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Land preservation decisions: theoretical and empirical analysis

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Land preservation decisions: Theoretical and empirical analysis

by

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For the Major Program

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ABSTRACT

There is a great concern that human actions are leading to increased rates of extinction of species. Ecologists have pointed out that the most important threat to wildlife comes from habitat alteration. The rapidly increasing human population and the resulting pressing demand for food and living space are pushing highly diverse natural areas into agriculture and other alternative uses. Recognizing this, the Federal agencies and private organizations, such as the Nature Conservancy, are becoming increasingly engaged in programs for conservation of species, where habitat restoration is an important component. However, this conservation is costly and there is uncertainty in the efficacy of preservation. Thus, it becomes important to consider these aspects for efficient conservation.

This dissertation examines the effects of uncertainty, ecological and land conversion irreversibility, and endogenous learning on land conversion decisions for species preservation. The preservation decision of three types of policymakers is investigated: active learner, passive learner and non-learner. These policymakers face the same optimization problem but differ in their behavior towards learning. An experimenting policymaker or active learner updates his beliefs and understands that his actions determine the extent of the information acquired. A non-experimenting policymaker or passive learner is a Bayesian learner who understands that the beliefs may be updated in the future but completely ignores the influence of his actions on the posterior beliefs and a non-learner is one who completely ignores the prospect of learning overtime. *Experimentation effect*, which compares the active learner's preservation action to that of a passive learner, is investigated. In addition, the difference between the action of a passive learner and non-learner, termed *Learning effect*, is also analyzed.

Another important aspect of wildlife conservation policy is to determine which land cover to adopt in order to benefit the species population. The applied work of this dissertation focuses on the

direct linkage between land use and species population. Through modelling pheasant population as a function of different habitats we provide guidelines to policymakers as to which land cover is beneficial for pheasants in Iowa. Also, regional variations in pheasant population response to habitat cover are brought to light. The data on pheasants is obtained from the IDNR annual roadside survey and the land use data source is the NRI.

CHAPTER 1. INTRODUCTION

There is a great concern that human actions are leading to increased rates of extinction of species. As one response, the Congress passed the Endangered Species Act (ESA) in 1973. Among other things, this act requires Federal agencies to undertake programs for the conservation of endangered and threatened species. Habitat restoration is an important component of these programs. The United States Fish and Wildlife Service (FWS), Environmental Protection Agencies (EPA), the United States Department of Agriculture (USDA), among other Federal agencies, are all actively involved in protecting and restoring habitats through purchase and contract of land. In addition, private organizations such as The Nature Conservancy, Ducks Unlimited and the Audubon Society are also engaged in this endeavor.

Conservation of biological diversity is of vital importance to humanity since some level of biodiversity is essential to the functioning of ecosystems on which we depend. The exceedingly high rate of species extinction is a manifestation and indicator of biodiversity loss. A species may also have current use value through returns from harvesting and wildlife related recreational activities. For example, in Africa harvested species make a considerable contribution to human welfare in the form of food. In the United States, a large percentage of the population participates in recreational activities in a given year, thus providing sizable gains from "eco-tourism". In addition to having current use value species may turn out to be valuable in the future and thus have positive option value [Arrow and Fisher, 1974; Fisher and Hanemann, 1986]. For instance the use of species is considered promising in developing new medicines to fight deadly diseases like cancer. Recent literature has studied the bioprospecting value of species conservation [Rausser and Small, 2000;

Barrett and Lybbert, 2000]. Furthermore, species also have existence value since people may yield utility from simply knowing that species exist.

Over-exploitation of species is considered to be one of the driving forces behind the increased rates of extinction of species. Species, as also other biological resources, are not given appropriate prices in the market place. Even in cases where they are traded directly in the market, species may have associated values that are not reflected in its price.[1] Agents who derive benefit from exploiting these resources seldom pay the full cost of their exploitation; instead, these costs are transferred to the society as a whole. Biological diversity, thus, is a standard case of a public good. Moreover, the costs of depleting biological diversity are usually intangible and widespread, and individuals and industries can often gain benefits without paying for them, which leads to the classic free rider problem. In fact, the species which are most exploited tend to be the ones with the weakest ownership. Most of the open access resources face this problem in the absence of well-defined property rights. Cornes and Sandler [1999] and Ostrom [1990] provide an excellent discussion of this problem.

Pollution of the atmosphere, water and soil may be another factor responsible for reducing or in some cases eliminating the population of species. Agricultural activities like spraying pesticides, irrigation and harvesting result in pollutants such as sediments, pesticides, and salts, which are major contributors to ground water contamination and adversely affect the water quality of lakes and rivers. According to a World Wildlife Fund (WWF) report, 60 million birds are killed annually by legal pesticide use in the United States. Soil microbes have also suffered from pollution as irrigated agriculture brings on salinization. In addition, excessive use of pesticides can contaminate the food chain: barn owl populations in the United Kingdom fell by around 10 percent due to the introduction of new pesticides (World Resources Institute). Air pollution is considered to be another source of dwindling populations of species. One of the serious consequences of air pollution

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[1]Many species are traded directly in the market as food (for example, species of fish). Also, demand for precious commodities, such as ivory, derived from species has impinged on some populations.

- global warming - could play havoc with the world's living organisms. In the Unites States rising seas in the next century may cover the entire habitat of at least 80 species already at the risk of extinction (World Resources Institute).

The most important threat to wildlife, however, comes in the form of habitat alteration [Primack, 1993; Maser, 1999; Sutherland and Hill, 1995; Outlook, 2000]. The rapidly increasing human population and the resultant pressing demand for food and living space is pushing highly diverse natural areas into agriculture and other development activities. This alteration is further encouraged by the fact that the benefits of conservation are often intangible, widely spread and not fully reflected in the market prices, in contrast to the benefits of exploiting these natural areas, which are usually easily measurable. Although forest conversion in the developed countries has not been as dramatic as in the developing countries,[2] forest degradation in these regions remains significant. Forest degradation endangers species survival and can also produce adverse changes in the local microclimates making native species more vulnerable to predators and disturbances such as drought and pest infestations.

Habitat loss is especially taxing for endemic species and migratory species. Since the former have a restricted range, habitat alteration could easily drive the species to extinction. Some 233 mammals and 160 birds are endemic to North America (Commission for Environmental Cooperation, 1999). Endemism in the United States is highest on islands, especially Hawaiian Islands, where 95 percent of the mollusks, 43 percent of the birds and 30 percent of the inshore fishes are unique to those islands [Allison et al., 1995; Hourigan and Reese, 1987]. Migratory species depend on suitable habitat in their summer and winter ranges and also along the course of their migratory route. Thus, the potential for adverse effects of habitat changes on migrant populations is high. In North America, Kirkland's warbler, Backman's warbler and the Whooping Crane are endangered because habitat in both their breeding and wintering ranges has shrunk.

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[2]In the developing countries within a span of just three decades (1960-90) one fifth of all natural tropical forest cover was lost.

There is, by and large, a consensus on the importance of species conservation and recognition of the seriousness of the threat to their long-term survival. The irreversibility aspect of this loss makes it necessary to take action to prevent the extinction of species. However, conservation comes at a cost. This cost includes the direct cost of purchasing and maintaining land for preservation as a wildlife habitat and the opportunity cost in terms of the forgone returns from this area. Thus, it is essential to judge the investments in conservation in economic terms. Often these investments have to be made under conditions of uncertainty regarding the effectiveness of the land as a wildlife habitat. As a result, it becomes difficult to have a deterministic estimate of the benefits associated with conservation action.

The purpose of this dissertation is manifold. It aims to bring out the different aspects of the problem of conservation of species by preservation of land. A theoretical model is developed to analyze a regulator's problem whose goal is to determine the optimal conversion of land with conservation of species as the objective. Two important innovations in addressing this problem are introduced. First, endogenous learning is introduced to the real options literature. There is uncertainty regarding the response of species to land preservation. Second, conflicting dual sources of irreversibility are incorporated in the model structure. Specifically, the loss of species is irreversible and the costs entailed in conversion of land to a preserved habitat are sunk. Thus, one of the contributions of this dissertation is to analyze the regulator's conservation problem as a continuous investment decision in light of the opposing forces of irreversibility when he is an active learner.

The uncertainty regarding the effectiveness of the converted land as a wildlife habitat is captured by assuming that the efficacy of land can either be "high" or "low". In the presence of uncertainty, the dual and opposing sources of irreversibility complicate the regulator's decision-making problem. If he invests too little in restoration, then this may lead to irreversible loss of species. On the other hand, conversion is costly. If the land converted turns out to be ineffective as a wildlife habitat,

it will be costly to reverse the purchase and sunk costs will be unrecoverable. Thus, both the "purchase" and "don't purchase" decisions contain an unrecoverable loss in the event that the decision is reversed. The regulator will want to incorporate these potential losses in an optimal preservation decision

Further, the regulator can learn about the efficacy of land by observing the outcome of the first period preservation decision and consequently can update his belief. The extent of learning, in turn, depends upon the first period decision. In other words, the regulator can "choose" how much future information he will receive. However, learning is not perfect since there is another source of uncertainty arising due to random environmental shocks. Adverse (favorable) shocks could bring about a decrease (increase) in the population of species irrespective of the type of land.

The regulator's problem is modelled as a closed loop stochastic dynamic optimization problem and the resulting optimal solution is analyzed. Taking this experimenting (active learning) solution as a benchmark, the optimization problem of a non-experimenting (passive) regulator and that of a non-learning regulator are studied. A passive regulator responds when he receives new information in the future, but ignores that his current actions influence the amount of future information. This scenario is similar to the typical real options approach. In contrast, a non-learner acts in the first period as if no new information will ever arrive. Experimentation effect, defined as the difference in the first period action of an experimenting and a non-experimenting regulator, is analyzed. Further, the learning effect, which corresponds to the difference in first period preservation decision of a passive regulator and that of a non-learner and thus measuring how the ability to learn affects the first period choice, is also studied.

The next chief contribution of this dissertation is to empirically study the direct link between species population and land use. In doing so, the important, yet complex, spatial and temporal correlations that characterize this problem, are also addressed. This empirical model is applied to a species of particular game importance in the Midwest: ring-necked pheasant populations. The

response of ring-necked pheasant populations to four land management practices is studied, the latter being: Conservation Reserve Program (CRP) land, pastureland, non-cultivated land and cropland, which includes corn and soybean.

The empirical analysis is conducted for two regions of Iowa: Northern Row Crop region and Southern Pasture region. Data on land uses is from the National Resources Inventory (NRI) database, while the pheasant count data is obtained from the Iowa Department of Natural Resource (IDNR). An important issue in applying spatial econometrics techniques is to identify a common spatial units to link the data sets. In this analysis, this common spatial unit to link IDNR annual pheasant count data and the NRI data on land use is identified as the polygons resulting from the intersection of the Major Land Resource Area (MLRA) and 8-digit Hydrological Unit Code (HUC). The Northern region has 14 such polygons, while the Southern region comprises of 9 polygons.

Spatial error dependence (spatial autocorrelation) is explicitly considered in this empirical model. Spatial dependence among the errors across observations can be expected to arise due to omitted variables that are themselves spatially correlated. In this study, disturbances in a polygon is likely to have similar effects on neighboring polygons due to their geographical proximity. A second feature of the error structure of this model is accounting for the possibility of temporal correlation of the data. Most studies of spatial dependence have abstracted from the potential complexities introduced by both space-time considerations. However, in this study, correlation across time (serial correlation) is likely to be important since many of the variables that influence the species population are either time invariant or highly correlated over time, for example the type of soil, presence of streams and other natural water sources, etc.

In addition to assessing the impact of four common land uses on pheasant counts, this study also tries to highlight the importance of regional variations in those impacts. This analysis demonstrates that the same land uses can have a regionally variable impact on pheasant count and this can be valuable in land management policies targeting conservation of wildlife.

Finally, this dissertation explores Bayesian inference of the response parameters of the four land uses on pheasant count. In the presence of spatial dependence of the errors, the posterior probability for these response parameters is constructed using Monte-Carlo simulation methods. This enables the study of the entire probability support of the response parameters. Gibbs and Metropolis-Hasting approaches are employed to obtain the Bayesian posterior estimates for the response parameters.

The remainder of the dissertation is organized as follows: Chapter 2 reviews the literature in detail. The background concepts, along with a discussion on the importance of species conservation, are also presented. The theoretical model for examining the regulator's problem and the role of learning in his decision-making is developed in Chapter 3. Chapter 4 presents the empirical model and reports the estimation results. Bayesian inference of the model parameters is conducted in Chapter 5. Finally, conclusions and policy implications are presented in Chapter 6.

CHAPTER 2.   REVIEW OF CONCEPTS AND LITERATURE

In the following sections the concepts behind the importance of species conservation and habitat restoration are reviewed. The various programs initiated by the federal agencies and the contribution of private agencies towards this cause are also examined. I review the relatively new but rapidly growing body of literature that studies the economics of conservation. Next, I look at the information economics literature and provide insights as to why experimentation may be important. Finally, a brief review of spatial econometrics literature and Bayesian approach to decision-making is presented.

2.1   Theory and Concepts

It is believed that some of our planet's greatest wealth is contained in its biological resources. However, the current processes of development are depleting these resources at such a rate that they are being rendered essentially non-renewable. As long as the average rate of withdrawal does not exceed the average rate of replenishment, a renewable resource is sustained overtime [Ostrom, 1990]. The current rate of extinction for birds and mammals is between 100 and 1000 times greater than would be expected to occur naturally (UNEP). Thus, effective systems of management are required to ensure that these resources not only survive, but also increase, providing the foundation for sustainable development and for stable economies.

The biological resources, such as forests, mountains, wetlands and marine habitats are the physical manifestation of Earth's biodiversity. It is standard in ecology to consider biodiversity at three levels: genetic diversity, species diversity and ecosystem diversity [Maser, 1999; McNeely,

1988]. Genetic diversity accounts for the variability within a species as measured by the variation in genes. Thus, a large population of a particular species greatly increases the chances of attaining a high genetic diversity. In the absence of genetic diversity the population can be more easily devastated by a disease or climatic disturbances. In contrast, species diversity is related to the variety of living organisms on Earth or a given area and finally, ecosystem diversity is associated with diversity and health of ecological complexes.

One essential element in maintaining biodiversity is to ensure that no species falls below the minimum critical population size. This is captured by the safe minimum standard (SMS) concept, which was initiated by Ciriacy-Wantrup [1964] and Bishop [1978]. Since loss of species entails an irreversible resource loss the SMS was advocated. However, SMS has been criticized for incompleteness and inconsistency [Norton, 1995; Krutilla and Fisher, 1975; Ready and Bishop, 1991]. Farmer and Randall [1998] present an insightful discussion on the pros and cons of SMS and suggest changes to it in order to reach a consensus.

Since the 1980s there has been a conscious effort towards dealing with key environmental problems like global warming, pollution and extinction of species. The growing recognition of these global environmental problems has resulted in numerous strategies developed to guide a sustainable approach to use of the earth's natural resources. The conservation of species has gained foremost importance. This is because the conservation of biodiversity has generally been interpreted in terms of species diversity.[1] Moreover, although the loss of biological diversity may take many forms, the extinction of species is usually taken to represent its most dramatic and irreversible manifestation.

The flow of accurate information on the status of species is critical to attempts at saving them. The number of documented species extinction over the past century is small compared to those predicted for the coming decades. This difference is due, in part, to the acceleration of rates of habitat loss over recent decades but also to the difficulty of documenting extinctions. Species are

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[1]This is usually referred to as 'species richness', or the number of species in a site or habitat (UNEP World Conservation Monitoring Commission, 1992).

generally not declared to be extinct until years after they have last been seen, thus figures for documented extinctions are highly conservative (WRI). Also the paper work involved in declaring a species endangered under the ESA takes time. In the past decade, at least 34 species or unique populations of plants and vertebrates have become extinct in the United States while awaiting federal protection (WRI).

Though there is recognition that one of the major threats to biodiversity is the loss of species there are some critics of this notion too. Some have argued that the rate of biodiversity loss is exaggerated and there is no need to be concerned about extinctions. However, although there is uncertainty about the exact rate at which the species are becoming extinct, there is no doubt among mainstream scientists that there is a real danger of mass extinction of species (Defenders of Wildlife, National Survey on Biodiversity). Another argument is that even if the risk of extinction is high, technological advances, such as genetic engineering, will ensure that this loss is not detrimental to human beings. In other words, extinctions do not matter. Technology has been successful in at least providing partial solutions to some environmental problems (such as ozone depletion, acid rain) in the form of alternative energy sources and industrial chemicals.[2] However, ecosystems are so complex and so little is understood about them that once destroyed it would be impossible to rebuild them on a large scale. Despite decades of trying, skilled specialists find it difficult or in many cases impossible even to restore damaged U.S. saltwater wetlands, which are some of the simplest in the world in terms of their species composition [Jordon and et. al, 1988]. In fact the ecological literature provides several examples of failed attempts of introducing a single new species into a functioning ecosystem. In one such case, opossum shrimp were introduced into Flathead Lake, in Montana, to provide a new food source for kokanee salmon, a popular game fish. Unpredictably, the opossum shrimp ate so much zooplankton that there was little available as food for the salmon. As a result, the population of salmon declined greatly, along with bald eagles that relied on them

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[2]Implementation though depends on the costs involved and political will.

[Primack, 1993].

Once the need for conservation has been recognized it is important that the conservation promoting agencies incorporate economic methods into their efforts to conserve biological diversity. In order to seek ways to use economic methodology to support conservation, it is essential to understand the major threats facing the existence of species. The traditional view is that the main reason for the dwindling populations of species is over-exploitation. Economists have cited the public good nature of biological resources as the chief reason behind the species and the ecosystems being over-exploited [Ostrom, 1990; Ready and Bishop, 1991; Fisher and Hanemann, 1986]. In addition, the social benefits derived from conserving these resources are often intangible and not fully reflected in the market price. Thus due to the presence of these externalities, the benefits of protecting natural areas are seldom fully reflected in the traditional cost-benefit analysis. In contrast, the benefits of exploiting resources can usually be easily measured.

Eminent biologist Wilson [1980] pointed out that the major threat lies in habitat alteration. This relates to land-use changes on a regional scale, which entail scaling down the natural vegetation of the area that often results in reductions in population of the species. The past decades have witnessed drastic shrinking of relatively undisturbed ecosystems. Ninety-eight percent of the tropical dry forest along Central America's Pacific coast has disappeared. It is estimated that one-third of the species in the United States are at risk because of habitat destruction and the consequent declining populations. In most cases, habitat alteration takes the form of direct conversion for agricultural purposes. Climate change, related to the change of regional vegetation patterns, is also cited as being responsible for the declining species population. This involves factors like global warming, which lead to a risk of species loss. Pollution of soil, water and the atmosphere is another major threat to the population of species.

2.2   Conservation Programs

One of the most effective and important ways of protecting species and their habitat is through the establishment of protected areas. In North America, approximately 2.5 million km^2 of land, freshwater and marine areas have been set aside as national parks and other types of protected areas (Commission for Environmental Cooperation 1999). This amounts to around 9 percent of North America's total land area. In the United States a number of Federal programs have been initiated to protect the species. In addition, several private organizations are also taking up this cause.

The Nature Conservancy is one of the world's leading private international conservational groups that has, since 1951, successfully protected more than 100 million acres of valuable land and waters worldwide. The mission statement of the Conservancy is to "preserve the plants, animals and natural communities that represent the diversity of life on Earth by protecting the land and waters they need to survive." The Conservancy and its members have been responsible for the protection of more than 12 million acres in the United States and it owns more than 1,300 preserves in the country (The Nature Conservancy's Annual Report, 2000). They employ a number of tools to accomplish the goal of preservation, including acquisition, conservation easements, and management assistance, among others. The Iowa Chapter, founded in 1963, has since then purchased over 6,000 acres of land. At present, they own 30 preserves, lease two and participate in the management of one (Annual Report, Fiscal Year 2000).

Another successful private organization working towards the endeavor of habitat restoration is National Wildlife Federation (NWF). This organization has been involved in restoring some of the remnants of the native prairie in the Dakota region. America's prairie grassland once covered forty percent of the continental U.S. However, only small fragments of these remain as prairies have suffered greater habitat conversion than any other North American habitat type. Consequently, the wildlife residing in this habitat has been severely effected. According to the latest newsletter

of NWF, 55 grassland species are either threatened or endangered with extinction and another 728 species are candidates for listing.

Other notable private agencies targeting conservation of wildlife through preserving their habitats are: Mule Deer Foundation (MDF), Nevada Waterfowl Association (NWA), Ducks Unlimited, Pheasants Forever among others. The MDF aims at the conservation of mule deer and blacktail deer and thus are involved in restoring improving and protecting their habitat. One of their main tools for accomplishing this is through land and easement acquisitions. The mission of NWF is to protect, restore, and enhance Nevada's wetlands and the wildlife dependent upon them, chiefly, waterfowl and shorebirds. They have been working closely with state departments and like-minded organizations such as Ducks Unlimited. Pheasants Forever is an important private organization involved in habitat restoration of pheasants. Since 1982, this organization has grown to include 55,000 members in 40 chapters across the U.S. and has raised and spent more than $7 mn on chiefly habitat restoration projects. In the twelve month period starting July 1, 1989 and ending June 30, 1990 they encompassed 155,700 acres through various projects across the country. Then there are organizations like Teeming with Wildlife (TWW), which is a coalition of more than 3000 groups that have joined together to protect the wildlife and their habitat by lobbying for increases in federal funding for wildlife conservation.

Among the federal programs, a program that has proven to be highly effective and widely accepted across the country is the Wildlife Habitat Incentives Program (WHIP). The Federal Agricultural Improvement and Reform Act of 1996 (Section 387), amended the 1985 Farm Bill authorizing WHIP as a voluntary program encouraging people to develop and improve habitat primarily on private land. This program is administered by the Natural Resources Conservation Service (NRCS), which is a division of the USDA. Through WHIP, NRCS provides both technical assistance and up to 75 percent cost-share assistance to landowners to apply an array of wildlife practices to develop habitat that will support upland wildlife, wetland wildlife, threatened and

endangered species, fisheries and other types of wildlife. The WHIP agreements between NRCS and the participant generally last 5 to 10 years from the date the agreement is signed. Of the total acreage enrolled in WHIP,[3] approximately 20 percent of the acreage will benefit threatened and endangered species. In the 1996 Farm Bill $50 million was authorized for this program, which was fully exhausted by 1999 (Budget Summary, NRCS). In order to continue the program new legislature plans to be proposed authorizing an additional $10 million in spending for WHIP in the next Farm Bill. In Iowa, areas targeted by NRCS include 14 counties in south central and west central Iowa for grassland restoration and six Northeast Iowa counties for riparian areas and cold-water stream restoration. The WHIP-funded stream enhancements support restoration work that has resulted in natural trout reproduction in 25 streams.

Several other federal programs initiated are broader in their approach, and are not entirely devoted to wildlife protection, but have conservation of species as one of their goals. The programs, including Environmental Quality Incentives Program (EQIP), Wetland Reserve Program (WRP), and Conservation Reserve Programs (CRP), provide incentive payments to landowners to voluntarily address threats to the environment by employing eco-friendly practices (cost-share programs).

Wetlands are beneficial in several ways, namely, providing wildlife habitat; improving water quality by filtering sediments and chemicals; protecting biological diversity etc. WRP is a voluntary cost-share program which provides an opportunity for eligible landowners to receive financial assistance to enhance wetlands in exchange for retiring marginal land from agriculture. WRP was reauthorized in the Farm Bill of 2002. CRP, established under the Food Security Act of 1985, also involves cost-share assistance to private landowners to convert highly erodible cropland to vegetative cover. An offspring of CRP, Conservation Reserve Enhancement Program (CREP), is a voluntary program for agricultural landowners. It was authorized in the 1996 Federal Agriculture

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[3]This is estimated to be 672,000 acres.

