AN ABSTRACT OF THE DISSERTATION OF

Patricia A. Berger for the degree of Doctor of Philosophy in Bioresource Engineering presented on December 6, 2002.
Title: The Development and Analysis of Future Agricultural Landscapes

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John P. Bolte

Alternative futures studies provide a way for policy-makers and stakeholders to investigate the future impacts of different management strategies by providing representations of possible outcomes. An alternative futures study was undertaken by the Pacific Northwest-Ecosystem Research Consortium for the Willamette River Basin, Oregon, USA, to determine how this regional system would respond to various drivers of change. To support this effort required the development of a simulation model that generates future agricultural landscapes in response to these drivers of change and the evaluation of the resulting landscapes to derive information useful for policy analysis and community discussions. These goals were achieved by creating a characterization of the initial agricultural system, developing an agricultural land-cover change model, and finally, integrating this model with scenario elements to produce the final agricultural landscape evolution model. An important part of the initial landscape characterization was determining the crop suitability class of the basin's agricultural soils for 14 commonly grown crops. Suitability rankings were generated by using rough-set rule induction to create predictive if-then rules that related a soil's biophysical characteristics to crop

production and then applying these rules to all the agricultural soils in the basin. After characterizing the agricultural system, a spatially explicit, multi-attribute decision model was developed to simulate a grower's crop-selection decision. This model used attributes describing a field's biophysical conditions and each crop's agronomic, economic, and management characteristics to select a field's preferred crop from a list of crop alternatives. Next, rules and constraints were formulated for each of the three policy scenarios: a continuation of current trends, an increased reliance on market forces to determine land use, and an increased emphasis on environmental restoration programs. The initial agricultural landscape depiction, crop selection model, and scenario rules were used to generate three future landscapes, each depicting an alternative state of the agricultural system in the year 2050. Then, landscape metrics and screening models were used to assess the agronomic and environmental condition of each agricultural landscape. Finally, this information was placed into the context of the Willamette River Basin, with suggestions for policy development and analysis.

The Development and Analysis of Future Agricultural Landscapes

by

Patricia A. Berger

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

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Patricia A. Berger, Author

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DEDICATION

To the memory of my father

Burton E. Berger

Creative Mind, Loving Heart, Valiant Sprit

THE DEVELOPMENT AND ANALYSIS OF FUTURE AGRICULTURAL LANDSCAPES

1. INTRODUCTION

To manage a regional system, decision-makers need to have an understanding of the long-term effects of current or proposed resource management policies, including processes that alter the current patterns of land cover or land use. The need to understand future impacts is especially critical for regional systems, where the complex interactions that take place among the different parts of the system increase the potential for unexpected, emergent behavior.

Alternative futures studies provide a way for policy-makers and stakeholders to investigate the future impacts of different management strategies by providing representations of possible outcomes. The purpose of such studies is not to predict the future, but to create and experiment with depictions of future conditions that are based on a consistent set of assumptions (Veeneklass and van den Berg 1995). These results can help policy-makers understand the potential consequences of their decisions, while providing communities with a broader perspective on future possibilities (Schoonenboom 1995).

Alternative futures models that include a geographical representation of the landscape provide a way to assess the cumulative effects of incremental land-cover and land-use changes on a system. These spatially explicit models are especially useful for regional systems, because the spatial extent of the region is often small enough to incorporate local information into the regional model. This research describes the application of such a spatially explicit alternative futures model to the agricultural lands of the Willamette River Basin, Oregon, USA.

1.1 Research Problem

The Willamette River Basin has an area of approximately 29,800 km^2 and a population of nearly two million people. It contains the primary urban areas and agricultural lands of the state and important timber stocks. Planners expect that competition for resources among metropolitan areas, agriculture, forestry, recreation, and wildlife habitat will be a major driver of change as the population in the basin increases over the next 50 years. However, the effect of this competition on the different systems is unknown.

To address this question, the Pacific Northwest-Ecosystem Research Consortium (PNW-ERC) and several stakeholder groups developed three alternative scenarios: The Plan Trend scenario extrapolates current trends into the future; the Development scenario eases restrictions on residential development of agricultural land; and finally, the Conservation scenario excludes expansive development in favor of habitat preserves and ecologically oriented management techniques.

The primary goal of this research was to develop a simulation model that would generate future depictions of the Willamette River Basin's agricultural landscape. A secondary goal was to compare and contrast the three future outcomes to assess the role agriculture played in the future ecological and socioeconomic conditions of the basin. The following research objectives were needed to accomplish these goals:

1. Characterize the agricultural system of the Willamette River Basin in a manner that supports the analysis of ecological and agronomic trajectories of change under current and future management scenarios.

2. Identify or develop the data sets and model requirements needed to support these characterizations.

3. Identify or develop spatially explicit analysis methods to assess the condition of the current and futures landscapes.

