is unusual in that it takes multiple disciplinary perspectives—ecological processes, agricultural science, economics, and hydrology, among others—seriously and simultaneously. Regulation of land uses and management practices is well suited to medium-resolution land imagery. Monitors can use simultaneously updated, geographically complete information rather than relying solely on sampling programs that require regulators to select representative sites over time and across space. Space-based data can be coordinated with direct sampling to improve inferences from images and to support enforcement efforts.

Although the full data required to reach conclusions are not available to BFRM, this work is a strong and ambitious initial step toward a framework supporting improved program evaluation. I consider some clarifications, limitations, and possible extensions of this work, with a focus on producing credible estimates to inform decisions about the use of MRLI.

10.C.1. Major Contributions

Satellite imagery supports multiple overlapping objectives in the regulatory and political arena. BFRM focus on one agricultural regulatory application, working to quantify the benefits from that use alone. In theory, one could aggregate up to a total value for a space-based observation program by considering all users, though as we can see from this relatively straightforward application, the informational and

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technical demands associated with such an effort would be very high. Additionally, for many earth observations satellites, information on all uses is likely to be confidential for reasons of national security, and some part of the value will be strategic or political—and thus more challenging to quantify than ecosystem services. It is perhaps better to think of VOI in this framework as valuing data access or specific data uses rather than a program as a whole. If this kind of use is the primary driver of value for the program in question, it should still be emphasized that estimates produced in this way, no matter how comprehensive, will be lower bounds of value rather than estimates of total value. Even rough information about the scale of a given use relative to uses for the satellite information as a whole would provide useful context for decisionmaking.

Some VOI quantification of the sort proposed is critical to maintaining and instrumenting costly space-based information resources. Cost-benefit analysis is mandatory in many public decisionmaking processes and a common, well-understood framework in the remainder. If those of us who use this information cannot usefully answer questions about what it enables us to do, it is difficult to justify maintaining either the systems themselves or access to the information. BFRM present a model to capture the benefit to a policymaker focused on risk management (for avoiding threshold environmental effects) and thus assess the value, to regulators and the public good, of operating with the additional clarity and scope offered by space observation systems.

I attempt to lay out some of the most interesting questions this work posed below, focusing on the economics of regulation. Moving this model from the general to the specific requires the authors to confront political and public choices that are difficult to observe or theorize about in a way that yields usable numbers. It will be important in applications that the assumptions used to develop the regulator's objectives and constraints are made transparent, and perhaps subjected to sensitivity analyses.

10.C.2. Social Preferences and Risk

In Sect. 10.2.3, the authors note that we can infer the optimal risk of failure (in a whole matrix of failure points reflecting reduced water quality due to pollution) of a given regulatory regime for the regulator and link this to social risk preferences. The regulator takes those social preferences as given from a 'higher level of authority.' In the illustrating example, the analyst must infer the political level of tolerance for a multitude of risks of reaching various pollution thresholds in various environmental media and locations. I would be interested in much more detail on how this matrix is populated; there is a small but longstanding literature on identifying the preferences of government bodies (McFadden 1975, 1976; Ross 1984 are identified in the chapter), but recent efforts (e.g., Ahlroth et al. 2010; DeCanio and Norman 2005) are in much narrower applications, and even in such settings, inferences based on political choice are met with considerable skepticism.

Social decisions should yield some sort of information about the willingness of society to make trade-offs and incur costs, but methods for determining political willingness to pay (or similar) are by no means well established. BFRM view the regulator's problem as one of reducing risk to an acceptable level without providing information on social risk aversion; individual and firm risk aversion are difficult to infer outside highly controlled settings (Chetty 2006 describes some of the complexities involved), and moving from individual choices to social choices involves a fairly fundamental determination about the relationship between a government and the citizenry: ought a government represent the median voter? Or should the state, with a (potentially) much longer lifespan and broader area of influence, worry more about the future than individuals?

It might be more feasible to go backward from costs incurred for specific environmental efforts rather than to look at political decisions directly: those probabilities can be translated into expected payouts to replace ecosystem services if they are reduced or eliminated by insufficiently stringent policy choices—and it may be that that's what BFRM will do to quantify the requirements of the higher governmental authority—but there is insufficient information for the reader on the methods envisioned for general applications of this framework at present.