Improvement and Reform Act. This program is a joint, state-federal land retirement conservation program which provides landowners incentive payments for installing specific conservation practices. Typically it entails agricultural landowners to enroll in contracts of 10 to 15 years in duration to remove lands from agricultural production.

A new program called Soil and Water Conservation Assistance (SWCA) has been authorized under the Agricultural Risk Protection Act of 2000 under the administration of NRCS. SWCA provides cost share and incentive payments to farmers and ranchers to voluntarily address threats to soil, water and related natural resources, including wetlands, and wildlife habitat. These contracts are for five to ten years. The federal cost share is 75 percent of the cost of an eligible practice and the SWCA is budgeted at $20 million for the fiscal year 2001. An important program that provides technical assistance is Grazing Land Conservation Initiative (GLCI). Established in 1991, GLCI's mission is to provide high quality technical assistance on privately owned grazing lands on a voluntary basis. The benefits derived from this program are among others, healthy wildlife populations and habitat; improved fisheries and aquatic systems; and healthy riparian areas.

2.3 Literature Review

In this section I review the environmental literature emphasizing on the studies which deal with investment decisions in the face of irreversibility and uncertainty. Finally, I review the experimentation literature and also briefly review the spatial econometrics techniques.

2.3.1 Environmental Economics

Development, as opposed to preservation of land, has been an issue studied in environmental economics for a long time. Arrow and Fisher [1974] and Henry [1974] dealt with the impact of uncertainty and irreversibility on development decisions. The concept of option value, advanced independently by them emphasizes on the importance of inter-temporal resolution of uncertainty.

They concluded that irrespective of the risk preferences of the decision maker, given the prospect of future information and the irreversible nature of the development decision, there is a premium attached with postponing development.

The seminal literature by Arrow and Fisher [1974]; Henry [1974]; Freixas and Laffont [1984] and others, has emphasized the role of irreversibility in environmental policy decisions. This literature shows that if a current decision is irreversible, then the possibility of getting better information in the future about future benefits or costs of current actions should lead to current decisions that involve a lower level of irreversible commitment than would be made if there was no possibility of getting better information. This has been referred to as the 'irreversibility effect'. In a widely cited paper, Chichilnisky and Heal [1993] have argued that this aspect of irreversibility should be taken into account in studying global warming. Ignoring this, they contest, may lead to significant understatement of the need for immediate reductions in emissions of greenhouse gases.

Epstein [1980] has, however, shown that this irreversibility effect may not hold for all models dealing with irreversibility and uncertainty in environmental decisions. He examines the effects on period 1 decision of the prior uncertainty in expectations by way of a consumption-savings model and a typical model of a production firm. Consumption of period 1 wealth is an irreversible decision since it limits future consumption-saving options. However, he finds that the first period consumption (savings) does not unambiguously fall (increase) in response to an earlier resolution of uncertainty. The parameter on which this response depends on is the relative risk aversion constant of the utility function. He shows a similar result considering a strictly concave production function for a profit maximizing firm producing a unit of output using labor and capital, where the output price is uncertain. Both factors of production must be hired or purchased in advance of the actual date but the lag is larger for capital. Again, he concludes that the direction of the optimal employment of capital with earlier resolution of uncertainty is not clear. It depends on the curvature of the value function with respect to the output price. Using these examples, he provides

sufficient conditions for the irreversibility effect to hold.

Ulph and Ulph [1997] address the same issue of how the possibility of getting better information affect future policies in the face of irreversibility and uncertainty in the context of global warming, where better information is sought about the possible extent of damages caused by global warming. They show that even for the simplest model of global warming neither of Epstein's sufficient conditions hold, hence leaving the question of whether the irreversibility effect applies to the global warming problem unanswered. Ulph and Ulph [1997] then proceed to derive an alternative sufficient condition for the irreversibility effect to hold for the global warming problem. Their sufficient condition states that if the irreversibility constraint bites in the case where there is no possibility of learning, then irreversibility effect must hold. In this case irreversibility effect implies that the stock of greenhouse gases at the end of the current period must be lower when there is a possibility of learning in the future about the damage costs of global warning than would be the case if there is no possibility of learning.

A notable paper in the same spirit as Fisher et al. [1972] is Miller [1981]. The former have stated that in the face of irreversible commitments of resources and rising relative benefits of preservation through time, development should proceed at a rate slower than that indicated by comparison of current benefits and costs. Miller [1981] brings out the irreversibility concept, using the standard inter-temporal welfare maximization model, with an application to the preservation of endangered species. Specifically he focuses on two points: first, the possibility of existence or utility value for a stock of wildlife species, and second the implications of irreversible commitments of resources.

The model structure is as follows. He assumes that there are two goods: a private good and a public good, the latter being the stock of a wildlife species. Production of each requires two inputs: land and non-land resource. The production functions of these two products are known with certainty[4] and also the resource constraints are given. There are S identical agents in this

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[4]Note, there is no uncertainty in this analysis.

economy.

Miller [1981] formulates a welfare maximization problem using a general social welfare function defined over the utility of S individuals for a planning horizon equal to T. As is standard, this welfare function is subject to the production functions of the two goods, the constraints on land and non-land resources, the irreversibility condition[5] and the adding up constraint for the private good. They show that if the irreversibility constraint is binding and the severity of this constraint is increasing over time (the lagrange multiplier corresponding to this constraint increases over time) leads to more land being devoted to species preservation as compared to when the irreversibility constraint is not binding. He also notes that the essence of the results is unchanged if instead it is assumed that the habitat can be reconverted at some cost. Then the lagrange multiplier corresponding to the irreversibility constraint is, in equilibrium, equal to the marginal cost of reconversion. Hence, conversion of land from habitat to private use should be more conservative if the marginal cost of conversion is rising with time.

An issue that often arises in the literature when evaluating the importance of preservation is option value. Whenever a decision has the characteristic that one of the possible outcomes is irreversible and there is some prospect of better information about the future benefits and costs of these outcomes, option value arises. Fisher and Hanemann [1986] have an excellent discussion on the role of option value in a cost-benefit analysis of resource development projects that effect habitat. They present a model of the decision to develop a natural environment that takes into account both the irreversibility of development and the uncertainty about the values development would preclude. However, in their analysis learning is assumed to be exogenous. They also work out an example in which they calculate the option value empirically and show that it may be substantial compared to the benefits estimated conventionally.

Most of the literature, including Arrow and Fisher [1974], Henry [1974], Capozza and Li [1994],

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[5]The irreversibility constraint is specifies that once the land has been used for the private good it can not be reverted back to being used for the public good, the latter being species habitat

Pindyck [2000] among others, deals with optimal timing of investment considering a binary choice model: to develop or not to develop. While the irreversibility arising from development activity is captured well in this literature, the irreversibility associated with environmental policy, such as investment in abatement capital to counter pollution or preservation of land to prevent extinction of species, has been largely ignored.

In the recent literature, however, some light has been shed on this issue. Kolstad [1996] has analyzed the existence of two types of irreversibility in the case of stock externalities. He discusses this in the context of the problem of global warming where the future damage caused by GHG is uncertain. In this scenario if one over-emits and then finds that the damage from the pollution stock is too high; one cannot immediately reduce that stock. Analogously, if one invests in pollution control and then learns that damage is low, one cannot instantly reduce the abatement capital stock. He concludes that only when one of the irreversibility constraints is binding does one obtain a bias in today's control decisions owing to irreversibility. In the absence of binding constraints if there is a bias in favor of the environment then it is a risk aversion and not irreversibility effect.

Pindyck [2000] considers two types of irreversibilities, working in opposite directions. First, sunk costs in the form of abatement investment. Second, environmental damage can be partially or totally irreversible.[6] He concludes that, in the presence of the irreversibility, an increase in uncertainty over the future social cost of the pollutant leads to a higher threshold for policy adoption. He argues that policy adoption involves a sunk cost associated with a discrete reduction in the entire trajectory of future emissions, whereas inaction over any small time interval only involves continued emissions over that interval. Thus, in his framework greater uncertainty always leads to greater delay, although the effect is smaller the smaller is the natural decay rate of emissions.

Pindyck [2000] develops a model with two types of irreversibility - sunk costs in the form of abatement investment and the irreversibility associated with environmental damage - and two

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[6]His conclusions are based on the assumption of complete irreversibility.

types of uncertainties, economic uncertainty, which relates to the uncertainty over the future costs

or benefits of environmental damage and its reduction and ecological uncertainty, which he terms as

the uncertainty over the evolution of the relevant ecosystems. He analyzes how irreversibility and

uncertainty[7] interact in affecting the timing of a one-time policy adoption decision aimed towards

the problem of global warming. He concludes that an increase in the level of uncertainty, whether

considering economic or ecological uncertainty, leads to a higher threshold for policy adoption.

Bosetti and Messina [2001] also look at a similar problem. However, unlike Pindyck [2000], who

analyzes the global warming problem, they deal with land allocation problem. They consider that

the decision maker has three options - to let the land remain in its present use, convert it into a

national park or develop it. Using a discrete choice infinite time model, they analyze the inter-

action between the two types of irreversibility and uncertainties entailed in the decision making.

The two types of uncertainties that they account for are market uncertainties; those associated

with returns from development and uncertainty regarding demand for wilderness. And environ-

mental uncertainty attached to the national park choice, depending on a vector of environmental

parameters.

Both the alternatives to the status quo option: development and land recovery/conservation

(National Park) entail sunk costs. These are the two types of irreversibility. The irreversibility

corresponding to the development option is perfect, i.e. land cannot be reverted while national

park at an additional cost the can be developed. They assume a probability for each of the states

of nature and this gets revised after every time period as more information comes forth. They

analyze how the threshold initial values of returns from both the development option and the

national park option, which separate the continuation (do not invest in the option) from stopping

(invest in the option) region, vary with the parameters of the model.

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[7]He treats economic and ecological uncertainty separately. In other words, the two types of uncertainties are not simultaneously present in his analysis.

2.3.2 Experimentation Economics

A number of studies within the literature on information economics have dealt with the effect of experimentation on the process of information acquisition and on the optimal level of the investment decision. An experimenting agent is said to be one who updates his beliefs (according to Bayes' rule) and understands that his actions determine the extent of the information acquired. In other words, he considers the effect of his present action on future beliefs. The behavior of an experimenting agent has been referred in the literature as *active learning*. On the other hand a non-experimenting agent is a Bayesian learner who understands all the dynamic implications of his action - the effect on the signal and thus, that the beliefs may be updated - but completely ignores the influence of his actions on the posterior beliefs. This is referred to as *passive learning*. While, an agent who does not update his beliefs at all is called a *nonlearner*. This literature also talks about a myopic agent, who completely ignores the future and solves a one period problem.

There are several of examples in the literature where information economics has been applied to deal with environmental problems. Polasky and Solow [2001] analyze the role of information in reserve site selection problem when the incidence of species is uncertain. The goal is then to select reserve sites to maximize expected coverage. This decision is constrained by the feasibility constraint, which fixes the number of sites that can be selected. The prior probability of incidence of species i in site j is known and denoted by p_{ij}. The resulting maximized expected coverage is denoted by M^*.

New information about species incidence is obtained, for example, through site surveys. The prior belief is updated according to Bayes theorem and the posterior probability of the incidence of species is obtained. The quality of this information flow or signal is given by the conditional probability that the survey detects the species given that it is present and is denoted as q.[8] Using the new solution, corresponding to the revised probability, the expected maximized expected coverage

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[8] This suggests that the signal is noisy. Though it is assumed that there are no false detections, the conditional probability of the survey detecting the species given its presence is not 1.

is denoted by: $E(M^*(Y))$. The value of information is then the following: $V(Y) = E(M^*(Y)) - M^*$.

Polasky and Solow [2001] employ stylized examples to analyze this value of information and arrive at some intuitive conclusions. They emphasize on the tradeoff between the quality of information as measured by q and the number of selected sites. When only one species is considered and the prior incidence probability of species is the same across all the sites they propose the following. The value of information is higher if the quality of the signal is high (say $q = 0.9$) and the number of the sites that can be selected are few compared to a scenario when the signal is of low quality and the number of sites that can be selected is high. Also, the gain in information will have no value if there is no constraint on the number of sites to be selected. Thus reflecting the general principle that information only has value when it may influence site selection.

Another notable paper on site selection under incomplete information regarding species incidence is Polasky et al. [2000]. Specifically, this paper compares the choice of sites when uncertainty regarding the species incidence is taken into account and the sites selected when the uncertainty is assumed away. They find that these different methods of site selection lead to different choices. Not surprisingly, these differences are significant when probabilities of species occurrences are not near 1 or 0.

An interesting paper that deals with flexible versus inflexible decision procedures, in other words the role of information, in environmental decisions is by Miller and Lad [1984]. They study a two-period decision problem involving a proposed resource development project. It is assumed that the resource under study can either be preserved or developed, where the latter is irreversible. In addition, the benefits and costs associated with the two activities are uncertain. They consider that the amount of learning depends upon the particular action taken in the first period (i.e. there's active learning). Note that they do not consider an either/or problem. Their characterization of the decision space is as follows:

$$D = \{(p_1, p_2) | p_1 \in [0, 1] \text{ and } p_2 \in [0, 1 - p_1]\}. \tag{2.1}$$

This represents that the undeveloped resource is limited or has been normalized to 1 and p_1 and p_2 denote the proportions to be developed in periods 1 and 2 respectively. They consider a fixed decision procedure - the p_1 and p_2 are decided upon in the beginning of the first period itself. Then they analyze a sequential (flexible) decision which entails active learning. They refute the Arrow and Fisher [1974] and Henry [1974] statement that when irreversible actions are being considered, an optimal sequential decision procedure always entails a more conservationist action in the first period as compared to a fixed decision. They conclude that the reverse might be true if the agent expects to learn that more development is better. In addition, they also discuss a *reneg value.* An agent following a fixed decision procedure might want to renege on the commitment of the second period development. This would depend on the difference between the expected payoff of switching and that associated with sticking to the commitment plus the reneging penalty.

There is a large literature on the effect of experimentation on the short run decisions. The analysis of experimentation has been applied in a number of studies. One such application is the affect of experimentation on consumer choices of a good of unknown quality. Consumers confronted with new products experiment with them to gain information on their quality. Thus the demand for experimental consumption might increase the total demand for new products over what it otherwise would be. Grossman et al. [1977] describe a situation faced by a consumer who buys, in addition to other goods, a drug of unknown reliability. In their model, the drug purchases reflect the consumers desire to learn through experimentation. They show that, when drug consumption affects health through a linear regression equation, the possibility of learning from experience induces experimentation which in turn causes the consumer to buy more of the drug than he would if no learning took place, other things being equal.

Freixas [1981] formally defined the distinction between non-experimenting behavior (passive learning) and experimenting behavior (active learning)in the context of an optimal growth model. He shows that Grossman et al. [1977] result applies when comparing the behavior of an exper-

imenting agent and a passive learner. However, it generally does not hold when comparing the first period decisions of an experimenting decision-maker to that of a non-learning decision-maker. Since, when comparing experimenting with non-learning the conclusions depend on the effect of learning. Specifically, whether learning decreases or increases the marginal rate of investment. Bertocchi and Spagat [1998] apply this definition of experimentation to a stochastic growth model and show that the effect of experimentation on the optimal level of investment can be negative. Another application that has attracted considerable attention is the affect of experimentation on the behavior of a monopolist facing an unknown demand curve [Mirman et al., 1993; Trefler, 1993; Mirman et al., 1994]. In these models monopolist experiments with either quantity or price to learn about the demand curve and hence increase future profits.

In the seminal models of experimentation [Prescott, 1972; Grossman et al., 1977] it was established that an agent who is learning about an unknown parameter sets a higher level of the decision variable in order to increase information. In this context, a higher level of the action is more informative, and since information is valuable (dispels uncertainty) the experimentation effect on the action is always positive. Prescott [1972] points out that such an action may reduce current expected returns since the agent's investment may be higher than the one period profit maximizing level. However, the information acquired can be used to improve future returns. Thus, he concludes that greater the uncertainty and longer the time horizon the more important experimentation will be. Another work similar in spirit to Prescott [1972] is that of Wieland [2000], who uses numerical methods to study this dynamic problem. However, he finds that even when uncertainty is low experimentation can yield higher action if it results in faster learning.

Most of the extant experimentation literature assumes that the dynamic aspect of the problem is solely attributed to the affect of today's action on the signal and consequently on future beliefs. However, there are a few exceptions. Sulganik and Zilcha [1997] analyze the possibility that the set of feasible actions may either expand or contract upon the revelation of some signal. Thus, in this

case the traditional conclusion that an agent would always (weakly) prefer more information since at the worst it could be ignored [Blackwell, 1953] may not hold good. For instance, the signals may have an impact on the prices of goods, which changes the budget sets of consumers and firms and hence the feasible set of future choices. Thus, they point out the trade-off between more accurate signals allowing better decisions versus more accurate signals possibly making desirable actions infeasible. Another example of signal dependent decision problems is analyzed by Datta et al. [2002]. They examine the issue of optimal experimentation in the context of problems in which today's signal is directly payoff relevant for the future. In their model, the first period decision and the signal enter into the next period's payoff; thus resulting in an additional connection between periods besides updating of beliefs. The effect of experimentation on the first period decision is, however, ambiguous in their study. They provide conditions under which experimentation leads to more or less information.

Bergemann and Valimaki [2000] develop a market model of experimentation with informational externalities. They consider the entry of a product of unknown quality, and purchases of the product yields information on its true quality. However, they assume that performance of the product is publically observation and thus agents can learn from experiments of others giving rise to the free rider problem; rather than perform a costly experiment himself, a buyer may opt to wait and see how the market evaluates the product. Keller and Rady [1999] study optimal experimentation by a monopolist who faces an unknown demand curve which is subject to random changes. Thus, in this case the per-period returns of the agent depend on an unobserved and *changing* state. They show that in such a scenario two qualitatively very different regimes, determined by the discount rate and the intensities of demand curve switching result. One regime is characterized by extreme experimentation and good tracking of the prevailing demand curve, while the other by moderate experimentation and poor tracking. Tonks [1984] analyzed the learning effect using the Grossman et al. [1977] model of experimental consumption, modified to allow for borrowing and saving. Using

a linear utility function in a two period model, he shows that the learning effect could lead to a lower first period action.

There are a few applications of experimentation in the macroeconomic policy modelling as well (for instance, Bertocchi and Spagat [1993]; Balvers and Cosimano [1994]). In these models the government chooses a monetary policy to influence some economic variable (like real output or inflation) with an objective to minimize the expected discounted sum of a function that depends on the deviation of the realized economic variable from its target. In such a scenario, there are unknown parameters governing economic activity that the policy maker can experiment and learn about.

Most analyzes of the effect of experimentation on short-run decisions assume that the information structure is noisy, i.e. for each value of the parameter, the signal is random. Datta et al. [2000] consider the effect of experimentation when the information structure is *noiseless*; given the parameter value, the signal observed by the agent is deterministic. They show that the presence or absence of noise in the the signal can dramatically affect the direction of experimentation. Bertocchi and Spagat [1993] and Datta et al. [2002] (in the presence of *signal dependence*) have shown that experimentation may reduce information. However, Datta et al. [2000] prove that if the information structure is noiseless, then the agents *never* experiment to reduce information. Thus, if higher level of action translates into greater informativeness, then in a noiseless information structure experimentation will always increase action.

2.3.3 Spatial Econometrics

The term spatial econometrics was coined by Jean Paelinck (Paelinck and Klaassen [1979]) in the early 1970s to designate a growing body of the regional science literature that dealt primarily with estimation and testing problems encountered in the implementation of multi-regional econometrics models. The domain of spatial econometrics is considered to be the collection of techniques that

deal with the peculiarities caused by space in the statistical analysis of regional science models.

The need for spatial econometrics arises since the standard econometrics techniques tend to ignore the spatial aspects of the issues and problems which can in turn lead to misguiding results. These *spatial effects* have been categorized into two broad types (Anselin [1988]). These are: *spatial dependence* and *spatial heterogeneity*. Of the two, spatial dependence or spatial autocorrelation is addressed most often, particularly following the seminal work of Cliff and Ord [1972]. It is referred to the lack of independence which is often present among observations in cross-sectional data sets. In regional issues and problems this dependence is determined by the notion of relative location or relative space, which brings out the effect of distance. However, this notion has been extended beyond the Euclidian sense to include policy space, inter-personal distance etc.

In several applied studies, data are obtained for observations which are ordered in space and time. Thus, in these cases observations can be characterized by their absolute location. Also, data is often organized by grid cells in an artificially constructed coordinate system, such as a digitized base map of geographical information system (GIS). One of the main methodological problems present in such cases is due to the existence of spatial dependence. This is considered to be the existence of a functional relationship between what happens at one point in space and what happens elsewhere. Two broad types of conditions that can lead to this dependence are: spatial error dependence and spatial lag dependence.

One of the reasons for spatial error dependence is measurement errors. Often data is collected in an aggregate form and measurement errors are likely. Moreover, they will tens to spill over across boundaries of spatial units. As a result, the errors of one observation say in spatial unit, i, will be correlated with that in another spatial unit, j. This spatial spill-over in measurement errors is an obvious cause for the presence of spatial dependence. Spatial error dependence can be present also due to omitted variables which are correlated across the spatial units. For example, the influence of climatic conditions on the population of a species may not be explicitly accounted for, however,

neighboring spatial units will have to deal with similar climatic conditions. Thus, leading to spatial error dependence.

The other type of spatial dependence is spatial lag dependence. This arises when a variable in one spatial observational unit directly influences the observations for that variable in another spatial unit in the system. In other words, this dependence is the result of a causal relationship among neighboring entities, e.g interaction.

In the presence of spatial dependence the standard econometric results do not carry over. This is primarily due to the multi-directional nature of the dependence in space which is opposed to, say, a clear one-dimensional situation in the case of dependence over time (serial autocorrelation). Spatial error dependence (spatial autocorrelation) results in the non diagonal structure of the disturbance variance-covariance matrix. Thus, the OLS estimator is unbiased but inefficient. In wake of the inappropriateness of the least squares estimator for models that incorporate spatial dependence, there are primarily two alternatives: the Maximum-Likelihood Estimation (MLE) approach and the Generalized-Moments Estimation (GME) approach.

The MLE approach is more widely used and is the standard approach for such models. However, the maximum-likelihood techniques become increasingly difficult as the sample size grows. Kelejian and Prucha [1999] developed the GME approach that has two important advantages over the MLE approach. The main advantage of this approach is that estimation involving large samples in also relatively straightforward. While it involves matrix multiplication and calculation of the trace of $W'W$, it involves neither the calculation of the determinant nor the eigenvalues of the spatial weight matrix, which are needed to carry out MLE. Thus, GME approach allows estimation with a more flexible functional form for the spatial weight matrix. Another advantage of GME approach is that it produces consistent estimates irrespective of whether the errors are normal. However, a major drawback of this approach is that standard errors can not be determined and it is more inefficient compared to the MLE approach.

The presence of spatial lag dependence (spatial autoregression), however, OLS estimator are biased as well as inconsistent. These models are more complicated to estimate than those having spatial error dependence. However, asymptotic properties of the MLE usually apply for these models under some standard conditions. In addition, the instrument variable (IV) method has also been advocated.

The second type of spatial effect, spatial heterogeneity, is related to the lack of stability over space of the behavioral or other relationships under study. Specifically, this implies that functional forms and parameters may vary with location and hence may not be homogeneous across the observational units. Another aspect of this heterogeneity is heteroskedasticity, which follows from missing variables or other forms of misspecification that can lead to the error terms with non-constant variance. Ignoring either aspect has consequences for the statistical validity of the estimated model such as biased parameter estimates (though not in the presence of heteroskedasticity only), misleading significance levels, etc.

Thus, the field of spatial econometrics can be considered to consist of those methods and techniques that, based on a formal representation of the structure of spatial dependence and spatial heterogeneity, provide the means to carry out the proper specification, estimation, hypothesis testing and prediction for models.