10.C.3. Regulator's Objectives

In the BFRM example, the regulator's objective is to maximize the total value of agricultural output, given the constraints established by the willingness of society to accept the ecological risks outlined above. The farmer's objective is to maximize profit. Thus, a farmer would prefer a lower yield method if costs were sufficiently reduced to preserve profits, but the regulator cannot support this. In the agricultural sector it is often the case that polluting inputs can be replaced with less polluting alternatives or increased handwork; as regulatory environments and water and land quality evolve over time, this may be a profit-maximizing, output-reducing solution, which appears to be excluded in this analysis.

It is not clear to me that EPA or USDA, the primary agencies in this environment, value total output over total profitability in this context. Readers would benefit from efforts to explain the motivation behind this modeling choice and its implications for VOI calculations. In particular, this choice seems closely tied to the choice to value MRLI information as some fraction of total farm revenues.

The language of the chapter seems to suggest that there is a positive value for the information from the satellite system only if the information allows the regulator to relax restrictions on farmers. I don't believe this is required in the model; if it is, the authors should explain their motivation in more detail or perhaps consider relaxing this assumption. Given the level of geophysical detail in the example, it seems plausible that relaxing nutrient loading restrictions in some places and tightening them in others might provide aggregate benefits. Additionally, there is value in improved information that leads to greater restrictions: if we've gotten the regulations wrong because a sampling regime or alternate set of instruments led us to underestimate aquifer risks, for example, we gain from the changes even if they reduce output or profits.

As an extension, a more dynamic perspective might allow adaptive management to be built in to policy choices. VOI would thus derive from a more flexible system as well as from a system that is better at a specific moment in time. Given the slow pace of the regulatory and legislative process, this would not entail changes in middle of a crop cycle; rather, a set of observations could mean that restrictions were automatically loosened or tightened according to a preset schedule, obviating the need for ongoing legislative action.

Also on a longer scale, it is worth constraining "optimal" policy choices in the model to those that are politically feasible and legally defensible. Detailed spatial data may reveal significantly different optimal restrictions on farmers in the same jurisdiction growing the same crop using the same technology. It would be disingenuous to suggest that the VOI is contingent on such policies' being enacted.

That said, given a broader array of policy choices, MRLI data combined with hydrologic and other spatial data could be used to improve environmental quality (or reduce risks to environmental services) at minimum costs by treating neighboring parcels differently. We might use these data to identify land values that may be declining to a point where the parcels are appropriate for conservation easements, for example, and payments could be based on forgone income opportunities.

It is also worth noting that in the longer term, VOI is very sensitive to the national or international policy regime in place. In addition to the gains from improved management of water resources, monitoring of agricultural land uses and changes will provide credible baselines for measuring carbon sequestration and perhaps granting offsets. This is true globally, of course, and in an environment where offsets are valuable, the entire community of nations included in the carbon dioxide regime would gain from the sum total of land imagery available. Establishing a baseline now, assuming monitoring of changes will be needed in the future, creates an option value for farmers and regulators anticipating policy changes of this nature.

10.C.4. Monitoring and Enforcement

Some of the value associated with MRLI in this context will come from the broad applicability to monitoring and enforcement of existing law. Monitoring and enforcement are currently exogenous in this model, but repeated imagery of all farmers in a region will affect compliance behavior. Although 17-day satellite sweeps and missed observations due to weather mean that enforcement opportunities from satellite information cannot be perfect, MRLI offers more observation of practices and outcomes (with less awareness of the specifics of observation than an inspector arriving at the farm gate) than conventional practice. Over time, habitual offenders should be identifiable, and for some rules even a single pass can provide evidence of noncompliance with watershed protection law. Even limited enforcement actions taken based on this information could have significant spillovers in compliance behavior for a region (Shimshack and Ward 2005).

Agricultural nonpoint sources are enormously significant nutrient sources in strained watersheds; resource limitations and the difficulty of tracing a given pollutant load to a specific plot of land mean that enforcement is difficult and inspections relatively rare. Improved compliance as a result of farmers' expectations about the use of satellite imagery (perhaps to direct site visits) will offer reduced uncertainty not only about watershed conditions but also about land use and growers' behavior as regulations change.

10.C.5. Baselines

When fuller data are available to complete the analysis envisioned in BFRM, clarity about the specific baseline considered (and alternative baselines) will be essential. If we are considering a proposed Landsat 10 mission, for example, it will have a value relative to no use of satellite imagery in regulatory decisionmaking, a value relative to the other satellites whose data will be used if the mission does not take place, and plausibly a value relative to whatever other alternatives may be available. Each of these alternatives also has costs, either to build and run or to purchase data from. We can then estimate how much of the value of the management plan derives from the improved information associated with the MRLI source. We will never make decisions about regulating agriculture for water quality protection in an information vacuum, so the marginal value is always contingent on our expectations about the information that will be available without the mission (or without a specific instrument's inclusion in the mission).