CHAPTER 3. IRREVERSIBILITY, UNCERTAINTY AND LEARNING IN LAND PRESERVATION DECISIONS

There is a great deal of concern that human actions are leading to increased rates of extinction of species. As one response, the Congress passed the Endangered Species Act (ESA) in 1973 which, among other things, requires Federal agencies to undertake programs for the conservation of endangered and threatened species. Land acquisition is an important component of these programs. This is primarily because the chief reason cited for the increasing rates of extinction of species is the loss of habitat [Maser, 1999; McNeely, 1988; Barbier et al., 1994]. The United States Fish and Wildlife Service (FWS), Environmental Protection Agencies (EPA), the United States Department of Agriculture (USDA) and other Federal agencies are actively involved in protecting and restoring habitats through purchase and contract of land. In addition, private organizations such as The Nature Conservancy, Ducks Unlimited and the Audubon Society are also engaged in this endeavor.

There is more or less a consensus on the importance of species conservation and recognition of the seriousness of the threat to their long-term survival. The irreversibility aspect of this loss makes it necessary to take action to prevent the extinction of species. However, conservation comes at a cost, which includes the direct cost of purchasing and maintaining land for preservation as a wildlife habitat and the opportunity cost in terms of the forgone returns from alternative uses of the land. Further, land conversion can be hard to reverse, and conservation decisions often have to be made under conditions of uncertainty regarding the effectiveness of land as a wildlife habitat.

In this chapter, we study the optimal land conversion decisions under uncertainty, learning, and irreversibility of both species loss and land conversion. In the presence of uncertainty about the

efficacy of land as a wildlife habitat, the dual and opposing sources of irreversibility complicate the regulator's decision-making problem. If he invests too little land, species may be irreversibly lost.[1] On the other hand, if the land converted turns out to be ineffective as a wildlife habitat, it will be costly to reverse the conversion and the sunk costs will be large. Thus both the "convert" and "don't convert" decisions potentially entail irreversible losses. Hence, the regulator will want to incorporate these potential losses in an optimal preservation decision. Further, by converting land, the regulator can learn overtime about the effectiveness of the land. As a result, in the second period he makes a more informed decision. The regulator realizes that the extent of learning depends upon his first period action. In other words, the regulator is assumed to be an active learner and thus can "choose" how much future information he will receive. Thus, with endogenous learning, the regulator may have incentive to convert more land in order to generate more information in the future.

This work introduces two important innovations in addressing this problem of species preservation. First, we introduce endogenous learning to the real options literature, and compare the optimal decisions of several types of regulators, having different attitudes towards new information. Specifically, we consider a regulator who is an *active* learner, that is one who recognizes the endogeneity of future flow of information, a *passive* learner who foresees future new information but fails to recognize its endogeneity, and a *non-learner* who expects no future information. Most of the real options literature while exploring the effect of learning overtime on an agent's present action considers learning to be exogenous [Arrow and Fisher, 1974; Fisher and Hanemann, 1986; Henry, 1974], that is, it explores the optimal decisions of a passive learner. Second, we incorporate the dual sources of irreversibility in preservation decisions and show how these affect the importance of being able to obtain new information. Recent studies on dual sources of irreversibility in environ-

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[1]We can interpret irreversibility in a broader sense. If the conservation effort is directed towards only one of the many possible habitats of a certain species, the failure at this one habitat does not represent the complete loss of the species. In this case, we assume that once failed, it will be too expensive to re-introduce the species to this habitat. Then as far as this particular habitat is concerned, the loss of species is irreversible.

ment protecting policies [Kolstad, 1996; Pindyck, 2000] usually conduct the analysis using a binary choice model, while we consider this as a continuous investment decision problem. In addition, we show the interacting effects of endogenous learning and the two irreversibilities.

The literature on information economics has a number of studies that deal with the effect of experimentation on the process of information acquisition and on the optimal level of investment decision. An experimenting agent can formally be defined as one who updates his beliefs (according to Bayes' rule) and understands that his actions determine the extent of the information acquired. In other words, he considers the effect of his present action on future beliefs. The behavior of an experimenting agent has been referred in the literature as *active* learning. On the other hand a non-experimenting agent is a Bayesian learner who understands all the dynamic implications of his action and that the beliefs may be updated in the future but completely ignores the influence of his actions on the posterior beliefs. This is referred to as *passive* learning. While, an agent who when making his present decision does not consider that he may update his beliefs in the future is called a *non-learner*. In other words, he rules out the prospect of learning overtime. The literature also considers a myopic agent, who completely ignores the future and solves a one period problem.

The regulator's problem is modelled as a two period closed-loop stochastic dynamic optimization problem. Adopting a model structure that is similar to Datta et al. [2002], we find that there is a positive "experimentation effect": the experimenting regulator converts more land than the passive regulator in order to get more information. This occurs since the latter understands the future learning potential but fails to consider the influence of his action on the extent of learning. We also derive the "learning effect", which measures how the ability to learn affects the first period choice. It corresponds to the difference in the first period preservation decision of a passive regulator and that of a non-learner. We show that the sign of the learning effect depends on the relative importance of the two irreversibilities. When species loss irreversibility is more important, the passive learner converts more land than the non-learner, in order to utilize the future information: if it turns out

that the land is effective, he wishes to "make sure" that the species survived the first period. On the other hand, if the conversion irreversibililty is more important, the passive leaner has incentive to convert less land in order to preserve flexibility in land conversion.

This chapter is organized as follows. In the next section, we lay out the components of the model and set up the optimization problem of the three types of regulators. Following which we solve their optimization problem and analyze the optimal solutions. Next, we carry out comparative statics analysis. Thereafter, the effects of experimentation and learning are studied. Finally, we discuss the policy implications of our findings and make concluding remarks.

3.1   A Model of Land Conservation

Consider a regulator who seeks to convert agricultural land into a wildlife habitat in an attempt to increase the population of a particular species.[2] However, the regulator is not certain about the efficacy of restoration. There is a chance that this restoration will be successful and the species numbers increase significantly. On the other hand, with some positive probability the restoration may turn out to be ineffective in saving the species. This uncertainty is captured by assuming that the effectiveness of land can be either "high" or "low" with a positive probability attached to each of these states.

We consider two periods, one and two, and in each period, the population of the species depends on the acres of land converted, the efficacy of the land as an habitat, and a random exogenous shock.[3] In particular, if x_1 acres of land is converted in the current period (period 1), at the end of the period the species population is

$$z_1(x_1, \theta, \epsilon_1) = f(x_1, \theta) + \epsilon_1, \tag{3.1}$$

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[2]For simplicity, we focus on one particular species, rather than a number of species. This could be a keystone species or a threatened/endangered species. Protecting keystone species is often a priority for conservation efforts since the existence of numerous other species depends on them. Thus, the loss of a keystone species can bring about a series of linked extinctions that result in a degraded ecosystem.

[3]In actuality a species population at a given point of time will depend on the level of population in the last period. Also the interaction and interdependence between species has been ignored for the sake of simplicity.

where θ denotes the land's effectiveness and $\epsilon \in [0, \infty)$ is the random shock which may be due to climatic conditions, changes in the population of related species, alterations in other habitats in case of migratory species etc. This shock affects the species population but is independent of the type of land. The function $f(.,.)$ can be considered to be analogous to a production function for the species, where we assume that $f_x > 0$, $f_{xx} < 0$, $f_\theta > 0$, $f_{x\theta} > 0$ and $f(0, \theta) = 0$ for all θ: more land improves the species population at a decreasing rate, and as θ rises, the population increases and the marginal "productivity" of land in preserving the species increases. Thus, higher θ indicates that the land more effective as an habitat. We also assume that $f_x(0, \theta)$ is sufficiently large for any θ, i.e., the marginal productivity of land is sufficiently high when there is no land in preservation. This condition will guarantee that some land will be converted in period one, i.e. $x_1 > 0$. Finally, since ϵ is distributed on $[0, \infty)$, the species population is never negative.

The regulator does not know the value of θ at the beginning of period one. He does, however, know that $\theta \in \{\theta^L, \theta^H\}$ with $\theta^H > \theta^L$, and $\theta = \theta^H$ with probability B_1. Parameter θ remains constant across the time periods, but the regulator's belief in period t, B_t, may change as time progresses and new information arrives. The random shocks ϵ_t, $t = 1, 2$, are i.i.d. with density function given by $g(\cdot)$ on $\Re_+$ and mean $\tilde{\epsilon}$. The random variables θ and ϵ_t are independent.

Active learning, in this model, is characterized by the assumption that as the regulator increases x_1, the signal becomes more informative and hence he learns more about the type of land. This is because higher the level of x_1 the more dominant the function $f(\cdot)$ and thus the influence of the environmental disturbance diminishes. Thus, with additional land converted the regulator learns more about the type of land. As an example, consider converting an acre of land as an experiment. Thus, an increase in the acres of land converted implies more experimentation. However, this interpretation of active learning does not apply to instances when the land converted i.e. experiments, involve different environmental shocks which aid in learning about the type of land.

To capture the irreversibility in the loss of species, we adopt the Safe Minimum Standard (SMS)

approach and assume that if the period one population, z_1, falls below a certain threshold level $\bar{z} > 0$, the species becomes extinct and hence the population in the second period is zero. The SMS approach to conservation was first proposed by Ciriacy-Wantrup [1964] in order to seek protection against the potentially irreversible losses of species. Subsequently, there has been an active interest in this approach [Bishop, 1978; Farmer and Randall, 1998; Castle et al., 1996]. This approach recognizes that it is pertinent to preserve some minimum level or safe standard of a renewable resource (for example, a minimum population of species) unless the social costs of doing so are considered to be excessive. In the United States, the ESA (1973), as amended, is consistent with the SMS.

In the second period, if the species survives the first period, the species population again depends on the total land area converted, the land's effectiveness, and the exogenous shock. That is,

$$z_2(X, \theta, \epsilon_2, z_1) = \begin{cases} f(X, \theta) + \epsilon_2 & \text{if } z_1 \geq \bar{z} \\ 0 & \text{if } z_1 < \bar{z} \end{cases} \tag{3.2}$$

where $X = x_1 + x_2$ is the total land converted in the two periods. Thus, x_1 has a direct positive effect on z_2 since the latter depends on the stock of land converted. It also affects z_2 indirectly through z_1 in determining whether the species survives until the second period.[4]

In addition to the species loss irreversibility, the conversion of land is also irreversible, i.e., once the land is converted to conservation areas, it may be too costly to revert the land back to its original agricultural use. For example, if preservation involves converting agricultural land to wetlands, reverting the wetlands back to agriculture is costly and can entail sizable fixed costs.[5] A preservation area may further spur related activities that are hard to reverse: reverting a conservation area back to its original use may destroy an eco-tourism industry, thereby incurring significant costs. For

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[4]In reality, if the species does survive, the second period population should depend on z_1 as well. In 3.2, we assume, for simplicity, that future population only depends on the total land available. Introducing a direct effect of z_1 on z_2 will not affect our major results.

[5]Zhao and Zilberman [1999] show that the degree of irreversibility is determined to a large part by the size of the fixed costs.

simplicity, we assume that converting land to conservation use is perfectly irreversible i.e., once preserved, the land cannot be reverted to its original use: $x_t \geq 0$, $t = 1, 2$.

Habitat restoration can involve several kinds of costs, including the conversion cost, i.e., the cost of converting agricultural land into a preservation area; the maintenance cost, or the cost of maintaining the preservation area; and the opportunity cost, which is the foregone agricultural profit. Some of these costs are sunk, such as the conversion cost, and some can be avoided if the land is reverted back, such as the opportunity cost. If reverting to agricultural use is not too costly, i.e., if there is no irreversibility constraint, the regulator may have incentive to revert if the land turns out to be ineffective in species preservation, in order to avoid the opportunity cost. Since we wish to investigate the role of the conversion irreversibility, for clarity of the model we focus on the per acre (marginal) opportunity cost, c. or the profit from agriculture. Then the total cost associated with x acres of land in conservation is assumed to be cx, and *if* conversion is reversible, the total benefit of reverting x acres is cx (in this case, $x < 0$).[6]

The benefit derived from preservation is an increasing function of the population of the species, denoted as $U(z)$. This may include use value, as well as the existence value. For simplicity, we assume that $U(z) = \gamma \cdot z$. The benefit function is invariant overtime with constant marginal benefit (i.e. γ is positive and constant over periods). Also benefit in a given period is derived from species population in that period. Again, our major results will be the same if $U(\cdot)$ is concave or if we explicitly introduce the existence value.

The regulator can learn overtime about θ, the effectiveness of land as a wildlife habitat. Given the land converted in the first period x_1 and prior belief B_1 that the land is of the "high" type, i.e. $\theta = \theta^H$, he knows that the density function of z_1 at the beginning of the first period is

$$h(z_1; x_1, B_1) = B_1 g(z_1 - f(x_1, \theta^H)) + (1 - B_1) g(z_1 - f(x_1, \theta^L)). \tag{3.3}$$

At the beginning of the second period he observes z_1, and can thus update his belief about θ

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[6]We could explicitly include the conversion and maintenance costs in our model. These costs would be zero when $x < 0$ if conversion is reversible. Our main results are the same.

using Bayes' Rule. In particular, in period two, his updated belief that $\theta = \theta^H$ is

$$B_2 = B(x_1, z_1, B_1) = \frac{B_1 g(z_1 - f(x_1, \theta^H))}{h(z_1; x_1, B_1)}. \tag{3.4}$$

Since B_1 is given, to reduce clutter, we will ignore the argument B_1 in functions $h(\cdot)$ and $B(\cdot)$ when convenient.

Given x_1, if z_1 turns out to be large, the regulator should infer that the land is more likely to be effective.[7] To guarantee this intuitive condition, we assume that $g(\cdot)$ satisfies the strict monotone likelihood ratio property (MLRP): $\frac{g'(\epsilon)}{g(\epsilon)}$ is strictly decreasing in ϵ. This property is satisfied by most of the commonly used density functions. From (3.4), this condition implies that $B_z(x_1, z_1) > 0$ (Appendix A).

As x_1 increases, the regulator learns more and is less uncertain about the value of θ in period two. The intuition is that in (3.1), the population z_1 is affected by two uncertainties, that of land effectiveness θ, and that of an exogenous shock ϵ_1. As x_1 increases, $f_{x\theta} > 0$ implies that the variation in θ will lead to more variation in z_1 or that the variation in ϵ is relatively unimportant in influencing z_1. Thus, observing x_1 and z_1, the regulator should be more confident in making inferences about the effectiveness of land, θ.

If the regulator wishes, he may convert more land in period one in order to have better information about the land's effectiveness in period two. Of course, a regulator may also ignore this endogeneity of information: he may act in the traditional real options framework and respond to future new information (in terms of observing z_1) as it arrives, but ignore the fact that he can influence the amount of future information by changing x_1. In other words, treat the flow of information to be exogenous. Still "worse", the regulator may even ignore the possibility of any new information in period two, and act as if $B_2 = B_1$. Following, Datta et al. [2002], we call the three types of regulators an active learner or experimenting regulator, a passive learner or non-experimenting regulator, and a non-learner, respectively.

---

[7]However, z_1 is a noisy signal since z_1 incorporates the effect of a stochastic environmental shock.

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Common to all three types of regulators is that they all recognize the dynamic link between the two periods in terms of the two irreversibilities. Given belief B_2 in period two, they all solve the following optimization problem

$$\max_{x_1} B_1 \gamma f(x_1, \theta^H) + (1 - B_1)\gamma f(x_1, \theta^L) + \bar{\epsilon} - cx_1 +$$

$$\delta\, E_{z_1 \geq \bar{z}} \left[\max_{x_2} B_2 \gamma f(X, \theta^H) + (1 - B_2)\gamma f(X, \theta^L) + \bar{\epsilon} - cX \right]$$

$$- \delta cx_1 H(\bar{z}_1, x_1)$$

$$(3.5)$$

such that $x_2 \geq 0$ and (3.1),

where $\bar{\epsilon} = \gamma\tilde{\epsilon}$ and $\delta \in [0,1]$ is the discount rate, $X = x_1 + x_2$, and $E_{z_1 \geq \bar{z}}$ is the expectation over z_1 for the range $z_1 \geq \bar{z}$, with the density function $h(z_1; x_1, B_0)$, and $H(\cdot)$ is the cumulative density function of $h(\cdot)$. The last term in the objective function appears due to the land conversion irreversibility. When the species does not survive, i.e. $z_1 < \bar{z}$, the benefit derived in the second period is zero. However, even though $x_2 = 0$, the opportunity cost of land converted in the first period exists and that is captured in the last term. Note that the expectation of ϵ enters additively in the payoffs. In addition, ϵ_1 affects the expected second period payoff via affecting the extinction probability of the species.[8]

The three types of regulators have different period two beliefs B_2. For the experimenting regulator, $B_2 = B(x_1, z_1)$ given in (3.4) and we denote his optimal solutions as $(x_1^*, x_2^*(x_1^*, z_1))$. For the passive learner, $B_2 = B^p(z_1)$: the belief only depends on z_1. The optimal solutions for a passive learner are denoted as $(\hat{x}_1, \hat{x}_2(\hat{x}_1, z_1))$. Since this regulator will respond to the new signals and the signals z_1 are generated according to (3.1), we know $B^p(z_1) = B(\hat{x}_1, z_1)$: the signal is that generated given x_1. For the non-learner, $B_2 = B_1$, and since the regulator does not expect any new signal in period two, his optimal x_2 depends only on x_1, and not on z_1. We denote the optimal solutions as $(\tilde{x}_1, \tilde{x}_2(\tilde{x}_1))$.

Since we assume that $f_x(0, \theta)$ is sufficiently high, the optimal first period decision always involves

---

[8]The existence value can be incorporated by adding it to the second period payoff if the species survives. Again, the main results remain unchanged.

$x_1 > 0$, for all types of regulators. Thus the land conversion irreversibility constraint is considered only in the second period.

3.2 Experimenting Regulator (Active Learner)

We now analyze the solution for the experimenting regulator's optimization problem. We use backward induction to solve (3.5). If $z_1 < \bar{z}$, the species are extinct and there will be no further action (though the opportunity cost cx_1 is still incurred). If the species survive, i.e. $z_1 \geq \bar{z}$, the second period value function is

$$V(x_1, B(x_1, z_1)) = \max_{x_2 \geq 0} \; B(x_1, z_1)\gamma f(X, \theta^H) + (1 - B(x_1, z_1))\gamma f(X, \theta^L) + \bar{\epsilon} - cX. \qquad (3.6)$$

Note that if the expected value of the marginal benefit of x_2 is lower that the marginal cost, c, the regulator may wish to choose $x_2^* < 0$. However, in that case the land irreversibility constraint $(x_2 \geq 0)$ will be binding and the regulator will be forced to choose $x_2^* = 0$. The Kuhn-Tucker (necessary) conditions are as follows

$$B(x_1, z_1)\gamma f_x(x_1 + x_2^*, \theta^H) + (1 - B(x_1, z_1))\gamma f_x(x_1 + x_2^*, \theta^L) - c \leq 0, \;\; x_2^* \geq 0$$

$$\text{and } x_2^*[B(x_1, z_1)\gamma f_x(x_1 + x_2^*, \theta^H) + (1 - B(x_1, z_1))\gamma f_x(x_1 + x_2^*, \theta^L) - c] = 0. \qquad (3.7)$$

Given x_1, if z_1 is higher or $B(x_1, z_1)$ is higher, x_2^* should also be higher since more effective land has a higher marginal benefit in conservation. From (3.7), for $x_2^* > 0$, we know

$$\frac{\partial x_2^*(x_1, z_1)}{\partial z_1} \propto B_z(x_1, z_1) \left[\gamma f_x(X, \theta^H) - \gamma f_x(X, \theta^L)\right]. \qquad (3.8)$$

Conditions $f_{x\theta} > 0$ and $B_z > 0$ then imply that $x_2^*(x_1, z_1)$ increases in z_1. Thus, given, x_1, there exists a critical level of z_1, denoted as $z_1^c(x_1)$, below which there will be no further conversion $(x_2^* = 0)$ and above which there will be positive conversion $(x_2^* > 0)$. For each x_1, the unique level of z_1^c is given by

$$B(x_1, z_1^c)\gamma f_x(x_1, \theta^H) + (1 - B(x_1, z_1^c))\gamma f_x(x_1, \theta^L) - c = 0. \qquad (3.9)$$

If $z_1^c \leq \bar{z}$, the irreversibility constraint is never binding in period two. This scenario is possible: if the regulator converted too little land in the first period but the species survives, he may infer that the land is likely to be effective and always choose to convert more in period two.

As noted earlier, the distinguishing feature of an experimenting regulator is that he understands that his first period action influences his beliefs in period two. Thus, his revised beliefs, $B_2 = B(x_1, z_1)$. Let us then analyze the sign of $B_x(x_1, z_1)$. Intuitively, as x_1 increases, there are two factors that affect the beliefs about θ. First, since z_1 is fixed, higher x_1 implies that more land is used to achieve the same species population z_1. Then it must be that the land is not as effective than as that when x_1 is low. That is, B_x tends to be negative. However, as discussed earlier, when x_1 rises, the regulator learns more about θ as the random shock ϵ becomes relatively unimportant. If indeed the land is more effective than previously believed, that is, if $B_2 = B(x_1, z_1) > B_1$, then more learning will make the regulator have a higher belief that the land is effective. That is, B_x should be positive. In contrast, if the land is indeed less effective than the prior belief, i.e., if $B_2 = B(x_1, z_1) < B_1$, then more learning leads to a lower B_2, or $B_x < 0$. The overall effect thus depends on the relative magnitude of these effects, specified in the following proposition (proved in Appendix B)

Proposition 1 *The sign of B_x is determined by*

$$B_x(x_1, z_1) \propto \frac{g'(z_1 - f(x_1, \theta^L))}{g(z_1 - f(x_1, \theta^L))} \, f_x(x_1, \theta^L) - \frac{g'(z_1 - f(x_1, \theta^H))}{g(z_1 - f(x_1, \theta^H))} \, f_x(x_1, \theta^H). \tag{3.10}$$

In particular, $B_x < 0$ if $B(x_1, z_1) < B_1$. When $B(x_1, z_1) > B_1$, sign of B_x is ambiguous.

Based on the optimal x_2^*, we can write the expected second period payoff as

$$
\begin{aligned}
W(x_1) =\ & \int_{\underline{z}}^{\infty} V(x_1, B(x_1, z_1)) h(x_1, z_1)\, dz_1 - \int_{0}^{\bar{z}} c x_1 h(x_1, z_1)\, dz_1 \\
=\ & \int_{\underline{z}}^{z_1^c(x_1)} \left[B(x_1, z_1) \gamma f(x_1, \theta^H) + (1 - B(x_1, z_1)) \gamma f(x_1, \theta^L) + \bar{\epsilon} - c x_1 \right] h(x_1, z_1)\, dz_1 \\
& + \int_{z_1^c(x_1)}^{\infty} [B(x_1, z_1) \gamma f(x_1 + x_2^*(x_1, z_1), \theta^H) \\
& \qquad + (1 - B(x_1, z_1)) \gamma f(x_1 + x_2^*(x_1, z_1), \theta^L) + \bar{\epsilon} - c(x_1 + x_2^*(x_1, z_1))] h(x_1, z_1) dz_1 \\
& - \int_{0}^{\bar{z}} c x_1 h(z_1, x_1)\, dz_1.
\end{aligned}
\tag{3.11}
$$

Define

$$
J(x_1) = B_1 \gamma f(x_1, \theta^H) + (1 - B_1) \gamma f(x_1, \theta^L) + \bar{\epsilon} - c x_1.
\tag{3.12}
$$

Thus the regulator's maximization problem at the beginning of the first period is as follows

$$
\max_{x_1}\ [J(x_1) + \delta W(x_1)].
\tag{3.13}
$$

3.3 Passive Learner and Non-Learner

The second period decision for the passive learner is structurally the same as that of the active learner: given x_1, the regulator updates his beliefs after observing z_1 and makes the decision on x_2 accordingly. However, an important difference is that while the active learner recognizes that his belief $B(x_1, z_1)$ is affected by x_1, the passive learner ignores this link and thus he considers his belief to be dependent only on z_1, given by $B^p(z_1)$.