If, as the authors suggest, the next-best information is from the Advanced Wide Field Sensor (AWiFS), which is under the charge of the Indian Space Research Organization, the VOI in the proposed Landsat mission is likely to be increased by the greater control U.S. agencies would have over Landsat. This is harder to quantify than the ecosystem services approach outlined in BFRM, but a simplified approach might rely on estimates of the probability of having to move from AWiFS to another next-best solution in a given year.

10.C.6. VOI and Time-Series Continuity

In the example given by BFRM, we are concerned with the value of information associated with Landsat imaging. One important area that is not yet extensively developed is the value of continuity in the time series. On a short-term basis, the value of one satellite mission relative to another may be roughly comparable, but most researchers would prefer a mission that offers greater continuity with past and future missions over one that does not. In particular, scientists and policymakers interested in climate change and in carbon sequestration rely on comparability of current and older imagery. Direct comparisons are especially useful for looking at trends over large scales when medium- and low-resolution imagery does not allow detailed observation of the phenomenon of interest: we may not be able to count the trees on a plot of land, but seeing how the same instrument records changing levels of things associated with trees (height of ground cover, albedo, etc.) allows us to make inferences about changing ecology, land use, and productivity over time.

Valuing this is more complex than valuing a given piece of data over its entire use cycle, which is itself not straightforward. The switch from SIC codes to NAICS codes for the collection and provision of industrial data by the U.S. government prompted some discussion of the value of continuous time-series information and of the processes used to connect different time series; the Census Bureau's Economic Classification Policy Committee (1993) report presents the core concerns of data collectors and users. It details millions spent to construct "bridge" data to help users get some of the benefits of the long series even after classification schemes has been changed to reflect new patterns of production and provide improved comparability across nations.

What value there is in continuity will not automatically accrue to ongoing Landsat missions. Each mission has differing instrumentation and data characteristics. The additional value of information that is part of a 40-year stream of information of the same sort is thus contingent on efforts to merge the varying Landsat series (or to merge Landsat data usefully with alternative space-based observations). Information about those costs or about the number and type of users who would benefit from more determined efforts in this direction is not readily available. It does, however, seem likely that efforts to connect data from various Landsat missions will be easier, cheaper, and more likely to be pursued by a single entity responsible for all the data than if Landsat observations were replaced by AWiFS, as in the illustrative case.

10.C.7. Additional Considerations

This work covers a very large area, and space precludes consideration of everything that is important or interesting in this context. An extended analysis might take into account some or all of the considerations in this section.

In BFRM, financials are allowed to fluctuate weekly in the model. This makes sense for inputs to production but is less appropriate for revenues, since farmers can typically store corn and soybeans for a time if prices are not favorable. This storage decision could be added to the model, or annual output price figures could be used to approximate outcomes of storage decisions and costs.

Consideration of farm- and community-level spatial interactions would be interesting. Do we allow the production decisions of farmers to affect those of other producers spatially near them? If one farmer changes her crop rotation, do the neighbors respond? There may be thin local markets in processing or storing facilities or farm labor, or limited transportation or storage infrastructure that vitiate incentives toward more homogenized crop patterns in a region. This could operate through increased input costs or input cost volatility, affecting expected profit and income volatility.

Analysts would also need fuller details on the actual instrumentation considered for a given mission and how it could be used. For those unfamiliar with the details of the program, information about what spectra will be measured at what level of detail, and which will be used for the regulatory purposes envisioned, would clarify the application of the methodology to the illustration. Is the regulator hiring staff to visually inspect images of farms? Are heat and albedo sensors informing estimates of growth rates or nitrogen concentrations in specific locations? VOI will be very sensitive to the specific instrumentation and uses envisioned.

Lastly, broader consideration of ecosystem services, including carbon sequestration, biodiversity support, and erosion outcomes, would provide more opportunities for enhanced regulatory decisionmaking, thus increasing the VOI to environmental management based on MRLI.

10.C.8. Conclusion

The authors integrate a complex set of hydrogeologic, biophysical, social, and economic models to provide an estimate of the state of water quality and agricultural products in a given region with regulators with identical preferences but two possible data sources. The value to society of better information in this setting is estimated by examining the effects of changes in regulations associated with higher-quality MRLI. Although applying this approach will be data and time intensive, and explaining it to decisionmakers will need to done very carefully, this is an important step toward estimating the value of satellite information in a broad array of uses.

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