Thus, if the species survives, the second period value function for the passive learner is: $V(x_1, B^p(z_1))$, where $V(\cdot)$ is given in (3.6). From (3.5) we know that the Kuhn-Tucker necessary conditions for passive learner's optimization problem is as follows

$$
B^p(z_1) \gamma\, f_x(x_1 + \hat{x}_2, \theta^H) + (1 - B^p(z_1)) \gamma\, f_x(x_1 + \hat{x}_2, \theta^L) - c \le 0,\quad \hat{x}_2 \ge 0
$$

$$
\text{and}\quad \hat{x}_2 \left[B^p(z_1) \gamma\, f_x(x_1 + \hat{x}_2, \theta^H) + (1 - B^p(z_1)) \gamma\, f_x(x_1 + \hat{x}_2, \theta^L) - c \right] = 0.
\tag{3.14}
$$

Similar to $z_1^c(x_1)$, we can define the critical z_1 level below which the irreversibility constraint binds, denoted as $z_1^d(x_1)$:

$$B^p(z_1^d)\gamma f_x(x_1, \theta^H) + (1 - B^p(z_1^d))\gamma f_x(x_1, \theta^L) - c = 0. \tag{3.15}$$

From (3.9) and (3.15), we know that $z_1^c = z_1^d$ only when $x_1 = \hat{x}_1$ since $B^p(z_1) = B(\hat{x}_1, z_1)$.

The expected second period payoff for the passive learner is

$$
\begin{aligned}
Q(x_1) = \ & \int_{\bar{z}}^{\infty} V(x_1, B^p(z_1))h(x_1, z_1)\,\mathrm{d}z_1 - \int_0^{\bar{z}} cx_1 h(z_1, x_1)\mathrm{d}z_1 \\
= \ & \int_{\bar{z}_1}^{z_1^d(x_1)} V(x_1, B^p(z_1))|_{x_2=0}\, h(x_1, z_1)\,\mathrm{d}z_1 + \int_{z_1^d(x_1)}^{\infty} V(x_1, B^p(z_1))|_{x_2=\hat{x}_2(x_1, z_1)}\, h(x_1, z_1)\,\mathrm{d}z_1 \\
& - \int_0^{\bar{z}} cx_1 h(z_1, x_1)\mathrm{d}z_1.
\end{aligned} \tag{3.16}
$$

Thus, passive learner's optimization problem in period one is

$$\max_{x_1}\ [J(x_1) + \delta Q(x_1)]. \tag{3.17}$$

The non-learner's second period payoff, if the species survives, is $V(x_1, B_1)$, which is independent of z_1. The expected second period payoff is[9]

$$R(x_1) = V(x_1, B_1)(1 - H(\bar{z}, x_1)) - cx_1 H(\bar{z}, x_1). \tag{3.18}$$

Thus, the non-learner's decision problem is

$$\max_{x_1, x_2} J(x_1) + \delta R(x_1), \tag{3.19}$$

Since there will be no information updating in the second period, this is equivalent to the case where the regulator chooses both x_1 and x_2 in the first period. The close loop decision in (3.5), therefore, reduces to an open loop problem. Substituting in $J(.)$ and $R(.)$, and comparing the first order conditions on x_1 and x_2, we find that the optimal decision always involves both x_1 and x_2 to be strictly positive. That is, irreversibility constraint is never binding. This observation is intuitive:

---

[9]Since $H(.)$ is the cumulative density function associated with $h(.)$, $(1 - H(\bar{z}; x_1))$ is the probability of z_1 being greater than $\bar{z}$ and thus the species surviving in period two.

given that the regulator has the same amount of information across the two periods, he will not convert too much land in period one so that he will have to revert part of it back in period two.

3.4 Comparative Statics

In this section we study how the first period level of preservation, x_1, affects the critical level of z_1 for the experimenting (active) and non-experimenting (passive) learner. In addition, we analyze the affect of x_1 on the optimal period two solution for the three types of regulators.

To find out how the critical level of z_1 for an experimenting regulator, z_1^c, depends on x_1, we apply the implicit function theorem to (3.9). Thus, the following holds

$$\frac{\partial z_1{}^c}{\partial x_1} \propto \frac{B_x\,\gamma[f_x(x_1 + x_2^*, \theta^L) - f_x(x_1 + x_2^*, \theta^H)] - [SOC]}{B_z\,\gamma[f_x(x_1 + x_2^*, \theta^H) - f_x(x_1 + x_2^*, \theta^L)]}, \tag{3.20}$$

where *SOC* is the second order maximization condition and hence is negative. We have shown earlier that $B_z > 0$ and $f_x(x_1 + x_2^*, \theta^H) > f_x(x_1 + x_2^*, \theta^L)$ by definition. Thus, we find that $\frac{\partial z_1{}^c}{\partial x_1} > 0$ if and only if $B_x < 0$. This inverse relation is quite intuitive. If an increase in x_1 results in a decrease in the posterior probability that $\theta = \theta^H$ then the conversion will be considered ineffective and it will be more likely that no land is further converted in period two. Thus, z_1^c should be higher.

Next, we analyze how $x_2^*(x_1, z_1)$ depends on x_1. From (3.7), we know

$$\frac{\partial x_2^*(x_1, z_1)}{\partial x_1} \propto B(x_1, z_1)\,\gamma f_{xx}(X, \theta^H) + (1 - B(x_1, z_1))\,\gamma f_{xx}(X, \theta^L)$$
$$+ B_x(x_1, z_1)\gamma\left[f_x(X, \theta^H) - f_x(X, \theta^L)\right]. \tag{3.21}$$

Thus, x_1 affects the second period conversion in two ways. The first two terms on the right hand side capture the traditional *substitution effect*: since x_1 and x_2 are perfect substitutes, as x_1 rises, less land needs to be converted in period two due to decreasing returns, i.e. $f_{xx} < 0$. However, with active learning, there is an additional effect on x_1: the belief $B(x_1, z_1)$ also changes as x_1 rises. The last term captures this *information effect*.

Since $f_{x\theta} > 0$, the direction of the information effect depends on the sign of B_x. If $B_x(x_1, z_1) > 0$, i.e., if after observing z_1, the regulator believes that the land is more effective as x_1 gets higher,

the information effect is positive and implies that more land should be converted. It works against the substitution effect, and if strong enough, may lead to $\frac{\partial x_2^*(x_1,z_1)}{\partial x_1} > 0$. However, if $B_x < 0$, the information effect is negative and works in the same direction as the substitution effect. From (3.20) and (3.21), we find that: $\frac{\partial z_1^c}{\partial x_1} > 0$ if and only if $\frac{dx_2^*(x_1,z_1)}{dx_1} < 0$. This can be interpreted as: if higher x_1 leads to less conversion in period two, it will also raise the likelihood that the land conversion irreversibility constraint is binding.

Next, we look at how the critical level of z_1 for a passive learner, z_1^d, depends on x_1. We apply the implicit function theorem to (3.15) and get the following

$$\frac{\partial z_1^d}{\partial x_1} \propto \frac{-[B^p \gamma f_{xx}(x_1 + \hat{x}_2, \theta^H) + (1 - B^p)\gamma f_{xx}(x_1 + \hat{x}_2, \theta^L)]}{B_z^p \gamma [f_x(x_1 + \hat{x}_2, \theta^H) - f_x(x_1 + \hat{x}_2, \theta^L)]}. \tag{3.22}$$

It has been shown earlier that B_z^p is positive and $f_{x\theta} > 0$ by definition. Since $f(.)$ is assumed to be a strictly concave function, we find that $\frac{\partial z_1^d}{\partial x_1} > 0$. That is, as the amount of land converted in the first period increases, since conservation in the two periods is perfectly substitutable, it becomes more likely that no land is further converted in period two. Hence z_1^d is higher.

The opposing effects are absent when studying the influence of x_1 on the second period optimal solution of a passive learner. From the first order conditions for $\hat{x}$ (3.14) we obtain

$$\frac{\partial \hat{x}_2(x_1, z_1)}{\partial x_1} \propto B^p(z_1)\gamma f_{xx}(X, \theta^H) + (1 - B^p(z_1))\gamma f_{xx}(X, \theta^L) < 0. \tag{3.23}$$

Thus, unlike in the case of active learner, as x_1 rises, there is only the substitution effect and thus due to diminishing returns, less land will be converted in the second period. This is intuitive since a passive learner ignores the influence of x_1 on learning. Thus, as more land is put under restoration in period one the optimal level of restoration in the second period falls for a passive learner.

A non-learner's optimization does not depend on z_1 since there is no updating.[10] We examine how $\check{x}_2$ depends on x_1. From (3.18) we find that $\frac{\partial \check{x}_2}{\partial x_1} < 0$. The intuition is the same as in the case of a passive learner.

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[10]The dependence is only to the extent that if $z_1 < \bar{z}$ then the species do not survive in period two.

3.5   The Effects of Experimentation and Learning

In this section, we study the differences among the first period conversions of the three types of regulators and show the importance of experimentation and learning in the decision making process. In the scenario where the first period action does not enter directly into the second period benefit function, experimentation can simply be identified by comparing the optimal first period choice to the myopic first period choice. This comparison is appropriate since information is the only connection across time periods. However, in our model, since the first period action directly enters the second period benefit function there is an additional connection between periods besides updating of beliefs. Therefore in this case the difference between the optimal first period choice and the myopic first period choice is not just due to experimentation. Following Freixas [1981] and Datta et al. [2002]. we define the *experimentation effect* as the difference between the optimal first period choices of the active and the passive learners. The passive learner understands all the dynamic implications of present action, namely that his present action may directly affect future payoffs and that beliefs may be updated, except for its effect on the distribution of future beliefs. This implies that any deviation of the passive learner's action from that of the active learner can be attributed to his ignorance of the endogeneity of information generation.

We define the *learning effect*, as the difference between the first period conversion decisions of the passive (non-experimenting) regulator and the non-learning regulator. This effect captures how the ability to learn (indicated by updating of beliefs) affects the first period choice. Combining the experimentation and learning effects, we obtain the difference in first period decision of an active learner and a non-learner or the overall effect of endogenous learning.

Note that in studying these effects, we focus on x_1. Since in order to tease out the experimentation effect it is crucial to compare the first period action, x_1. This is because x_1 is the variable that indexes the experiment. The experimenting regulator understands that higher x_1 would enable him to get more information and hence alters it accordingly. However, a passive learner when choosing

x_1 is oblivious of its impact on the distribution of the posterior belief. Similarly, for analyzing the learning effect it is important to compare the first period action since when choosing x_1, the regulator, considers whether or not he will be updating his beliefs in the next period. Comparing the second period decision, x_2 does not help in reflecting on the informational generation. Since, in the second period, given the signal and the prior belief even a so called non-learner might update his beliefs and hence act like a passive learner.

3.5.1 Experimentation Effect

The MLRP and concavity of $f(.,\theta)$ ensure that the objective function of the passive learner's optimization problem (3.5) has a unique solution. However, the objective function of the active learner (3.13) may not be concave, because of the non-concavity of the value of information (Radner and Stiglitz [1984]). Following Datta et al. [2002], we state that there is a positive (negative) experimentation effect, i.e., active experimentation leads to more (less) information, if the set of optimal solutions to (3.13) lies to the right (left) of $\hat{x}_1$, the unique solution to the passive learner's optimization problem. In other words, experimentation effect is positive (negative) if the difference between the objective function of the experimenting and the non-experimenting regulator is non-decreasing (non-increasing).

Taking the difference between (3.13) and (3.5) and evaluating the derivative w.r.t. x_1, we know that the experimentation effect depends on

$$\delta\left[W_x(x_1) - Q_x(x_1)\right],\tag{3.24}$$

where,

$$W_x(x_1) = \int_{\underline{z}}^{\infty} \left[(V_B(x_1, B(x_1, z_1))B_x + V_x)h + Vh_x\right]\mathrm{d}z_1 - \int_0^{\bar{z}}(ch + cx_1h_x)\,\mathrm{d}z_1,\tag{3.25}$$

and

$$Q_x(x_1) = \int_{\underline{z}}^{\infty} \left[V_x(x_1, B^p(z_1))\,h + V\,h_x\right]\mathrm{d}z_1 - \int_0^{\bar{z}}(ch + cx_1h_x)\,\mathrm{d}z_1.\tag{3.26}$$

47

Since $B^p(z_1) = B(x_1, z_1)$, for a given x_1, we know

$$[W_x(x_1) - Q_x(x_1)] = \int_{\bar{z}}^{\infty} B_x(x_1, z_1) \left[\gamma f(X, \theta^H) - \gamma f(X, \theta^L)\right] h(x_1, z_1, B_1) \, dz_1. \tag{3.27}$$

where we have applied the envelope theorem to (3.6) to obtain V_B. Applying the Theorem in Datta et al. [2002], we can show that (3.27) is positive (Appendix C). That is, experimentation leads to a higher level of x_1. As discussed earlier, the difference between an experimenting and a non-experimenting regulator lies in whether or not he understands that his action influences his posterior beliefs. A passive or non-experimenting regulator understands all the dynamics of the problem but fails to consider the influence of his action on his process of learning. Thus, if this link is understood then at the margin the regulator will invest more in order to get more information.

3.5.2 Learning Effect

In order to bring out the learning effect, we adopt the same technique as employed to tease out experimentation effect. In particular, we need to determine the sign of $Q_x(x_1) - R_x(x_1)$.

From (3.18) that $V_x(x_1, B_1) = 0$, as the second period conversion x_2 is always positive for the non-learner. Thus,

$$R_x(x_1) = \int_{\bar{z}}^{\infty} V(x_1, B_1) h_x(z_1, x_1) dz_1 - \int_0^{\bar{z}} (ch + cx_1 h_x) dz_1. \tag{3.28}$$

For the passive learner, expanding (3.26), we know

$$\begin{aligned} Q_x(x_1) = \quad &- \int_0^{\bar{z}} (ch + cx_1 h_x) \, dz_1 \\ &+ \int_{\bar{z}}^{\infty} V(x_1, B^p(z_1)) \, h_x(z_1, x_1) \, dz_1 \\ &+ \int_{\bar{z}}^{z_1^d} V_x(x_1, B^p(z_1))|_{x_2=0} \, h(x_1, z_1) \, dz_1 \\ &+ \int_{z_1^d}^{\infty} V_x(x_1, B^p(z_1))|_{x_2=\hat{x}_2(x_1,z_1)} \, h(x_1, z_1) \, dz_1. \end{aligned} \tag{3.29}$$

The last line is zero as $V_x = 0$: this can be shown from the first order condition on x_2 when $x_2 > 0$. Further, $V_x < 0$ when $x_2 = 0$: when the irreversibility constraint is binding, the regulator would

have wanted to reduce the area in conservation, and further increase in x_1 only reduces the second period payoff. From (3.28) and (3.30), we know

$$Q_x(x_1) - R_x(x_1) = \int_{\bar{z}}^{\infty} [V(x_1, B^p(z_1)) - V(x_1, B_1)]h_x(z_1, x_1)\mathrm{d}z_1$$

$$+ \int_{\bar{z}}^{z_1^d} V_x(x_1, B^p(z_1))|_{x_2=0} \, h(x_1, z_1)\mathrm{d}z_1. \tag{3.30}$$

The second term of the right hand side, which is negative, is due to the *investment irreversibility*: expecting that he may have converted too much, a passive learner may have incentive to reduce x_1. This term measures the marginal loss from a higher x_1 when the irreversibility constraint becomes binding.[11]

The first term on the right hand side measures the additional benefit of being able to utilize the new information when the species survives. This term is positive, because as x_1 increases, the species is more likely to survive, and the new signals will be more useful. (In the extreme, if the species will never survive, no signal will be useful.) To show it is positive, let $\bar{\bar{V}}(z_1) = V(x_1, B^p(z_1))$ and $\bar{\bar{R}}(z_1) = V(x_1, B_1)$ for $z_1 \geq \bar{z}$, and $\bar{\bar{V}}(z_1) = \bar{\bar{R}}(z_1) = 0$ for $z_1 < \bar{z}$. Since V is increasing z_1, $\bar{\bar{V}} - \bar{\bar{R}}$ is non-decreasing in z_1, and strictly increasing in z_1 for some z_1. Further, as x_1 rises, the distribution $h(z_1; x_1)$ shifts to the right, or increases in the sense of first order stochastic dominance. Then $\int_{\bar{z}}^{\infty} [V(x_1, B^p(z_1)) - V(x_1, B_1)]h_x(z_1, x_1)\mathrm{d}z_1 = \int_{\bar{z}}^{\infty} [\bar{\bar{V}}(z_1) - \bar{\bar{R}}(z_1)]h_x(z_1, x_1)\mathrm{d}z_1 > 0$. Therefore, the first term on the right hand side of (3.30) arises due to the *species loss irreversibility*. Thus, the learning effect depends on the relative magnitudes of the effects of investment and ecological irreversibilities.

The learning effect depends on the relative magnitudes of the effects of the land conversion and ecological irreversibilities. The two irreversibilities require opposite land conversion decisions in order for the regulator to utilize the more information available in the second period. Given land conversion irreversibility, the way to increase the flexibility in the second period is to reduce the current land conversion: if the land turns out to be effective, more land can always be converted,

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[11]Note that the constraint is never binding for the non-learner.

and if the land turns out to be ineffective, there is not much regret. Given ecological irreversibility, however, the regulator has incentive to convert more land in order to "make sure" that the species survives until the second period, in order to utilize the new information: the new information is valuable only if the species survives.

3.6   Conclusions and Policy Implications

Conservation of species is important and this realization led to the Endangered Species Act in 1973 and other wildlife protection programs in the United States. Though the irreversibility associated with the species loss is well understood, it is often overlooked that this conservation comes at a cost. Ando et al. [1998] have pointed to this and noted that it is crucial to conserve efficiently. They address the problem of efficiently allocating scarce conservation resources in the selection of sites for biological reserves. Conversion of land from other uses, such as agriculture, to wildlife habitat may entail irreversibility and sunk costs when the efficiency of land as a wildlife habitat is uncertain. Thus, we assert in this analysis that these dual sources of irreversibility have to be considered when choosing the level of land preservation.

In this chapter, we showed the effects of uncertainty, ecological and land conversion irreversibility, and endogenous learning in land conversion decisions for species preservation. While the learning endogeneity or active experimentation always leads to more land to be converted to preservation areas, the prospect of future information itself may or may not lead to more conversion depending on the relative importance of the two irreversibilities. Future information promotes land conversion only when the ecological irreversibility is more important than land conversion irreversibility. If land converted to species preservation areas can be easily reverted back to its original (e.g. agricultural) use, and if the species involved is difficult to be reintroduced once lost, the ecological irreversibility will be more important, and overall endogenous learning will lead to more current land conversion.

Although we do not conduct a formal welfare analysis, we know that the solution of the active learner represents the socially optimal land conversion decisions. The ranking of the welfare under passive learning and non-learning is not clear, again depending on the sign of the learning effect. If, as we discussed above, the learning effect is positive (and thus is in the same direction as the experimentation effect), we obtain an unambiguous ranking in the order of active learner, passive learner, and non-learner. In this case, recognizing future information alone will improve social welfare.

CHAPTER 4. WILDLIFE PRESERVATION: A SPATIAL-TEMPORAL ANALYSIS

While ecologists and wildlife managers increasingly understand the complex relationships between habitat, size and health of wildlife populations, much uncertainty remains about the direct linkages between alternative forms of land use and species populations. These uncertainties, combined with the inherent randomness of populations associated with stochastic weather and environmental shocks can make conservation planner's decision making extremely challenging.

The central Midwest region of North America has historically been associated with the greatest abundance of grassland birds and important game species, such as ring-necked pheasants. However, surveys indicate reduction in avian populations, particularly the abundance of pheasants since 1970s (Dahlgren [1988]; Suchy et al. [1991]). Wildlife managers have pointed out that the large-scale changes in land use, especially in relation to intensified farming and habitat fragmentation, have been a major factor in the decline of ring-necked pheasant populations (Farris et al. [1977]; Warner et al. [1984]; Warner and Etter [1986]; Clark et al. [1999]). Midwest has been a target of a lot of such studies since the introduction of agriculture has been largely responsible for the elimination of the native prairie habitat throughout this region of United States. Especially agricultural changes, such as intensive farming of row crops, larger and more mechanized farms, correspond with declines in population of many grassland birds (Best et al. [1997]; Johnson et al. [1995]).

Since the 1980s, however, several federal conservation programs have been introduced to reverse this declining trend of avian populations. Among others, the Conservation Reserve Program (CRP) is especially noteworthy. The CRP provision of the 1985 Food Security Act (1985 Farm Bill) paid

farmers to retire highly erodible land from cropland and plant it to grass, trees, or other approved perennial vegetative cover for 10 or more years. This was enforced through contracts between the farmer and USDA. Though the primary benefit of this program is reduction of soil erosion, an important secondary benefit, often touted, is the creation of wildlife habitat. Several studies have investigated this claim and found evidence of a positive contribution of CRP to wildlife (Reynolds et al. [1994]; King and Savidge [1995]; Riley [1995]; Best et al. [1997]; Nusser et al. [2002]).

The regional coverage and the sources of data for this study are closely related to Nusser et al. [2002]. They, however, use a different methodology to study the effects of CRP on ring-necked pheasants. Specifically, they consider the relationship between the temporal trends for land cover/use and pheasant populations to investigate whether large-scale landscape changes induced by CRP were associated with temporal trends of pheasant populations in Iowa. This was done by modelling temporal changes within each spatial unit and obtaining summary parameters for land use and pheasant population. They found that the wildlife benefits were the highest in regions where CRP replaced cropland.

In this chapter, an empirical model to study the conservation of species and their habitat through preservation of land is laid out.[1] The model is applied to a species of particular game importance in the Midwest: ring-necked pheasants. We analyze the response of ring-necked pheasants to four land uses in Iowa: CRP land, pastureland, non-cultivated land and cropland. This study is conducted at a regional scale and not at field level, which allows us to make recommendations for wildlife policy for a region as a whole. Also this study looks at the impact of CRP on pheasant populations in relation to the other land uses in the region. Through this research we aim to provide guidelines on the impact of CRP with respect to the land cover-mix. Moreover, this analysis takes into account spatial and temporal correlations that exist when evaluating such relationships. Most of the studies in the literature have abstracted from addressing the spatial and temporal aspect.

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[1]In this work we study the relationship between the land cover and abundance of species and not the impact of land use on species richness.

The impact of CRP and other land uses on the abundance of ring-necked pheasants is studied separately for two regions of Iowa: the Northern row crop region and Southern pasture region. These regions are selected primarily because of their difference in terms of the land cover mix. While the Northern region is chiefly under row crops, the Southern region is primarily pastureland. Thus, it is interesting to investigate the impact of CRP in these diverse land cover regions and find out if this has an important repercussion on the impact of CRP on pheasant populations.

The next section lays out the spatial-temporal model. Thereafter, the data sources are discussed at length. Estimation results are presented in section 3. Section 4 discusses the chief findings of this study and lists the policy implications.

4.1 Spatial Model

The relationship between species population and land uses is analyzed using a linear model. The analysis is carried out separately for two regions corresponding to MLRAs within Iowa: the Northern row crop region and the Southern pasture region. The dependent variable is the species count along predetermined routes in the region and the main explanatory variables of interest are the share of land under four land use practices.

The relationship between the population of species and each of the land uses is modelled as:

$$y_{it} = \alpha + \delta_i \, d_i + \theta^c \, x_{it}^c + \theta^p \, x_{it}^p + \theta^n \, x_{it}^n + \theta^{cs} \, x_{it}^{cs} + \epsilon_{it}, \text{ where } i = 1, \ldots n \text{ and } t = 1, \ldots T, (4.1)$$

where y_{it} is the average number of pheasants per mile counted on routes in polygon i at time t, x_{it}^c denotes the share of land under CRP, x_{it}^p is the share of land under pastureland, x_{it}^n denotes land share under non-cultivated land and x_{it}^{cs} is land share under corn and soybean. These shares are calculated by dividing the total acreage in a land use by the total acreage of the corresponding polygon, in other words it is the proportion of the polygon under a particular land use. The polygons, in a given region, are denoted by i and T is the total number of time periods considered. The regression constant is denoted by α, while δ_i is a set of dummy variables to capture the

differences between polygons. Thus, $d_i = 1$ for polygon i and is zero otherwise. The above can be compactly written as

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\theta} + \boldsymbol{\epsilon}. \tag{4.2}$$

The dependent variable vector $\mathbf{Y}$ is a $nT \times 1$ vector and the explanatory matrix, $\mathbf{X}$ is $nT \times (n+4)$. Note that the response parameters are assumed to be constant across polygons in the region of study.

The effectiveness of the practices is captured by $\boldsymbol{\theta}$, a $(n+4) \times 1$ vector of unknown parameters, which includes the response parameters: $\theta^c, \theta^p, \theta^n, \theta^{cs}$, and the regression constant and dummy variables coefficients. In addition to the response uncertainty, there is another source of uncertainty in the model in the form of an additive error denoted by a $nT \times 1$ vector, $\boldsymbol{\epsilon}$. This random shock may be due to climatic conditions, changes in the population of related species or other environmental factors. It affects the species population but is assumed to be independent of the land use.

According to classical assumptions, the error terms have constant variance (homoskedasticity) and are uncorrelated (zero autocorrelation). However, spatial autocorrelation is likely in this study of the effect of various land uses on species population.[2] Spatial autocorrelation or spatial dependence is likely in studies where boundaries for spatial units (polygons) are drawn for conducting analysis and thus are, in a sense, arbitrary. This is intuitive: due to their geographical proximity there are a number of variables that are likely to have a similar impact on the pheasant population across these polygons. For instance, the presence of streams, type of soil, weather patterns and other natural variables are expected to have similar impact across polygons. These omitted variables result in the disturbances being correlated spatially. Spatial dependence can also be a result of measurement errors. These errors tend to spill over across the boundaries of spatial units. As a result, the errors in spatial unit i, are likely to be related to the errors in a neighboring unit j.

Formally, spatial dependence is defined as a functional relationship between neighboring points

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[2]In a later section, specific tests are done to validate the presence of spatial autocorrelation.

(of observation) in space (Anselin [1988]). There are potentially two sources of spatial dependence that can cause econometric problems. First, spatial lag dependence, which is a result of causal relationships among neighboring points of observation (in this case, polygons). These structural spatial dependencies across observations on the dependent variable usually arise due to the interaction of dependent variables across spatial units. This type of dependence is often found in studies of urbanization. While analyzing the factors responsible for urbanization, it is found that urbanization in one region often "spills-over" to neighboring regions. Second, spatial error dependence or spatial autocorrelation can occur. The spatial dependence among the errors usually results from omitted variables that are themselves spatially correlated.[3]

Dependence of the spatially lagged dependent-variable form would occur only if the species population in one polygon is directly affected by the size of the population in a neighboring polygon. There is little reason to expect such dependence and to keep the model relatively simple, spatial dependence in the form of only spatial autocorrelation is modelled in this study. If the error terms are spatially correlated, ordinary least squares (OLS) produces unbiased but inefficient parameter estimates and biased estimates of standard errors. As a result, hypothesis testing using OLS estimates of standard errors will be inaccurate.

The standard method adopted for correcting spatial autocorrelation requires assuming a structure for the spatial dependence and estimating one or more parameters in conjunction with the parameters of the economic model. Specifically, this involves choosing a form for a spatial weight matrix, $\mathbf{W}$, which contains information on the assumed spatial relationship between all pairs of errors. For instance, the i, j^{th} element of W, denoted by w_{ij}, represents the potential spatial dependence between the ith and j^{th} error, where by definition $w_{ij} = 0 \ \forall \ i = j$. Anselin [1988] proposed the following model for a spatial autoregressive process

$$\mathbf{Y} = \mathbf{X}\theta + \epsilon \quad \text{where} \quad \epsilon = \lambda \mathbf{W}\epsilon + \mathbf{u}. \tag{4.3}$$

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[3]The spatial autocorrelation could also arise due to measurement errors that are systematically related to location. For example, census data that are averaged over a larger area in rural block groups than in urban ones.

As per the model framework discussed earlier in this section, $\mathbf{W}$ is an $nT \times nT$ matrix, $\mathbf{u}$ is an $nT \times 1$ vector of random errors terms, with zero mean and a constant variance, and λ is the scalar coefficient of spatial autocorrelation.[4]

The spatial weight matrix is constructed using information from the spatial structure of the set of data observations. The most frequently used spatial weight matrix in the literature is the first-row contiguity matrix. The source of locational information, in this case, is contiguity, which reflects the relative position in space of one regional unit of observation to other such units. Anselin [1988] has an extensive discussion on the several ways of defining this contiguity relationship. In this study, the rook-contiguity matrix will be used. In this interpretation of contiguity, $w_{ij} = 1$ for regions that share a common boundary and $w_{ij} = 0$ otherwise. Thus, in each row the non-zero column elements correspond to contiguous spatial units. By convention, a spatial unit is not contiguous to itself, which results in the diagonal elements being zero. This spatial weight matrix is row standardized such that each row's elements sum up to one. This "row-standardization" is done to avoid certain statistical difficulties. These deal with the problem that the model is undefined for certain eigenvalues of the spatial weight matrix. An excellent discussion of these difficulties is provided in Bell and Bockstael [2000].

As an alternate to the standard contiguity matrix, a distance-decay form of the spatial weight matrix is also used in some studies (Cook and Pocock [1983], Bell and Bockstael [2000] and Paez et al. [2002]). This spatial weight matrix allows neighbors to have differential impact. For instance, error terms associated with close neighbors may have higher correlation than those of more distant neighbors. Here, elements of the spatial matrix are often posited as being inverse functions of the distance between observations.[5] In this analysis, an inverse-distance spatial weight matrix has not been used primarily due to the irregular and different shape of the polygons (spatial units) under

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[4]Note, in this model the variance of ϵ is assumed to be the same for all points of observation (polygons) in the region under study. However, the variance-covariance matrix, unlike in the standard classical case, is non-diagonal.

[5]Usually the Euclidian distance is considered. However, *distance* can be defined in terms other than geographic. For example, Case et al. [1993] use differences in per capita income and proportion of the population who is black to define "distances" between counties.

study. As can be noticed in Figure 1, the centroids calculated by using the software Space-Stat differ significantly from those evaluated using the ESRI Arc View software. Hence implying that, at least in this study, the results would depend heavily the method used to calculate the centroids.

The extant literature on spatial econometrics models has largely ignored the potential of temporal dependence that may be present among data observed at different points in time. In fact, the majority of the expositions of spatial dependence of one form or another abstract from the potential complexities introduced by space-time and are estimated as pure cross-sectional regressions.[6] However, in many cases, it is likely that the spatial process of interest will also have a temporal dimension, so that correlations across both space and time will be present. The existence of these dual correlations is possible when modelling the dependence of species population on land uses. The reason for this is that many of the variables that influence the species population are either time invariant or highly correlated over time, for example the type of soil, presence of streams and other natural water sources, etc. If serial correlation is ignored the estimators, though still unbiased and consistent, are inefficient. In the case of positive serial correlation, for instance, this loss of efficiency will be masked by the fact that the estimates of the standard errors will be smaller than the true standard errors, thus falsely increasing their apparent precision (Pindyck and Rubinfeld [1991]).

Accounting for temporal dependence (or serial correlation), in addition to spatial dependence, complicates the modelling of this problem. However, if temporal dependence is ignored, it is likely that the reliability of the coefficient estimates will be overstated. There are several ways to specify the temporal dependence in space-time models, depending on the assumed structure of the spatial-temporal relationship. In this study, the chief interest is to capture the serial correlation that is likely to arise if factors omitted from the model are correlated across time periods. Such a structure would imply that the total effect of a random error is not instantaneous, but it is also felt in future

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[6]Some notable exceptions include Hsieh et al. [2001], Pace et al. [1998] and Hordijk and Nijkamp [1978].

periods (Judge et al. [1988]).

Among the various admissible forms of serial correlation, the first-order autoregressive serial process, AR(1), is the most popular and has proved to be useful in many economic applications (Judge et al. [1988]). The AR(1) process can be written as follows

$$u_t = \phi u_{t-1} + v_t, \quad \text{where } t = 2, \ldots, T \text{ and } |\phi| < 1. \tag{4.4}$$

The error term, u_t, depends on its previous value, u_{t-1}, with the lag coefficient denoted by ϕ. The $v's$ are uncorrelated random variables with zero mean and constant variance, σ^2.

Thus, the model accounting for both spatial and temporal dependence can be written as follows

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\theta} + \boldsymbol{\epsilon},$$

$$\boldsymbol{\epsilon} = \lambda \mathbf{W}\boldsymbol{\epsilon} + \boldsymbol{u},$$

$$\boldsymbol{u} = \phi\boldsymbol{u} + \boldsymbol{v}, \quad \text{where } \boldsymbol{v} \sim N(0, \sigma^2). \tag{4.5}$$

In this model, $\mathbf{Y}$ is a $nT \times 1$ vector of observations of the dependent variable, $\mathbf{X}$ is a $nT \times (n+4)$ matrix of explanatory variables and $\boldsymbol{\theta}$ is a $(n + 4) \times 1$ vector of response parameters. The spatial matrix, $\boldsymbol{W}$, is $nT \times nT$ and λ is a scalar spatial dependence coefficient, which captures any spatial dependence inherent in the data. $\boldsymbol{\epsilon}$ is a $nT \times 1$ vector of regression disturbances. While $\boldsymbol{u}$ is a $nT \times 1$ vector of disturbances that follows an AR(1) process, ϕ is the lag parameter for this process and $\boldsymbol{v}$ is an $nT \times 1$ vector of innovations, which is assumed to consist of normal i.i.d. errors with mean zero and variance, σ^2. Note that all the coefficients are fixed across all observations in time and space.[7]

4.1.1   Estimation Methods

The OLS estimator is unbiased but inefficient in the presence of spatial dependence in residuals. This results from the non-diagonal structure of the disturbance variance-covariance matrix. There

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[7]Seemingly Unrelated (SUR) model and other similar models, such as spatial SUR, are ruled out since if the response changes every time period then there would be little point in modelling these relationships. Also, since the polygons correspond to the same MLRA, the response is unlikely to be very different for each polygon. In addition, the dummy variables for each polygon are likely to capture any polygon-wise differences.

are primarily two alternatives: Maximum-Likelihood Estimation (MLE) approach and Generalized-Moments Estimation (GME) approach.

The MLE approach is more widely used and is the standard approach for such models. However, the maximum-likelihood techniques can become increasingly difficult as the sample size grows. Kelejian and Prucha [1999] developed the GME approach that has two important advantages over MLE. The main advantage of this approach is that estimation involving large samples is also relatively straightforward. While it involves matrix multiplication and calculation of the trace of $W'W$, it requires neither the calculation of the determinant nor the eigenvalues of the spatial weight matrix, which are needed to carry out MLE. Thus, GME allows estimation with a more flexible functional form for the spatial weight matrix. Another advantage of GME is that it produces consistent estimates irrespective of whether the errors are normal or not. However, a major drawback of this approach is that standard errors for the spatial dependence coefficient can not be determined. In this analysis, since the sample size is not very large, the MLE approach is adopted.

The first comprehensive treatment of MLE for regression models with spatial dependence, in the form of a spatial lag or a spatial error term, was given by Ord [1975]. An important aspect of the likelihood function here is the Jacobian[8] of transformation, which takes the form $|\mathbf{I} - \rho\mathbf{W}|$ and $|\mathbf{I} - \lambda\mathbf{W}|$ respectively, for the spatial lag and spatial autoregressive error models, with ρ and λ as the corresponding spatial dependence coefficients and $\mathbf{W}$ being the spatial weights matrix.

Referring to the space-time model employed in this analysis, (4.5), the covariance matrix of the error terms, u, is given by the following

$$E[u_t, u'_s] = \sigma^2 \, \Psi(\phi), \tag{4.6}$$

---

[8]In contrast to the time-series case, the spatial Jacobian is not the determinant of a triangular matrix, but of a full matrix.

where,

$$\Psi(\phi) = \frac{1}{1-\phi^2} \begin{pmatrix} 1 & \phi & \phi^2 & . & . & . & \phi^{T-1} \\ \phi & 1 & \phi & . & . & . & \phi^{T-2} \\ \phi^2 & \phi & 1 & . & . & . & \phi^{T-3} \\ . & . & . & . & & & . \\ . & . & . & . & . & & \\ . & . & . & & . & & . \\ \phi^{T-1} & \phi^{T-2} & \phi^{T-3} & . & . & . & 1 \end{pmatrix} \otimes I_n. \qquad (4.7)$$

Note that since the **u**'s are assumed to be generated by an AR(1) process with $|\phi| < 1$, the successive correlation coefficients, $\phi, \phi^2, \phi^3, \ldots, \phi^{T-1}$, decline geometrically. As illustrated in standard econometrics texts (Judge et al. [1988], Green [1997]) a transformation matrix, $P(\phi)$, is calculated such that, $(P(\phi)'P(\phi)) \otimes I_n = \Psi^{-1}(\phi)$. Thus, the transformation matrix $P(\phi)$ is as follows

$$P(\phi) = \begin{pmatrix} \sqrt{1-\phi^2} & 0 & 0 & . & . & . & 0 \\ -\phi & 1 & 0 & . & . & . & 0 \\ 0 & -\phi & 0 & . & . & . & 0 \\ . & & . & . & . & & . & . \\ . & & . & . & . & & . & . \\ . & & . & 0 & . & . & 1 & 0 \\ 0 & & 0 & 0 & . & . & -\phi & 1 \end{pmatrix}. \qquad (4.8)$$

The space-time model can be transformed by pre-multiplying $(P \otimes I_n)$,

$$Y^* = (P \otimes I_n)Y,$$

$$X^* = (P \otimes I_n)X,$$

$$\epsilon^* = (P \otimes I_n)\epsilon,$$

$$u^* = (P \otimes I_n)u. \qquad (4.9)$$

Thus, after transforming the data by pre-multiplying $(P \otimes I_n)$ the model can be written as follows

$$Y^* = X^*\theta + \epsilon^*$$

$$\epsilon^* = \lambda W \epsilon^* + u^*$$

where $E[u^*] = 0$, $E[u^* u^{*\prime}] = \sigma^2$. \hfill (4.10)

This model can now be estimated using the spatial model proposed by Anselin [1988] and discussed above. In other words, the same estimation scheme can be applied to this transformed model, the only differences being that the MLE of one more parameter, ϕ, needs to be estimated and the Jacobian transformation needs to be recalculated for this model.

In (4.10) the relationship between the error terms can be expressed as follows

$$(I - \lambda W)\epsilon^* = u^*. \hfill (4.11)$$

Thus, substituting (4.11) the model can be rewritten as following

$$Y^* = X^*\theta + A^{-1}u^*,$$

or $\quad AY^* = AX^*\theta + u^*$, where $A = (I - \lambda W)$. \hfill (4.12)

As pointed out previously, the spatial weight matrix, $\mathbf{W}$, captures the spatial relationship between the polygons. Since multi-periods are being considered in this analysis the spatial matrix will be a block diagonal matrix with the same sub-matrix on the diagonal terms. This is because the assumed spatial structure is considered to be invariant across time periods. Thus, the spatial weight matrix,

which is block diagonal can be expressed as follows

$$
W = \begin{pmatrix}
\mathbf{W_1} & 0 & . & & . & . & 0 \\
0 & \mathbf{W_1} & & & & & 0 \\
0 & & \mathbf{W_1} & & & & 0 \\
. & & & . & & & . \\
. & & & & . & & . \\
. & & & & & . & \\
. & & & & . & & . \\
. & & & & & . & . \\
0 & . & . & & & . & . & \mathbf{W_1}
\end{pmatrix}
\tag{4.13}
$$

where, $\mathbf{W_1}$ is the sub-matrix that represents the spatial relationships between polygons in one period. Note that by convention the diagonal elements in each sub-matrix are set to zero while the off-diagonal elements of the sub matrix reflect the assumed spatial relationship between two polygons. After the weights are calculated, the elements of each row of $\mathbf{W}$ are normalized so that they sum to unity.

The likelihood function has to be based on Y, and hence it is necessary to introduce the concept of a Jacobian, which allows the joint distribution for Y to be derived from that of u^*. The log-likelihood function then is the following

$$
L = -\frac{nT}{2} \cdot \ln(2\pi) - \frac{nT}{2} \cdot \ln(\sigma^2) + (n/2)\ln(1 - \phi^2) + \ln|A| - \frac{1}{2\sigma^2}(u^{*'}u^*)
$$

with

$$
u^{*'}u^* = (Y - X\theta)'A'\Psi^{-1}A(Y - X\theta),
\tag{4.14}
$$

where $(n/2)\ln(1 - \phi^2)$ and $\ln|A|$ are the Jacobian of the transformation from u^* to Y. The unknown parameters to be estimated are θ, λ, ϕ and σ^2.

4.1.2 Testing for Spatial Dependence

The most widely used approach for testing spatial dependence is the Moran I test with the null hypothesis being absence of spatial dependence. The test statistic involves calculation of OLS residuals and can be written as follows

$$I = [N/S] \cdot [e'We]/e'e, \tag{4.15}$$

where e is the vector of OLS residuals, W is the spatial weight matrix, N is the number of observations, and S is a standardized factor, equal to the sum of all elements in the weight matrix. The asymptotic distribution of the Moran statistic with regression residuals was developed by Cliff and Ord [1972]. This distribution for a properly transformed variate, is shown to correspond to the standard normal.

Another set of tests for spatial dependence are based on maximum likelihood estimation. These include the Wald, Likelihood Ratio, and Lagrange Multiplier tests. The Lagrange Multiplier test is based on estimation under the null hypothesis only. This results in an easily implemented statistic, which is derived from OLS residuals and some additional calculations of weight matrix traces. However, the three maximum likelihood based tests are asymptotically equivalent, though typically different in finite samples (Anselin [1988]).

4.2   Data

The spatial model is applied to a species of particular game importance in the Midwest: ring-necked pheasants. The land uses considered are: Conservation Reserve Program (CRP) land, pastureland, non-cultivated land and cropland. CRP is a federal program established under the Food Security Act of 1985 (FARM Bill) to assist private landowners to convert erodible cropland to vegetative cover, such as tame or native grasses, wildlife plantings, trees, filterstrips, or riparian buffers. CRP establishes wildlife habitat as well as other benefits such as reducing soil erosion, reducing sedimentation in streams and lakes and improving water quality. Pastureland includes

land that has a vegetative cover of grasses, legumes, and/or forbs. Non-cultivated land includes permanent hayland and horticultural cropland. In this analysis, cropland includes land under corn and soybean.

4.2.1 Land use Data

Data on land uses is obtained from the National Resources Inventory (NRI) database. The NRI is a sample survey, conducted every four years, designed to provide information on status and trends for land use and natural resource conditions on non-federal land in the United States. The 1997 NRI provides results that are nationally consistent for all non-federal lands for four points in time: 1982, 1987, 1992, and 1997. Data recorded on cropland, non-cultivated land, CRP land and pastureland, are also available for each of the three calendar years preceding the current inventory year (cropping history).

This sample survey is conducted by the National Resources Conservation Service (NRCS), an agency of the U.S. Department of Agriculture (USDA), in cooperation with the Iowa State University Statistical Laboratory. Data for the 1997 NRI were collected for more than 7,061 locations in Iowa by NRCS field personnel, resources inventory specialists, and remote sensing data collectors at the Inventory Collection and Coordination Site in Ames, Iowa. The NRI was scientifically designed and conducted and is based on recognized statistical sampling methods. NRI data are statistically reliable for national, regional, state and substate analysis. Generally, however, interpretations at the local level, such as, county level or 8-digit Hydrological unit area, may be misleading.

4.2.2 Pheasant Data

The pheasant data is obtained from the Iowa Department of Natural Resources (IDNR), which uses an annual roadside survey to assess its upland game populations. Survey routes are approximately 30 miles long and are entirely on gravel roads. There are 233 current and historical routes

in Iowa. Routes were digitized using an ARC/INFO geographic information system (GIS). Counts for these routes are viewed as an indicator of population trends rather than an actual estimate of pheasant populations.

This survey is conducted between August 1 to August 15. During this period, when conditions are favorable, Iowa DNR biologists and conservation officers drive their assigned routes, at 10-15 mph, and count all the pheasants and other game species that they identify. These routes are evenly spread in all of Iowa's 99 counties, and were selected purposively by IDNR staff in representative areas of the landscape where pheasants might be observed. Nearly all the routes originally established have been surveyed using standardized protocols (Suchy et al. [1991]) each year since 1962.

4.2.3 Common Spatial Unit

A key step in carrying out this analysis is to identify a common spatial unit to link the IDNR annual species count data and the NRI data on land use. This is done using polygons defined by the intersection of Major Land Resource Area (MLRA) and 8-digit Hydrological Unit Code (HUC), as done in Nusser et al. [2002]. MLRAs are multi-county areas distinguished by regions of relatively homogenous climate, physiography, soils, and land use (USDA, Soil Conservation Service 1981). HUCs designate geographic areas of a surface drainage basin or a combination of drainage basins.

The choice of the spatial polygon was based on the consideration that it can be identified by variables in both databases. The MLRA x HUC polygons are more consistent with regard to land use and physiography, also the data available from NRI sample points and pheasant survey routes with a polygon provide a better fit for studying the relationship between land use and pheasant populations than other spatial aggregations. As pointed earlier, the NRI data is considered to be unsuitable to be used at the county level. Nusser et al. [2002] investigated the use smaller polygons defined by MLRA x HUC x county boundaries for linking the two datasets, but found

that many contained either no NRI points or no pheasant routes. In addition, the NRI data set is recommended to be used with regard to some type of geographical factor, such as state, county, HUA, and MLRA (NRCS [2001]). Thus, this prevents us from forming route centric polygons.

For this study we divide the resulting 81 polygons into six regions: Northern row crop, Northeastern grain, Mississippi river, Western livestock, Eastern livestock and Southern pasture, corresponding to MLRAs within Iowa. When a route crossed two or more polygons, it is assigned to the polygon that contained the longest portion of the 30 mile route. The analysis is conducted separately for the Northern row crop region and Southern pasture region for the years 1987-1995. The choice of regions is based on the fact that these regions have varied characteristics. Northern row crop region is primarily under corn and soybean while the majority of land in Southern pasture region is under CRP and pastureland.

4.3   Estimation Results

In the following sections, results from estimation of the spatial-temporal model for the Northern row crop region and Southern pasture region are presented. The bias corrected (BC) 90 percentile confidence interval for the response parameter estimates is calculated using the Bootstrap method.

4.3.1   Southern Pasture Region

In the Southern region, the intersection of MLRAs and HUCs results in 12 polygons. However, three polygons do not have sizable data points and are thus deleted from the analysis. Thus, this analysis is conducted for 9 polygons in the Southern pasture region. The total acreage of this region is almost 4 million acres. Figure 4 shows the relative position and size of the Southern pasture region, while Figure 3 provides a detailed view of this region with the polygons enumerated.

The pheasant and land use data, for each of the polygons, is observed for the time period: 1987-95. Thus, the total number of observations for this region are 63. The yearly average of CRP

land is 257,690 acres. Pastureland and non-cultivated land average 985,940 acres and 88,257 acres, respectively. Cropland, in the southern pasture region, averages 1,014,300 acres per year for the time period under study. Thus, on an average, around 60 percent of the total southern pasture region is under these four land uses.

Before applying the spatial-temporal model to this data set some tests are conducted to detect the presence of spatial correlation in residuals and thus validate the use of this model. Table (4.1) shows the results of the four tests conducted. All the tests have a null hypothesis of zero spatial dependence in residuals. The Moran I-statistic, based on least-squares method, takes a value of 2.96 and hence is greater than the critical value of 1.96, implying that the null hypothesis of no spatial correlation can be rejected.[9] As noted in an earlier section, a number of other asymptotic approaches based on maximum likelihood estimation exist for testing whether the residuals are spatially correlated. Some of the important ones include: Likelihood Ratio (LR) test, Wald test and Lagrange Multiplier (LM) test. For instance, the LR test is based on the difference between the log likelihood from the spatial model and the log likelihood from a least-squares regression. The LR value represents a statistic that is distributed as $\chi^2(1)$. Referring to Table (4.1), the LR value of 6.7381 is greater than the $\chi^2(1)$ critical value, thus the null hypothesis can be rejected. The Wald and LM statistics are also distributed as $\chi^2(1)$ and their values, 7.7321 and 7.1879 respectively, are greater than the critical value. Hence these two tests also indicate the presence of spatial correlation in the residuals.

Next, to investigate the presence of serial correlation in the data the Durbin-Watson test is employed. The statistic for the Southern region is 1.5607, with the null hypothesis of zero serial correlation. For the linear regression model at hand, this value lies between the upper and lower limit of the critical value and hence is in the inconclusive region. Thus, the Durbin-Watson statistic

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[9]Note that the Moran I test, unlike the other tests that are based on the likelihood function, relies on the least-squared method. Thus in the presence of serial correlation, in order to use this test, the errors need to be transformed. However, in this study, since the serial correlation coefficient turns out to be insignificant the Moran I-statistic is reported without doing this transformation.

Table 4.1   Tests for spatial correlation in residuals in Southern region

Moran-I test	
Moran I	0.2946
Moran I-statistic	2.9769
Marginal Probability	0.0047
mean	-0.0367
variance	0.0124

LM error test	
LM Value	7.1879
Marginal Probability	0.0073
chi(1)	6.6350

LR error test	
LR value	6.7381
Marginal Probability	0.0094
chi(1)	6.6350

Wald Test	
Wald value	7.7321
Marginal Probability	0.0055
chi(1)	6.6350

does not throw any light in this case. Since, there is a high probability that there are omitted variables in this model, serial correlation is assumed to be potentially present and the analysis is carried out accounting for both serial correlation and spatial dependence of the residuals.

The parameter estimates of the spatial model are reported in Table (4.2), with an asterisk indicating significance at the 90% confidence level. About half of the coefficients for the dummy variables are significant. Another point to note is that the significant dummy variable coefficients for the polygons take a negative value. This indicates that there are some extraneous negative influences on the pheasant populations in this region.

The impact of CRP land and pastureland on pheasant population is positive and significant. The regression coefficient for CRP is 2.35, which measures the increase in pheasants/mile associated with a marginal increase in the proportion of land under CRP. In contrast, a marginal increase in the proportion of pastureland is estimated to increase the pheasants/mile by about 8. A qualitative implication of this result is that while both CRP land and pastureland have a positive impact on pheasant count, for this region, the marginal impact of pastureland is greater than that of CRP land. The average elasticity of CRP land is 9.53, implying that a one percent increase in the share of CRP land results in a change in percentage pheasant population per mile of 9.53. The average elasticity of pastureland is 151.

Non-cultivated land and cropland are found to have a significant and negative impact on pheasant population. A marginal increase in the proportion of non-cultivated land decreases the pheasants counted per mile by 0.27. An increase of one unit in the proportion of cropland results in a decrease in pheasant counts per mile by around 0.01. Thus, the negative marginal impact of cropland is lower than that of non-cultivated land. It is important to note that only 25 percent of this region is comprised of cropland. The average elasticity of non-cultivated land is -0.49 and that of cropland is -0.21.

The spatial dependence coefficient takes a value of 0.35 and is significant. Thus, there is

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Table 4.2 Southern Pasture Region: Spatial Model Estimates

Parameter	Spatial Model Estimates (t-statistics are in parenthesis)
$\hat{\alpha}$	0.40 (0.60)
δ_1	0.07 (0.50)
δ_2	-1.53^* (-1.66)
δ_3	-1.56 (-1.12)
δ_4	-1.8 (-1.64)
δ_5	-1.24^* (-2.12)
δ_6	-1.5^* (-1.97)
δ_7	-0.04 (-1.02)
δ_8	-0.59 (-1.22)
$\hat{\theta}^c$	2.35^* (1.73)
$\hat{\theta}^p$	7.82^* (1.95)
$\hat{\theta}^n$	-0.27^* (-1.75)
$\hat{\theta}^{cs}$	-0.01^* (-1.66)
$\hat{\lambda}$	0.35^* (2.83)
$\hat{\phi}$	0.07 (0.66)
σ^2	0.35
R^2	0.52

positive spatial correlation between residuals across polygons. This is quite intuitive since their geographical proximity dictates that disturbances in one polygon would also have a similar impact on neighboring polygons. For instance, the presence of streams, type of soil and other natural variables are expected to have similar impact across polygons. These omitted variables are likely to result in the disturbances being correlated spatially.

In contrast, the serial correlation coefficient is found to be insignificant. Thus, there is no evidence of correlation of residuals over time periods. Serial correlation was expected to be present in this data set primarily due to the omitted variables of the model, which were likely to be correlated over time. However, the inclusion of dummy variables for each of the polygons may explain the absence of serial correlation in the residuals. The R^2 statistic is 0.52. Thus, 52% of the variation in the dependent variable is explained by the regressors of the model.

Next, to calculate the confidence intervals for the parameter estimates we employ the bootstrap method with bias correction. In many situations when the sample size is relatively small using this method may lead to substantial corrections, which improves the inferential accuracy of the interval estimate (Efron and Tibshirani [1993]). This improved version of the percentile method is denoted as BC_a, the abbreviation standing for bias-corrected and accelerated. The percentiles used in this version depend on two numbers $\hat{a}$ and $\hat{z}_0$, called acceleration and bias-correction, respectively. The bias correction ($\hat{z}_0$) component accounts for possible bias in the bootstrap estimate whereas the acceleration constant $\hat{a}$ accounts for the possible change in the standard deviation as the estimate changes. Efron and Tibshirani [1993] point out that a more common problem is the presence of bias and hence it is dealt with here by calculating bootstrap confidence intervals that are corrected for bias.

The first step in estimating the BC confidence interval is the same as the percentile procedure, namely drawing bootstrap replications from the sample data with replacement, the size of these replications being the same as the original sample. This is done B times, i.e. the number of these

replications is B. The percentile confidence interval is denoted by: $(\hat{\theta}^{*(\alpha)}, \hat{\theta}^{*,(1-\alpha)})$, where $\hat{\theta}^*$ denotes the bootstrap parameter estimate, $\hat{\theta}^{*(\alpha)}$ is the 100αth and $\hat{\theta}^{*(1-\alpha)}$ is the $100(1-\alpha)$th percentiles of $\hat{\theta}^*$. That is, $\hat{\theta}^{*(\alpha)}$ is the $B \cdot \alpha$th value in the ordered list of replications of $\hat{\theta}^*$

For the bias corrected confidence interval, the percentiles additionally depend on $\hat{z}_0$. The value of the bias-correction component, $\hat{z}_0$, is obtained directly from the proportion of bootstrap replications less than the original estimate and is given by the following:

$$\hat{z}_0 = \Phi^{-1}\left(\frac{\#(\hat{\theta}^*(\mathbf{b}) < \hat{\theta})}{B}\right),$$
(4.16)

$\Phi^{-1}(.)$ indicates the inverse function of a standard normal cumulative distribution function. The BC confidence interval is given by:

$$(\hat{\theta}^{*(\alpha_1)}, \hat{\theta}^{*(\alpha_2)}),$$
(4.17)

where

$$\alpha_1 = \Phi(2\hat{z}_0 + z^{(\alpha)})$$

$$\alpha_2 = \Phi(2\hat{z}_0 + z^{(1-\alpha)}).$$
(4.18)

Here $\Phi(.)$ is the standard normal cumulative distribution function and $z^{(\alpha)}$ is the 100αth percentile point of a standard normal distribution.

The BC method for obtaining the bias corrected confidence intervals has two important theoretical advantages over the percentile method. First, it is transformation respecting. This implies that the BC endpoints transform correctly if we change the parameter of interest from θ to some function of θ. The second advantage of the BC method concerns its accuracy. These intervals have been shown to be second-order accurate (Efron and Tibshirani [1993]). This means that its errors go to zero at a rate $1/n$ in terms of the sample size n. On the other hand, errors for the percentile method and the standard method of obtaining confidence intervals are an order of magnitude higher.

Table 4.3   BC: 90 percentile confidence intervals.

Parameter	MLE	CI
$\hat{\theta}^c$	2.35	(0.01, 3.15)
$\hat{\theta}^p$	7.82	(0.08, 12.65)
$\hat{\theta}^n$	-0.27	(-0.35, -0.001)
$\hat{\theta}^{cs}$	-0.01	(-0.03, -0.0002)

However, applying the bootstrap method to models with spatial dependence needs special attention due to two issues. One issue pertains to the design of resampling. An important consideration in this technique is independence of observation vectors from which resampling is done. This is necessary to ensure that an empirical density can be assumed with equal probability for each observation. Also, it prevents resampling from destroying the inherent structural characteristics of the data set. However, in the presence of spatial dependence the data points are, by definition, not independent. Thus, in the case of spatially dependent residuals, resampling has to be done from residuals after taking account of spatial dependence. For instance, in this study, resampling is done from

$$u^* = AY^* - AX^*\hat{\theta}, \qquad (4.19)$$

where u^* is independent and normally distributed.

The second implementation issue in spatial models relates to the choice of an estimator for the coefficients of the model. As pointed out earlier, OLS is unsatisfactory and thus an alternative has to be employed. MLE can be used as an alternative though carrying out the Bootstrap technique with MLE can be computationally demanding.[10] In this analysis, the bias corrected confidence intervals are calculated. These BC 90 percentile confidence intervals for estimates of the four land uses are reported in Table (4.3).

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[10]For this analysis, using a 2.4 megahertz machine, carrying out 1000 bootstrap replications took 10 hours for the Northern region and 7 hours for the Southern region.

4.3.2 Northern Row Crop Region

In the Northern region, the intersection of MLRA and HUC results in 20 polygons. However, only 14 polygons are considered since the other 6 polygons do not have sizable data points. The total acreage of this region is 7,578,400. Figure 4 shows the relative position and size of the Northern row-crop region, while Figure 2 provides a detailed view of this region with the polygons under study being enumerated.

As in the Southern region, the time span considered here is also the period 1987-1995. Thus, total observations of pheasant count and land uses for this region are 98. The yearly average of CRP land is 106,600 acres. It is important to note here that even though the total acreage in the Northern region is much greater than in the Southern region, the average CRP land in the latter is around twice of that in the former. The yearly average of pastureland and non-cultivated land is 371,530 acres and 18,729 acres respectively. Cropland averages 5,713,600 acres for the time period under study. At an average, around 81 percent of the total Northern row-crop region is under these four land uses.

In order to validate the use of a spatial-temporal model for this data set, tests are conducted to detect the presence of spatial correlation and serial correlation in residuals. Table (4.4) shows the results of four tests conducted to test the presence of spatial dependence in residuals. These are the same tests which were used for the Southern region. All the tests have a null hypothesis of zero spatial dependence. The Moran I-statistic takes a value of 2.27 and hence is greater than the critical value of 1.96, implying that the null hypothesis of no spatial correlation can be rejected. For the tests based on maximum likelihood estimation, the Wald value of 13.5495 is greater than the critical value 6.6350 and thus the null hypothesis of no spatial dependence in residuals can be rejected. Similarly, the LR and LM tests also reject the null hypothesis of no spatial dependence of errors since the LR value of 7.56 and LM value of 7.53 are greater than the critical value.

Next, to investigate the presence of serial correlation in the data the Durbin-Watson test is

Table 4.4   Tests for spatial correlation in residuals in Northern region

Moran-I test	
Moran I	0.1746
Moran I-statistic	2.2756
Marginal Probability	0.0300
mean	-0.0224
variance	0.0075

LM error test	
LM Value	7.5284
Marginal Probability	0.0368
chi(1)	6.6350

LR error test	
LR value	7.5603
Marginal Probability	0.1460
chi(1)	6.6350

Wald Test	
Wald value	13.5495
Marginal Probability	0.0002
chi(1)	6.6350

employed. The statistic takes a value of 1.9934 for the Northern region, with a null hypothesis of zero serial correlation. This value is lower than the upper bound of the Durbin-Watson statistic (the 5 percent critical value) and hence according to this test the null hypothesis can not be rejected. However, this test may not be foolproof and failing to account for autocorrelation when it is present is almost surely worse than accounting for it when it is not (Green [1997]). Hence, this analysis accounts for both spatial dependence and serial correlation in residuals.

The parameter estimates of the spatial model are reported in Table (1.5), with an asterisks denoting significance at 90% confidence level. The intercept is found to be positive and significant. Around half of the dummy variable coefficients are significant and, with the exception of one, all the significant coefficients are positive. Thus, this indicates that there are extraneous positive influences on the pheasant population in this region.

The impact of CRP land and pastureland on pheasant count is positive and significant. The response parameter estimate of CRP is 10.04, which is the increase in pheasants/mile associated with a marginal increase in the proportion of land under CRP. A marginal increase in the proportion of pastureland results in an increase of around 5 pheasants per mile. Thus, these figures imply that while both CRP land and pastureland have a positive impact on pheasant count, the marginal impact of CRP land is twice that of pastureland. Calculating the average elasticity of CRP land, we find that is equals 14.24, implying that a one percent increase in the share of CRP land results in a change in percentage pheasant population per mile of 14.24. The average elasticity of pastureland is 27.

Non-cultivated land has a negative and significant impact on pheasant count. A marginal increase in noncultivated land decreases the average pheasant count per mile by 9.5. The estimation results show that cropland has a negative and significant effect on pheasant count. The average pheasant count per mile decreases by 1.37 due to a marginal increase in cropland. Note that this is the marginal impact when 75 percent of the region is comprised of cropland. The average elasticity

Table 4.5   Northern Row Crop Region: Spatial Model Estimates

Parameter	Spatial Model Estimates (t-statistics are in parenthesis)
$\hat{\alpha}$	0.3412* (2.94)
δ_1	0.8501* (2.29)
δ_2	−0.4108 (-0.23)
δ_3	1.5597*(2.51)
δ_4	0.2624* (1.81)
δ_5	0.4377 (0.43)
δ_6	0.1080* (2.02)
δ_7	−0.6605 (-0.12)
δ_8	0.4671 (0.79)
δ_9	0.2513 (1.13)
δ_{10}	0.6579 (0.54)
δ_{11}	0.3367 (0.46)
δ_{12}	2.1677* (2.02)
δ_{13}	−0.1672* (-3.84)
$\hat{\theta}^c$	10.04* (1.86)
$\hat{\theta}^p$	4.95* (1.88)
$\hat{\theta}^n$	−9.93* (-1.89)
$\hat{\theta}^{cs}$	−1.37* (-1.63)
$\hat{\lambda}$	0.31* (3.07)
$\hat{\phi}$	0.12 (1.07)
σ^2	0.48
R^2	0.56

Table 4.6 BC: 90 percentile Confidence Intervals.

Parameter	MLE	CI
$\hat{\theta}^c$	10.04	(7.89, 19.54)
$\hat{\theta}^p$	4.95	(1.82, 10.71)
$\hat{\theta}^n$	-9.93	(-17.59, -0.38)
$\hat{\theta}^{cs}$	-1.37	(-3.70, -0.001)

of non-cultivated land is -3.48 and the average elasticity of cropland is -67.37.

The estimate of the spatial dependence coefficient takes a value of 0.31 and is significant. Thus, for this region also we find evidence of a positive spatial dependence in residuals across polygons. This provides support to the intuition that disturbances in one polygon will also have a similar effect on the neighboring polygons and thus residuals across polygons will be positively correlated. This can primarily be attributed to their geographical proximity. However, the serial correlation coefficient is found to be insignificant. Thus, there is no evidence of any correlation of residuals over time. The statistic, R^2, which measures the "goodness of fit" of the model to the data is 0.56. Thus implying that 56% of the variation in the dependent variable is explained by the explanatory variables of this model.

To compute the confidence intervals for the parameter estimates of the model the Bootstrap method is once again applied. The bias corrected 90 percentile confidence intervals for estimates of the four land uses are reported in Table (4.6).

4.4 Discussion

In this chapter, we have analyzed the response of species population to common land practices using land use data for Iowa. The species considered is one of the important game species of the Midwest: ring-necked pheasants. This analysis was conducted separately for two regions of Iowa

corresponding to the MLRA: the Northern row crop region and the Southern pasture region. This choice was based on the observation that these regions have polar characteristics in terms of the land cover. The Northern row crop region is chiefly under row crops, the Southern pasture region is chiefly under CRP and pastureland. Employing an empirical model we accounted for the spatial and temporal correlations likely in such an analysis.

The use of a spatial model is validated in both the Northern row crop region and Southern pasture region. The spatial dependence coefficient is found to be positive and significant in both the regions under study. This is intuitive as due to their geographical proximity there are a number of variables that are likely to be spatially correlated. These omitted variables result in the disturbances being correlated spatially. Spatial dependence can also be a result of measurement errors. These errors tend to spill over across the boundaries of spatial units. As a result, the errors in spatial unit i, are likely to be related to the errors in a neighboring unit j. The serial correlation coefficient is found to be insignificant possibly due to the inclusion of dummy variables for each polygon, which might have captured the omitted variables likely to be correlated over time.

The intercept for the Southern region was not significant while almost all the significant coefficients of dummy variables were found to be negative indicating presence of extraneous negative influences on pheasant counts. These influences may relate to geographic features of the polygons, weather characteristics, hunting pressures etc. In the Northern region, the intercept is positive and significant. Around half of the dummy variable coefficients are significant and positive. This indicates that this region is possibly conducive for pheasant populations.

Summarizing the results for the Southern region, CRP and pastureland have a positive impact on pheasant counts. As reported in the previous section (Table 4.2), the marginal impact of pastureland on pheasant count is higher than that of CRP. The impact of non-cultivated land and cropland is found to be negative, with the negative marginal impact of non-cultivated land being higher than that of cropland. This can be explained by the fact that only 25% of land in

this region is under cropland. In addition, corn is a food source for pheasants and it also provides nesting shelter for pheasants in winter. However, since corn is harvested and hence does not provide undisturbed habitat for pheasants, it can have a negative impact on their populations, as illustrated in this study. On the other hand, non-cultivated land primarily included permanent hayland and horticultural cropland, which do not provide a suitable habitat for pheasant populations.

For the Northern region, CRP land and pastureland have a positive marginal impact on pheasant counts while non-cultivated land and cropland have a negative marginal impact. A marginal increase in CRP land increases the average pheasant count per mile by around 10. The marginal impact of pastureland is smaller, it increases pheasants count per mile by around 5. Non-cultivated land and cropland have a negative impact on the pheasant count. A marginal increase in non-cultivated land is estimated to decrease the average pheasants count per mile by around 9, while cropland decreases the pheasants count by around 1.

In order to better understand the sign and magnitude of these coefficients, it is necessary to know more about the composition of the two regions. Approximately one-third of the land in the Southern region, at an average, comprises of CRP and pastureland. On the other hand, in the Northern region the acreage under these two land uses averages around 6 percent. As is evident from the results reported in Table (4.2) and Table (1.5), the marginal impact of CRP in the northern region is much higher than its impact in the southern region. Whereas the negative marginal influence of cropland is smaller in the southern region compared to the northern region. As pointed out earlier this may be due to the fact that at an average 75 % of the land in the Northern region is under cropland, while this figure for the Southern region is only 25 %.

This analysis identifies several important and interesting issues. It establishes the presence of spatial dependence in residuals of regressors relating land use to wildlife counts and hence the importance of accounting for the spatial aspect in such studies. CRP land is found to have a positive impact on pheasant populations while cropland is estimated to have a negative influence.

In addition to assessing the impact of four common land uses on pheasants, this study also highlights the importance of regional variations in those impacts. Thus, this analysis demonstrates that the same land uses can have a regionally variable impact on pheasant count. For instance, increasing cropland in Northern region is found to have a greater negative impact on pheasants compared to Southern region. A marginal increase in the proportion of CRP land in Northern region has a much higher positive impact on pheasant counts compared to the Southern region. Understanding this can be valuable in land management policies targeting conservation of wildlife since it can facilitate efficient conservation.

- ▲ **Centroids using ESRI**
- ● **Centroids using SpaceStat**
- **Southern region of Iowa**
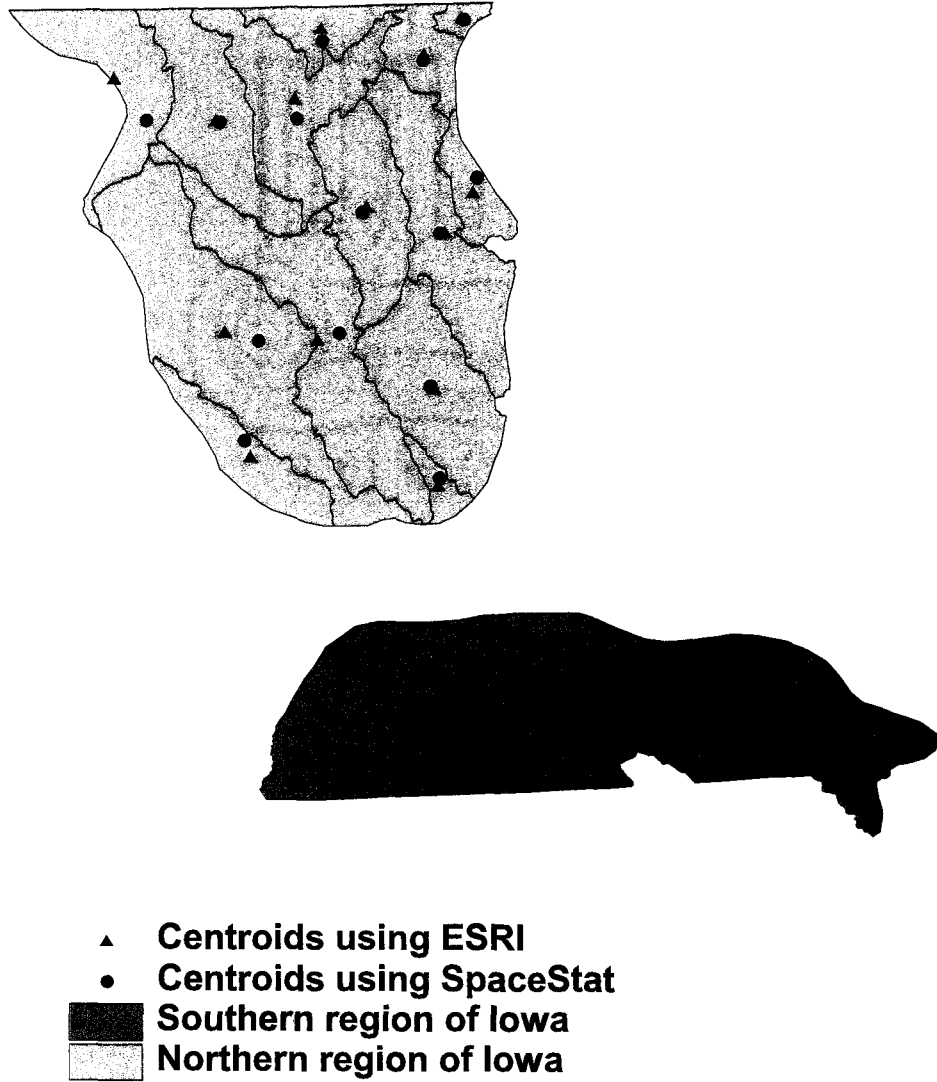- **Northern region of Iowa**

Figure 1   Centroid

Figure 2   Northern Row Crop Region
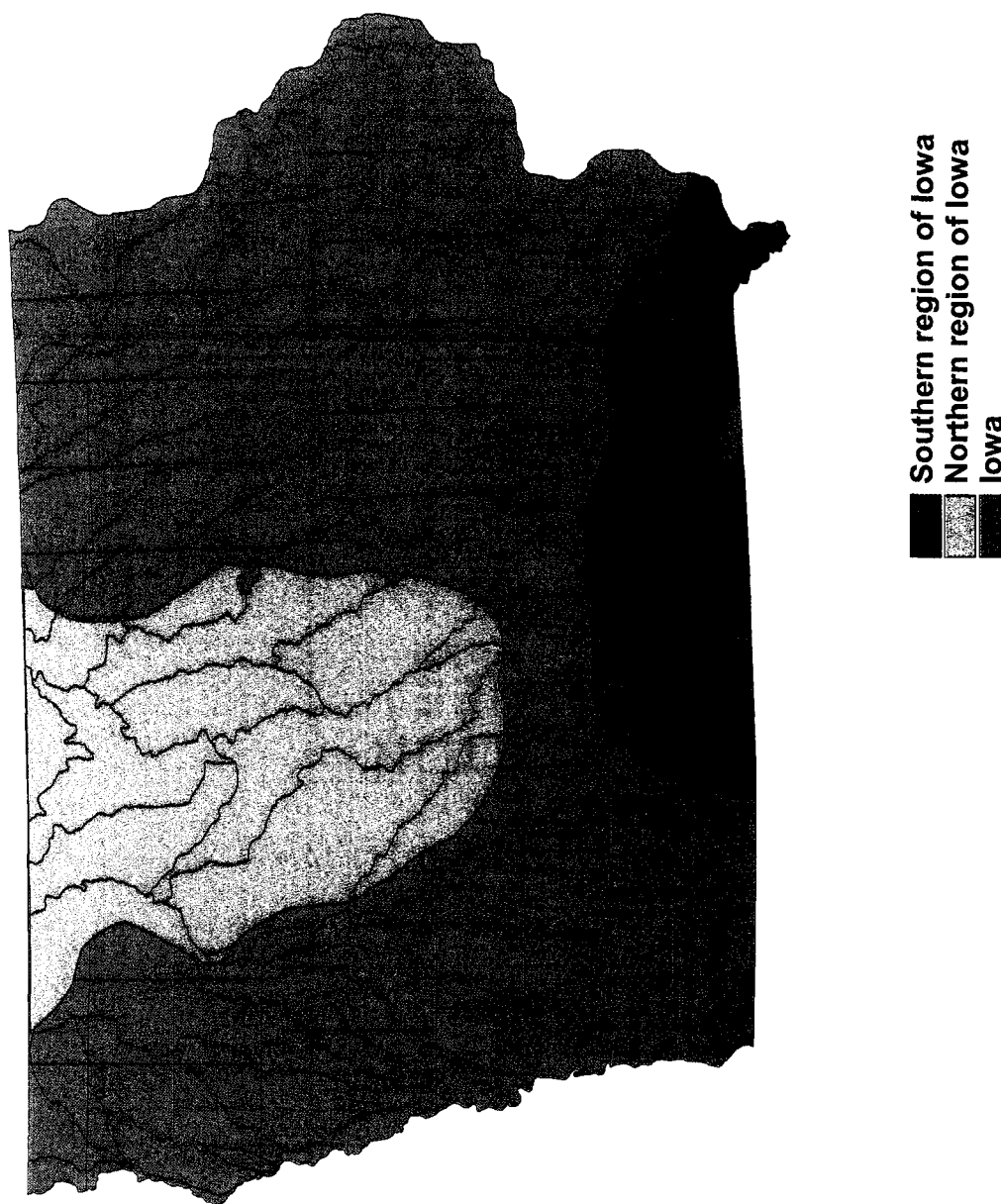

Figure 3   Southern Pasture Region

Figure 4   The relative size and position of the two regions under study
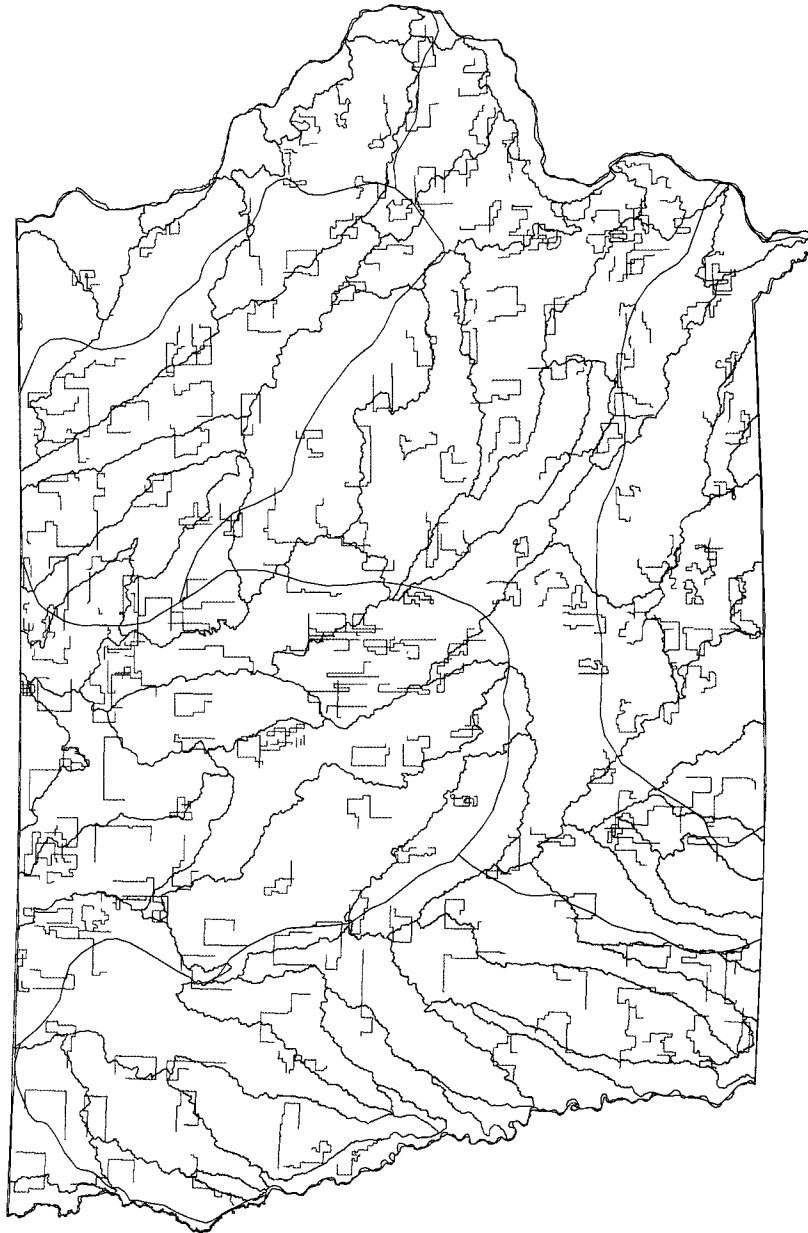
Figure 5 IDNR annual survey routes

CHAPTER 5. WILDLIFE PRESERVATION DECISIONS: A BAYESIAN APPROACH

Bayesian approach, over the years, has attracted a lot of attention in varied studies. Two key advantages have especially been highlighted in the literature. First, Bayesian approach explicitly accounts for the inherent uncertainty of the problem at hand. Second, this approach incorporates all the available information to produce estimates for the parameters of the model. Although the theoretical advantages of Bayesian methods are noteworthy, the practice of Bayesian techniques has proved to be a stumbling block in its propagation. However, due to recent advances in computing, these difficulties have been mitigated to a large extent.

In this chapter, a Bayesian spatial model is employed to study the effect of various land uses on pheasant populations. The posterior estimates for the parameters of the model are obtained using a Markov Chain Monte Carlo simulation method known as the Gibbs algorithm. In the next section, the methodology is explained in detail. Thereafter, this approach is applied to study the response of ring-necked pheasants to four land uses and obtain the posterior estimates for the response parameters. Finally, the results are analyzed along with the cost aspect of preservation in order to provide useful guidelines for wildlife managers.

5.1 Methodology

Bayesian approach to inference has existed for a long time (Zellner [1971]), however, recent advances in its implementation have led to a revival of interest in these methods. Specifically, these advances relate to better numerical computation techniques, such as Markov Chain Monte

Carlo (MCMC) methods, which have facilitated the construction of the posterior distribution, making it much easier than the past approaches that relied on analytical solutions for the posterior distribution.

An important aspect of Bayesian methodology is its focus on distributions for both the data and parameters. Another notable feature of this methodology is that it uses all the available information as the basis for inference. Bayes rule involves combining the data distribution, embodied in the likelihood function, with the prior distributions to produce the posterior distributions for parameters of the model. Thus, the information for constructing a posterior distribution comes both from the sample data, in the form of the likelihood function, as well as previous information embodied in the prior distributions assigned to the parameters. Prior distributions reflect the existing information on parameters of the model. These priors can be based upon a previous sample or can be subjective, being suggested by experts in the field. Such priors are known as *informative priors*. On the other hand, if reliable previous information does not exist then uniform or "flat" priors are adopted. These are called *diffuse priors*.

Consider the following spatial model

$$y = x\theta + \epsilon$$

$$\epsilon = \lambda W \epsilon + u,$$

(5.1)

where y is the dependent variable, x is the vector of explanatory variables and θ is the vector of response parameters. ϵ is the vector of disturbances which are spatially correlated. The spatial dependence coefficient is denoted by λ and W is the spatial weight matrix, which contains all the information about the assumed spatial structure of errors, and $u \sim N(0, \sigma^2 I_n)$. The above can be rewritten as follows

$$y = x\theta + (I_n - \lambda W)^{-1}u,$$

(5.2)

or

$$Ay = Ax\theta + u,$$

(5.3)

where $A = (I_n - \lambda W)$. The likelihood function for this model can then be written as:

$$L(y|\beta) \propto |A|\,\sigma^{-n}\,exp\{-(1/2\sigma^2)\,(y - x\,\theta)'\,A'\,A\,(y - x\,\theta)\}. \tag{5.4}$$

The parameters of the model, denoted by β in the above expression, are the response parameter vector, θ, the spatial error dependence coefficient, λ, and the error variance, σ^2.

The prior densities of the parameters are expressed as:

$$p(\theta) = \pi_1(\theta),$$

$$p(\lambda) = \pi_2(\lambda),$$

$$p(\sigma) = \pi_3(\sigma). \tag{5.5}$$

Assuming θ, λ and σ to be independent results in a joint prior density for the parameters of the following form

$$p(\theta, \lambda, \sigma) = \pi_1(\theta)\,\pi_2(\lambda)\,\pi_3(\sigma). \tag{5.6}$$

The joint posterior distribution for the parameters of the model is found from the direct application of Bayes Rule, which is the product of the likelihood function (5.4) and the joint prior distribution (5.6) and can be expressed as follows

$$P(\lambda, \theta, \sigma|y) \propto \pi_1(\theta)\,\pi_2(\lambda)\,\pi_3(\sigma)\,|A|\,\sigma^{-n}\,exp\{-(1/2\sigma^2)\,(y - x\,\theta)'\,A'\,A\,(y - x\,\theta)\}. \tag{5.7}$$

The above distribution forms the starting point for the derivation of various marginal and joint posterior distributions for combinations of the parameters. Inference for the parameter of interest can be achieved by integrating out the other parameters, the latter often being referred to as 'nuisance' parameters. As is apparent, the expression for the posterior distribution (5.7) is complicated and usually cannot be solved analytically.

The complex nature of the posterior distribution has in the past restricted the applicability of the Bayesian approach to simple models. However, in recent years statisticians have been increasingly drawn to Markov chain Monte Carlo (MCMC) methods to simulate complex, nonstandard

multivariate distributions. The two most important and widely used MCMC methods are the Gibbs algorithm and the Metropolis-Hastings (M-H) algorithm. Both these methods involve sampling from particular distributions. The draws are Markov chain because each value depends only on the immediately preceding one, and the methods are Monte Carlo because random draws are taken. The next couple of paragraphs provide the details on these methods.

The Gibbs algorithm works on the premise that although the joint posterior distribution is complex, the conditional posterior distributions for the various parameters of the model can be simulated from easily. The Gibbs sampler works as follows, first starting (initial) values of the parameters of the model are chosen. For this spatial model, the initial values of the parameters can be denoted as $\lambda(0)$, $\theta(0)$ and $\sigma^2(0)$. The next step entails sampling from the conditional distributions. Firstly, sample from $P(\theta|y, \lambda(0), \sigma^2(0))$ to get $\theta(1)$ (mean of the distribution). Next, sample from $P(\lambda|y, \theta(1), \sigma^2(0))$ to get $\lambda(1)$ and then finally sample from $P(\sigma^2|y, \theta(1), \lambda(1))$ to obtain $\sigma^2(1)$. This process is then simply repeated many times, each time using the previously generated parameter values to generate the next set. This repetition can be done anywhere between 10000 to 30000 or more times. It is a general practice to throw away the first n values generated to allow the Markov chain to approach its equilibrium distribution, namely the joint posterior distribution of interest. These n values are known as "burn-in" and vary anywhere between 100 to 2000 or higher, depending on the specifics of the problem. The values generated after the "burn-in" are then averaged to obtain estimates of the parameters of interest. Casella and George [1992] present an intuitive exposition of the Gibbs sampling algorithm.

The other important MCMC method is the M-H algorithm, which was developed by Metropolis et al. [1953] and was subsequently generalized by Hastings [1970]. This algorithm is extremely versatile and gives rise to the Gibbs sampler as a special case, as pointed by Gelman [1992]. M-H sampling algorithm works in a similar manner to Gibbs sampling in that the set of parameters is updated in turn and then the procedure is repeated. However, the updating procedure is different.

For each parameter at each time step a new value is generated from a "proposal distribution". Then this value is compared to the old value and is accepted with a probability so that the draws are actually simulating from the posterior distribution. If the new value is rejected then the parameter retains its old value. As in the Gibbs sampler, the draws are regarded as a sample from the target density only after n draws so that the effect of the starting values can be ignored. Chib and Greenberg [1995] present an excellent discussion of this algorithm.

5.2   Posterior Estimation

Bayesian spatial model is employed to study the response of pheasant population to four different land uses. These land uses are: CRP land, pastureland, non-cultivated land and cropland. The data for the pheasant count and land use are the same as used for the spatial-temporal model studied in the previous chapter. The details of the data sources can be found therein. In this study, the spatial dependence of errors is accounted for, however, time dependence is not considered since the analysis conducted in the previous chapter demonstrated the lack of evidence to support the presence of serial correlation. This Bayesian analysis is also conducted separately for both the Southern pasture region and the Northern row crop region.

We apply the model presented in (5.1). y is a $nT \times 1$ vector of pheasant counts per mile in i polygons and t time periods, where $i = 1 \cdots n$ and $t = \cdots T$, x is a $nT \times (n+4)$ vector of the proportion of land in four land uses and polygon-wise dummy variables. The vector of response parameters and dummy variable coefficients is denoted by θ, whose dimension is $(n+4) \times 1$. Bayesian posterior estimates for the response parameters θ, and the spatial dependence coefficient, λ, are obtained using MCMC techniques. The estimation is carried out using both a diffuse prior and an informative prior for the parameters of the model. The following sections report the results.

5.2.1 Bayesian Estimation with Diffuse Prior

In the absence of any information about the parameters of the model the Bayesian analysis is conducted using diffuse priors. These priors take the following form (5.5),

$$\pi_1(\theta) \propto \text{constant}$$

$$\pi_2(\lambda) \propto \text{constant}$$

$$\pi_3(\sigma) \propto \sigma^{-1}. \tag{5.8}$$

The product of these prior densities and the likelihood function (Bayes Rule) then yields the following posterior distribution:

$$P(\theta, \lambda, \sigma | y) \propto |A| \, \sigma^{-(n+1)} \, exp\{-(1/2\sigma^2)\,(y - x\,\theta)'\, A'\, A\,(y - x\,\theta)\}, \tag{5.9}$$

where $A = (I_n - \lambda W)$.

Application of the Bayesian spatial model with diffuse or 'non-informative' priors results in Bayesian posterior estimates that are very similar to the MLE. This is clear and intuitive in theory. When the prior is diffuse the posterior is essentially the likelihood function. In other words, since the prior density is a constant the posterior is influenced only by the likelihood function. In practice, however, the two estimates may not be identical since location of the posterior depends on the constants and hence this can influence the outcome of estimation.

Table (5.1) reports the Bayesian posterior estimates for the Southern region using diffuse priors for all the parameters of the model. The p values of these estimates are also reported in the table and the significant estimates (at 95% confidence level) are highlighted by an asterisk. MCMC simulation method using Gibbs algorithm is employed to obtain the posterior estimates. The number of draws are taken to be 10000 and the 'burn-in' draws are 2000. The initial (starting) values for the parameters of interest are taken to be the MLE. The spatial dependence coefficient is

Table 5.1   Southern Pasture Region: Posterior Estimates for Bayesian Spatial Model

Parameter	Posterior Estimates	
	Estimate	p value
$\hat{\alpha}$	0.28	0.3224
δ_1	0.04	0.4522
δ_2	−1.83*	0.0492
δ_3	−1.22*	0.0455
δ_4	−1.78*	0.0243
δ_5	−1.29*	0.0014
δ_6	−1.89*	0.0510
δ_7	−0.08	0.4490
δ_8	−0.69	0.4987
$\hat{\theta}^c$	1.20*	0.0384
$\hat{\theta}^p$	7.69*	0.0202
$\hat{\theta}^n$	−0.26*	0.0433
$\hat{\theta}^{cs}$	−0.002*	0.0324
$\hat{\lambda}$	0.29*	0.0195
σ^2	0.28	
R^2	0.48	

restricted to be between the range $(1/\lambda_{max}, 1/\lambda_{min})$, where λ_{max} and λ_{min} are the maximum and minimum eigenvalue of the spatial weight matrix, which took the values 1 and -1.4259, respectively. This restriction is made on the spatial coefficient to keep the spatial model defined.

The intercept is found to be insignificant, while most of the coefficients for the dummy variable are significant. All the significant dummy variable coefficients are negative, thus suggesting the presence of extraneous negative influences on pheasant counts in these polygons. The posterior estimates for CRP land and pastureland are positive and significant. The response estimate for

CRP land is 1.2, which is the increase in pheasants/mile for a marginal increase in the proportion of CRP land. A marginal increase in pastureland is found to increase pheasants/mile by around 7.69. Thus, while both CRP land and pastureland have a positive influence on pheasant populations the posterior estimates indicate that the marginal impact of pastureland is stronger than that of CRP land for this region. Non-cultivated land and cropland are found to have a significant and negative impact on pheasant count. A marginal increase in non-cultivated land decreases the pheasants/mile by 0.26, whereas a marginal increase in cropland results in an estimated decrease in pheasants/mile of around 0.002. Hence, the marginal negative impact of cropland is much weaker than that of non-cultivated land.

The posterior estimate of spatial dependence coefficient is significant and equal to 0.29. Thus, there is evidence of positive spatial correlation between residuals across polygons. This implies that disturbances in one polygon has similar impact on the other polygons in the region. This is intuitive as, given the geographical proximity of the polygons, there are a number of variables which are likely to have a similar impact across polygons. The R^2 statistic is 0.48, implying that 48 % of the variation in the dependent variable is explained by the variables of the model.

Next, the Bayesian spatial model is applied to the Northern region and the posterior estimates of the parameters of the model are reported in Table (5.2). Again, MCMC method using Gibbs algorithm is applied to obtain these posterior estimates with the starting values of the parameters being the MLE. The number of draws are taken to be 10000 and the first 2000 draws were discarded ('burn-in'). The spatial dependence coefficient is restricted to be between the range $(1/\lambda_{max}, 1/\lambda_{min})$, where λ_{max} and λ_{min} are the maximum and minimum eigenvalue of the spatial weight matrix, which, for this region, took the values 1 and -1.3963 respectively.

The intercept is found to be positive and significant. Three of the dummy variable coefficients are significant with one on them being negative and the other two positive. The negative coefficient is in absolute value smaller than the positive intercept. Thus, there is evidence of positive extraneous

influences on the pheasant populations in this region.

The impact of CRP land and pastureland on pheasant count is found to be positive and significant. The estimate for the response parameter for CRP land is 11.05. This implies that for a marginal increase in the proportion of CRP land the pheasants/mile increase by 11.05. A marginal increase in the proportion of pastureland results in an increase of around 6 in pheasants/mile. Thus, the posterior estimates for the response parameters show that while both CRP land and pastureland result in an increase in the pheasant count, the marginal impact of CRP is stronger than that of pastureland land in the Northern region. The positive marginal impact of both CRP land and pastureland on pheasant populations is found to be much greater in the Northern region as compared to the Southern region, (Table (5.1) and Table (5.2)), this difference is especially pronounced in the case of CRP.

Non-cultivated land and cropland are found to have a negative and significant impact on the pheasant count. It is estimated that a marginal increase in non-cultivated land results in a decrease in the pheasants/mile by around 10. A marginal increase in cropland is estimated to decrease the pheasants/mile by around 1.44.

The posterior estimate of the spatial dependence coefficient takes a positive and significant value of 0.28. Thus, this illustrates that disturbances in one polygon leads to similar effects on the other polygons in this region. Again, providing ground for the intuition that due to their geographical proximity there are a number of variables which are likely to have a similar impact across polygons and lead to spatial correlation.

5.2.2 Bayesian Estimation with an Informative Prior

The importance and meaningfulness of Bayesian analysis is higher when there exists some information for the parameters, apart from the sample observations. In such a case, Bayesian analysis allows inference, for parameters of the model, to be based on all the available information.

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Table 5.2 Northern Row Crop Region: Posterior Estimates for a Bayesian
Spatial Model

Parameter	Posterior Estimates	
	Estimate	p value
$\hat{\alpha}$	0.24*	0.0447
δ_1	0.86	0.2621
δ_2	−0.43	0.2019
δ_3	1.54*	0.0011
δ_4	0.24	0.4309
δ_5	0.42	0.2547
δ_6	0.10	0.40
δ_7	−0.67	0.0826
δ_8	0.45	0.3285
δ_9	0.25	0.2123
δ_{10}	0.64	0.1261
δ_{11}	0.32	0.3378
δ_{12}	2.17*	0.0342
δ_{13}	−0.18*	0.0038
$\hat{\theta}^c$	11.05*	0.0012
$\hat{\theta}^p$	6.07*	0.0209
$\hat{\theta}^n$	−10.02*	0.0248
$\hat{\theta}^{cs}$	−1.44*	0.0284
$\hat{\lambda}$	0.28*	0.0111
σ^2	0.40	
R^2	0.62	

Thus, the entire information set is utilized.

Here, the response parameters are assumed to be normally distributed. The error variance is assumed to be have an inverted gamma distribution. Since much is not known about the spatial correlation coefficient except for its range, λ, is assumed to have uniform distribution with the bounds being $(1/\lambda_{max}, 1/\lambda_{min})$, where λ_{max} and λ_{min} are the maximum and minimum eigenvalue of the spatial weight matrix respectively. These assumptions are not based on a previous sample, however, these are popular distributions which have intuitive appeal in describing these parameters.

The informative priors then take the following form (5.5),

$$\pi_1(\theta) \propto N(\mu, \Sigma)$$

$$\pi_2(\lambda) \propto U((1/\lambda_{max}, 1/\lambda_{min}))$$

$$\pi_3(1/\sigma^2) \propto \text{Gamma}\,(\nu, d0), \tag{5.10}$$

where, μ and Σ are the mean vector and variance-covariance matrix of the response parameters, respectively. While, ν and $d0$ denote, respectively, the mean and variance for the inverse of error variance.

The Bayesian spatial model using informative priors is applied to the Southern region and the posterior estimates of the parameters of the model are reported in Table (5.3). The parameter estimates significant at 95% confidence intervals are marked with an asterisks. The MCMC method using the M-H algorithm is used to obtain the posterior estimates. The number of draws are taken to be 10000, where the first 2000 are omitted. As noted in Table (5.3), the intercept is insignificant and around half of the dummy variable coefficients are significant. All these coefficients are negative thus suggesting that there are negative extraneous influences on the pheasant count in this region.

The posterior estimates for CRP land and pastureland are positive and significant. The estimates indicate that a marginal increase in CRP land leads to an increase of about 1.75 in pheasant count. The marginal impact of pastureland on pheasant count is found to be stronger compared to CRP. A marginal increase in pastureland is estimated to increase pheasant count by around

Table 5.3   Southern Pasture Region: Posterior Estimates for a Bayesian
Spatial Model with an Informative Prior

Parameter	Posterior Estimates	
	Estimate	p value
$\hat{\alpha}$	0.32	0.3308
δ_1	0.11	0.3398
δ_2	−1.43*	0.1063
δ_3	−0.98	0.3971
δ_4	−1.46*	0.0518
δ_5	−0.87	0.2383
δ_6	−1.42*	0.0189
δ_7	0.15	0.4320
δ_8	−0.47	0.2497
$\hat{\theta}^c$	1.75*	0.0381
$\hat{\theta}^p$	6.34*	0.0507
$\hat{\theta}^n$	−0.12*	0.0398
$\hat{\theta}^{cs}$	−0.02*	0.0440
$\hat{\lambda}$	0.20*	0.0465
σ^2	0.30	
R^2	0.50	

6. Non-cultivated land and cropland are found to have a negative impact on pheasant count with a marginal increase in non-cultivated land decreasing the pheasants/mile by 0.12 while the same increase in cropland decreases pheasants/mile by around 0.02.

The spatial dependence coefficient is found to be significant and positive. Thus providing evidence for positive effects of disturbances in neighboring polygons. The fit of the model, as indicated by the R^2 statistic, is found to be 0.50, implying that 50% of the variation in the dependent variable is explained by the variables of the model.

Next, the Bayesian spatial model with informative priors is applied to the Northern region. The posterior estimates of the model are reported in Table (5.4). The intercept is found to be negative and significant. Around half of the dummy variable coefficients are significant, with equal number being positive and negative. CRP land has a significant positive impact on pheasant count. A marginal increase in CRP land is found to increase pheasants/mile by around 10. The significant positive influence of pastureland is smaller, with a similar increase in pastureland leading to an increase in pheasants/mile by around 2. Non-cultivated land and cropland are both found to have a negative influence on pheasant count, with the marginal negative impact of non-cultivated land being greater than that of cropland. A marginal increase in non-cultivated land decreases pheasants/mile by around 2. Whereas the same increase in cropland is estimated to decrease pheasants/mile by around 1.

The spatial dependence coefficient is found to be positive and significant. Thus lending support to the intuition that disturbances in one polygon lead to similar effects on neighboring polygons. The R^2 statistic is 0.60, implying that 60% of the variation in the dependent variable is explained by the variables of the model.

Table 5.4 Northern Row Crop Region: Posterior Estimates for a Bayesian
Spatial Model using an informative prior

Parameter	Posterior Estimates	
	Estimate	p value
$\hat{\alpha}$	-0.38^*	0.39
δ_1	0.31^*	0.0341
δ_2	-0.69	0.0669
δ_3	1.56^*	0.0011
δ_4	-0.30	0.3192
δ_5	0.22	0.4895
δ_6	0.04	0.4450
δ_7	-0.84^*	0.0398
δ_8	0.19	0.3493
δ_9	-0.02	0.1194
δ_{10}	0.28	0.2091
δ_{11}	-0.05	0.4192
δ_{12}	1.52^*	0.0278
δ_{13}	-0.62^*	0.0216
$\hat{\theta}^c$	10.01^*	0.0016
$\hat{\theta}^p$	2.14^*	0.0368
$\hat{\theta}^n$	-2.17^*	0.0463
$\hat{\theta}^{cs}$	-1.03^*	0.0449
$\hat{\lambda}$	0.15^*	0.0282
σ^2	0.42	
R^2	0.60	

5.3   Discussion

In this chapter, Bayesian methodology is applied to spatial econometric modelling and estimation. An important aspect of Bayesian method is that it focuses on obtaining the entire probability support for the parameters of the model and this is done using all the available information, namely, the sample data and prior information. Thus, Bayes rule involves combining the data distribution embodied in the likelihood function, with prior distributions for the parameter, to obtain the posterior distribution of the parameters of the model. This distribution then forms the basis for inference.

Bayesian methodology has existed for a long while, however, the past approaches relied on the analytical solution of the posterior distribution, which in most cases is extremely complex. Thus, from an applied perspective making Bayesian methods almost redundant. However, the recent computing advances have made the application of Bayesian method fast and simple.[1] Gibbs sampling and M-H algorithm are important methods for simulating the posterior distribution and obtaining the posterior estimates of the parameters of interest. These methods rely on Monte Carlo simulations and in fact using the MCMC methods for estimation is faster than MLE. In this study, the Gibbs sampler has been applied to obtain the posterior estimates for the parameters of the spatial model.

In this analysis, Bayesian approach is carried out using both an informative prior and a diffuse prior. The Bayesian posterior estimates using a diffuse prior tend to be similar to the MLE since with a diffuse prior the likelihood function dominates. The informative priors used are subjective. The posterior estimates using diffuse priors indicate that CRP and pastureland have a positive marginal impact on pheasant population in both the regions under study. However, this positive impact is much more pronounced in the Northern region as compared to the Southern region.

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[1]In fact, in many cases, Bayesian procedures turn out to be simpler than MLE since the former does not require maximization of any function. For some models, the maximization of the likelihood function can prove to be difficult numerically.

Table 5.5 Southern Pasture Region: Posterior Estimates for a Bayesian
Spatial Model with an Informative Prior versus a diffuse prior

Parameter	Posterior Estimates		Diffuse Prior	
	Estimate	p value	Estimate	p value
$\hat{\alpha}$	0.32	0.3308	0.28	0.3224
δ_1	0.11	0.3398	0.04	0.4522
δ_2	−1.43*	0.1063	−1.83*	0.0492
δ_3	−0.98	0.3971	−1.22*	0.0455
δ_4	−1.46*	0.0518	−1.78*	0.0243
δ_5	−0.87	0.2383	−1.29*	0.0014
δ_6	−1.42*	0.0189	−1.89*	0.0510
δ_7	0.15	0.4320	−0.08	0.4490
δ_8	−0.47	0.2497	−0.69	0.4987
$\hat{\theta}^c$	1.75*	0.0381	1.20*	0.0384
$\hat{\theta}^p$	6.34*	0.0507	7.69*	0.0202
$\hat{\theta}^n$	−0.12*	0.0398	−0.26*	0.0433
$\hat{\theta}^{cs}$	−0.02*	0.0440	−0.002*	0.0324
$\hat{\lambda}$	0.20*	0.0465	0.29*	0.0195
σ^2	0.30		0.28	
R^2	0.50		0.48	

Specifically, the positive marginal impact of CRP on pheasants/mile in the Northern region is found to be 11 while that in the Southern region it is only 2.35. The posterior estimates for the response parameters for non-cultivated land and cropland turn out to be negative for both the regions. The negative marginal impact of non-cultivated land and cropland is much higher in the Northern region as compared to the Southern region.

These posterior estimates cannot be directly compared to the MLE for the response parameters in the previous chapter since while the Bayesian estimation has been applied to a spatial model,

in the previous chapter, a spatial-temporal model was analyzed. However, broad conclusions are found to be similar. The spatial-temporal study also indicated that CRP and pastureland have a positive impact on pheasant population where the positive marginal impact of CRP in Northern region was found to be more pronounced than in the Southern region. Cropland was found to have a negative impact on pheasant population in the two regions for both the studies.

The posterior estimates using an informative prior also provide evidence for the positive impact of CRP and pastureland on pheasant populations. Again, it is found that between the two regions under study the positive marginal impact of CRP is greater in Northern region compared to the Southern region. While cropland is found to have a similar negative impact on pheasant populations in both the regions.

The spatial dependence coefficient is found to be positive and significant. Thus, indicating the presence of positive spatial correlation across polygons. In other words, disturbances in the neighboring polygons are found to be correlated. This is intuitive since due to their geographical proximity there are a number of variables that are likely to have a similar impact on the pheasant population in these polygons. For instance, the presence of streams, type of soil and other natural variables are expected to have a similar impact across polygons. These omitted variables result in the disturbances being correlated spatially. Another reason that may lead to spatial correlation in the disturbances is measurement errors. If similar errors are made in collecting data across polygons, this can lead to spatial dependence of disturbances.

The purpose of this analysis is that it can serve as a guide for policy makers with an objective to conserve wildlife, in this case, pheasants. This analysis indicates that while CRP and pastureland are beneficial for the pheasant population, cropland is found to have a negative marginal impact. In addition, studying the Northern and Southern region of Iowa, it was found that CRP has a much higher positive marginal impact on pheasant population in the former region compared to the latter. In other words, if the proportion of land devoted to CRP is increased marginally in both

Table 5.6   Northern Row Crop Region: Posterior Estimates for a Bayesian
Spatial Model with an informative prior versus a diffuse prior

Parameter	Informative Prior		Diffuse Prior	
	Estimate	p value	Estimate	p value
$\hat{\alpha}$	-0.38^*	0.39	0.24^*	0.0447
δ_1	0.31^*	0.0341	0.86	0.2621
δ_2	-0.69	0.0669	-0.43	0.2019
δ_3	1.56^*	0.0011	1.54^*	0.0011
δ_4	-0.30	0.3192	0.24	0.4309
δ_5	0.22	0.4895	0.42	0.2547
δ_6	0.04	0.4450	0.10	0.40
δ_7	-0.84^*	0.0398	-0.67	0.0826
δ_8	0.19	0.3493	0.45	0.3285
δ_9	-0.02	0.1194	0.25	0.2123
δ_{10}	0.28	0.2091	0.64	0.1261
δ_{11}	-0.05	0.4192	0.32	0.3378
δ_{12}	1.52^*	0.0278	2.17^*	0.0342
δ_{13}	-0.62^*	0.0216	-0.18^*	0.0038
$\hat{\theta}^c$	10.01^*	0.0016	11.05^*	0.0012
$\hat{\theta}^p$	2.14^*	0.0368	6.07^*	0.0209
$\hat{\theta}^n$	-2.17^*	0.0463	-10.02^*	0.0248
$\hat{\theta}^{cs}$	-1.03^*	0.0449	-1.44^*	0.0284
$\hat{\lambda}$	0.15^*	0.0282	0.28^*	0.0111
σ^2	0.42		0.40	
R^2	0.60		0.62	

the regions, then the increase in pheasant count is estimated to be around five times more in the Northern region compared to the Southern region.

Thus, one of the important policy implications drawn from this study is that putting land under CRP satisfies the policy maker's objective of conservation. Moreover, devoting land to CRP in the Northern region is found to be more effective in meeting this goal than doing so in the Southern region. However, this analysis has so far not dealt with the issue of costs. Devoting land to CRP and pastureland involves taking land out of agrarian production. Thus, these conservation efforts then involve two kinds of costs: a direct cost of purchasing the land[2] and the opportunity cost in terms of the lost crop yields. Adding the cost perspective leads to questions such as, is it cost effective to conserve land in the Northern region compared to the Southern region?

In an attempt to answer these cost issues, two statistics are analyzed. First, to gauge the direct cost of conversion, land values in the two region are studied. The land values are obtained from the Iowa land values survey (2002) that is conducted by the Iowa State University Extension department. They provide the dollar values of land per county. The land value of counties lying within the Northern region and the Southern region average $ 2,422 and $ 1,203, respectively. Second, in order to get an estimate for the opportunity cost, the yields of row crops such as corn and soybean need to be obtained for the two regions under study. The predicted yields are likely to change with time because of advances in crop production technologies. Thus, instead of looking at actual yields, the corn suitability ratings (CSR), an index to soil productivity is considered (Miller [2002]). CSR is an index procedure developed in Iowa to rate each different kind of soil for its potential row-crop productivity. Soil profile properties and weather conditions are dominant factors that affect productivity. Also, slope characteristics are taken into consideration. Thus, CSR is an index that can be used to rate one soil's potential yield production against another over a period of time.[3] Ratings range from 100 (best) to as low as 5 for soils with severe limitations for

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[2]Even in cases where land is not purchased, the farmers have to be compensated for taking land out of agriculture.
[3]This yield is referred to as the potential since this is the yield prediction under the assumption that high

row crops. These ratings are available per county. The rating of counties in the Northern region averages 72, while the same figure for the Southern region is 44.

The objective of the policy maker is taken to be maximizing the number of pheasants. The utility derived can be considered to be directly proportional to the number of pheasants[4] or its monotonic transformation. This objective is likely to be constrained by a budget. As mentioned earlier, the total cost of conservation comprises of the direct cost of purchasing or leasing land and the indirect cost that accounts for the opportunity cost of conversion. Through the reliable estimates (cited above) it is found that the direct cost of conservation in Northern region is roughly twice that in Southern region. While the indirect cost, obtained by comparing the potential yield ratings in both the regions of study, is estimated to be be around one and half times more in the Northern region. However, given that the response estimate of CRP to pheasant population in the Northern region is around five times higher than that associated with the Southern region, it appears likely that increasing the proportion of land under CRP in the Northern region serves the goal of the policy maker.

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management techniques are adopted.

[4]The proportionality constant depends on how much the community values pheasants and this aspect will not be deliberated upon here.

CHAPTER 6.   CONCLUSIONS

This dissertation investigated the linkage between land use decisions and the resulting wildlife populations. We focused on these land use management issues, with the objective of species conservation, through both theoretical modeling and empirical work. In the theoretical analysis, we explicitly incorporated uncertainty in benefits of species conservation as a result of land conversion to a wildlife habitat, from alternative uses such as agriculture, and explored the opportunity of learning overtime. The empirical work looked at the direct linkages between four land uses and pheasant populations in Iowa. This was done using pheasant data from IDNR annual road side survey and the land use data was obtained from the NRI for the period: 1987-1995.

In the next section we discuss the conclusions from the theoretical analysis. Thereafter, the results from the empirical study are summarized. Finally, the policy implications of these findings and the direction of future work are presented.

6.1   Theoretical Analysis

Conversion of land from other uses, such as agriculture, to wildlife habitat may entail irreversibility and sunk costs when the efficiency of land as a wildlife habitat is uncertain. Thus, we asserted in this analysis that these dual sources of irreversibility have to be considered when choosing the level of land preservation. In addition, the impact of learning on preservation decisions was studied when both economic and ecological irreversibility are taken into account. Thus, we showed the effects of uncertainty, ecological and land conversion irreversibility, and endogenous learning on land conversion decisions for species preservation.

We studied the preservation decisions of three types of policymakers: active learner, passive learner and non-learner. These policy makers face the same optimization problem but differ in their behavior towards learning. *Experimentation effect*, which compares the active learner's preservation action to that of a passive learner, was investigated. In addition, the difference between the action of a passive learner and a non-learner, termed *Learning effect*, was also analyzed.

We concluded that while the learning endogeneity or active experimentation always leads to more land to be converted to preservation areas, the prospect of future information itself may or may not lead to more conversion. This depends on the relative importance of the two irreversibilities. Future information promotes land conversion only when the ecological irreversibility is more important than land conversion irreversibility. If land converted to species preservation areas can be easily reverted back to its original (e.g. agricultural) use, and if the species involved is difficult to be reintroduced once lost, the ecological irreversibility will be more important, and overall endogenous learning will lead to more current land conversion.

6.2 Empirical Analysis

The empirical work studied the impact of four land uses: CRP, pastureland, non-cultivated land and cropland, on species population in Iowa. The species considered is one of the important game species of the Midwest: ring-necked pheasants. This analysis was conducted separately for two regions of Iowa corresponding to the MLRA: the Northern row crop region and the Southern pasture region. This choice was based on the observation that these regions have varied characteristics in terms of land cover. The Northern row crop region is chiefly under row crops, while the Southern pasture region is chiefly under CRP and pastureland. Employing an empirical model we accounted for the spatial and temporal correlations likely in such an analysis.

We found that CRP and pastureland have a positive impact, while cropland and non-cultivated land have a negative impact, on pheasant populations across the two regions of Iowa. However,

significant regional differences in these impacts were observed. The positive marginal impact of CRP on pheasant population was found to be about five times greater in the Northern region compared to the Southern region.

Thus, this analysis identified several important and interesting issues. It established the presence of spatial dependence in residuals of regressors relating land use to wildlife counts and hence the importance of accounting for the spatial aspect in such studies. In addition to assessing the impact of four common land uses on pheasants, this study also highlighted the importance of regional variations in those impacts. Thus, this analysis demonstrated that the same land uses can have a regionally variable impact on pheasant count in Iowa. A marginal increase in the proportion of CRP land in Northern region has a much higher positive impact on pheasant counts compared to the Southern region. Understanding this can prove to be valuable in land management policies targeting conservation of wildlife since it can facilitate efficient conservation.

6.3 Policy Implications and Future Work

Preservation of land for species conservation has been recognized as an important policy objective. However, this is a costly endeavor and hence preservation decisions need to consider the cost aspect. Also an inherent component of such preservation is uncertainty regarding efficacy of this preservation as a wildlife habitat. The analysis presented in this dissertation studied the preservation decisions of policymakers who differ in their behavior towards learning about this uncertainty. Although we did not conduct a formal welfare analysis, we know that the solution of the active learner represents the socially optimal land conversion decisions. The ranking of the welfare under passive learning and non-learning is not clear, again depending on the sign of the learning effect. If, as we discussed earlier, the learning effect is positive (and thus is in the same direction as the experimentation effect), we obtain an unambiguous ranking in the order of active learner, passive learner, and non-learner. In this case, recognizing future information alone will improve social

welfare.

Another important aspect of wildlife conservation policy is to determine which land cover to adopt in order to benefit the species population. This was the aim of the empirical component of this dissertation. Through modeling pheasant population as a function of different habitats we provide guidelines to policymakers as to which land cover is beneficial for pheasants in Iowa. Also, regional variations in pheasant population response to habitat cover are brought to light. For example, a program like CRP provides multiple environmental benefits, thus it becomes important to be able to distinguish regional variation in those benefits. This study indicates that CRP has a much greater positive marginal impact on pheasant populations in the Northern region compared to the Southern region of Iowa.

As part of future work, it would be interesting to conduct a case study of a federal regulation and investigate the welfare implications of the different learning approaches. This would enable us to empirically compare the alternative decision rules.

APPENDIX

Appendix A

Given the same amount of land in conservation x_1, a higher z_1 implies that land is more likely to be effective. This intuitive condition is guaranteed if $g(.)$ satisfies the the strict monotone likelihood ratio property (MLRP). In other words we can show that $B_z > 0$ if the MLRP holds.

The sign of B_z depends on the following

$$B_1\, g'(z_1 - f(x_1, \theta^H))\, h(z_1, x_1, B_1) - B_1\, g(z_1 - f(x_1, \theta^H))\, h_z.$$

Simplifying the above we get the following expression

$$B_1(1 - B_1)[g'(z_1 - f(x_1, \theta^H))\, g(z_1 - f(x_1, \theta^L)) - g(z_1 - f(x_1, \theta^H))\, g'(z_1 - f(x_1, \theta^L))].$$

Thus, B_z is positive if the following is true

$$\frac{g'(z_1 - f(x_1, \theta^H))}{g(z_1 - f(x_1, \theta^H))} > \frac{g'(z_1 - f(x_1, \theta^L))}{g(z_1 - f(x_1, \theta^L))}.$$

The above is simply the definition of MLRP i.e. $\frac{g'(\cdot)}{g(\cdot)}$ is strictly decreasing in its argument ϵ.[1]

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[1] Note that since $f(x_1, \theta^H) > f(x_1, \theta^L)$ it implies that $z_1 - f(x_1, \theta^H) < z_1 - f(x_1, \theta^L)$.

Appendix B

Proof of Proposition 1. Equation (3.10) can be directly obtained from the expression for $B(x_1, z_1)$

$$B_2 = B(x_1, z_1, B_1) = \frac{B_1 g(z_1 - f(x_1, \theta^H))}{h(z_1; x_1, B_1)}.$$

The MLRP of $g(\cdot)$ and the fact that $z_1 - f(x_1, \theta^L) > z_1 - f(x_1, \theta^H)$ imply

$$g'(z_1 - f(x_1, \theta^L))/g(z_1 - f(x_1, \theta^L)) < g'(z_1 - f(x_1, \theta^H))/g(z_1 - f(x_1, \theta^H)).$$

Note also that $0 < f_x(x_1, \theta^L) < f_x(x_1, \theta^H)$. Thus, if $g'(z_1 - f(x_1, \theta^H)) > 0$, then $g'(z_1 - f(x_1, \theta^L))$ can either be positive or negative, and we always have $B_x < 0$. However, if $g'(z_1 - f(x_1, \theta^H)) < 0$, then $g'(z_1 - f(x_1, \theta^L)) < 0$ and the sign of B_x is positive.

This can be interpreted in terms of the relationship between $B(x_1, z_1)$ and B_1. Note that MLRP implies that $g(\cdot)$ is unimodal: $g'(\epsilon) > 0$ when ϵ is to the left of the modal point, and $g'(\epsilon) < 0$ when ϵ is to the right of the modal point. Thus when $g'(z_1 - f(x_1, \theta^H)) \leq 0$ and hence $g'(z_1 - f(x_1, \theta^L)) \leq 0$, both $z_1 - f(x_1, \theta^H)$ and $z_1 - f(x_1, \theta^L)$ are to the right of the modal point. When $B(x_1, z_1) < B_1$, this implies that $g(z_1, f(x_1, \theta^H)) \leq g(z_1, f(x_1, \theta^L))$. This will be true only when $g'(z_1 - f(x_1, \theta^H)) \geq 0$ and thus $B_x \leq 0$.

From (3.4) we know that $B(x_1, z_1) > B_1$ if and only if $g(z_1, f(x_1, \theta^H)) \geq g(z_1, f(x_1, \theta^L))$. In this case the sign of $g'(z_1, f(x_1, \theta^H))$ is indeterminant, which subsequently determines the sign of B_x. ∎

Appendix C

In order to prove that experimentation effect is positive we apply the Theorem in Datta et al. [2002], which states:

THEOREM: *If the MLRP holds, then experimentation increases information if V_B is nondecreasing in z_1; that is, V is supermodular in (B, z_1). If, however, V_B is nonincreasing in z_1 and V_B is affine in B, then experimentation reduces information.*

In our application, from equation (3.27) we know that V_B is

$$[\gamma f(X, \theta^H) - \gamma f(X, \theta^L)],$$

where, $X = x_1 + x_2^*(x_1, z_1)$. From (3.8), we know that x_2^* is increasing in z_1 if MLRP holds. Condition $f_{x\theta} > 0$ then ensures that V_B is nondecreasing in z_1. Thus, experimentation increases information. Since x_1 orders information, we can conclude that experimentation effect is positive. That is, experimentation leads to a higher level of x_1.

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