4. Assess the role of agriculture in altering the ecological and socioeconomic conditions of the basin.

5. Identify areas within the basin that are particularly susceptible to positive or negative change as a result of agricultural activity.

1.2 Solution Approach

The agricultural landscape is a complex system, with agricultural practices affecting the surrounding environment, while societal choices affect agricultural production and land management. This complexity suggested a multi-scale approach, integrating processes from the field scale (cropping system) with those of the watershed (biophysical) and basin (economic) scales into an object-oriented simulation model.

The first step in model development was to gather the data sets necessary to characterize the current agricultural system. One of the primary factors that influence crop-selection decisions for a given field is the crop suitability, defined as the potential yield of the crop under a high level of management. Chapter 2 describes how this issue was cast as a rule induction problem, which was solved by the development of a decision table characterizing the concept of crop production potential, the use of rough sets theory to create rules, and the evaluation of the rules to produce a final rule set for each of 14 commonly grown crops.

Chapter 3 continues the development of the data sets necessary to characterize the current agricultural system, including the characteristics of representative crops, the location and attributes of agricultural fields, and the decision paradigm of agricultural producers. It then describes the development of a multi-attribute decision model for crop selection, CropDM, which generates future depictions of agricultural land cover based on the availability of suitable land and sufficient water, and the crop's expected costs, returns, and management requirements.

The final step in model development was to make the agricultural landscape respond to alterations in the state of the basin, especially land-use conversion and changes in water allocation that were provided by other members of the PNW-ERC. Chapter 4 begins with a description of how the CropDM model was extended to provide for the effects of field fragmentation, water reduction, and land-use change. Next, metrics were defined to assess the impact of agricultural land-cover change on the region and the effects of resource allocations on the agricultural system, at both the basin and watershed scale. Finally, Chapter 4 concludes with a discussion of how these results can be used to inform future management policies for the Willamette River Basin.

The final chapter contains the major conclusions of this research and its contribution to environmental modeling and futures studies. Also included are suggestions for further applications of the methods developed and avenues for future research.

2. ROUGH SET RULE INDUCTION FOR SUITABILITY ASSESSMENT

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2.1 Abstract

The data that characterize an environmental system are a fundamental part of an environmental decision-support system. However, obtaining complete and consistent data sets for regional studies can be difficult. Data sets are often available only for small study areas within the region, while the data themselves contain uncertainty due to system complexity, differences in methodology, or data collection errors. This paper presents rough-set rule induction as one way to deal with data uncertainty while creating predictive if-then rules that generalize data values to the entire region. The approach is illustrated by determining the crop suitability of fourteen crops for the farmland of the Willamette River Basin, Oregon, USA. To implement this method, environmental and crop yield data were spatially related to individual soil units, forming the examples needed for the rule induction process. Next, four learning algorithms were defined by using different subsets of environmental attributes. ROSETTA, a software system for rough set analysis, was then used to generate rules using each algorithm. Cross-validation analysis showed that all crops had at least one algorithm with an accuracy rate greater than 68%. After selecting a preferred algorithm, the induced classifier was used to predict crop suitability for each crop over the remainder of the farmland. The results suggest that rough set rule induction is a useful method for data generalization and suitability analysis.

2.2 INTRODUCTION

Uncertainty is an inherent part of the environmental data used in the decision support systems that assist resource management decision-making. This uncertainty is due to inherent system complexities, and to differences in data collection method or errors in data measurement and entry. In regional management, problems with uncertainty are compounded by data scarcity, as the information needed to model regional systems is often available only for small study areas, providing insufficient data to support even a first-order analysis. Thus, techniques that can both cope with uncertainty and generalize available data to a wider area should prove useful to environmental modelers and resource managers. This paper presents one such approach, rule induction using rough set theory, illustrated by the assessment of crop suitability for the farmland in the Willamette River Basin, Oregon, USA.

The motivation for this research was the need for spatial data layers of commercial-level crop production potential for use in a regional simulation model (Berger and Bolte, in press); therefore, crop yield estimation was determined to be the appropriate suitability characteristic for the assessment. Traditional approaches for crop yield estimation include intuitive yield estimates, historical records, rating schemes, statistical models, and crop-growth models (van Diepen et al. 1991). A more recent approach uses supervised machine learning techniques, where a system acquires knowledge from examples by 'learning' patterns in the data. These patterns are then used for either knowledge discovery or prediction. For crop yield prediction, supervised learning methods are especially suitable when examples relating environmental characteristics to crop yield values exist for a representative, but limited, portion of the study area. Wang (1994) uses such a supervised learning method by implementing a neural network within a geographic information system (GIS) to estimate crop yield for five crops in Java, Indonesia. However, little other work has been done in this application area.

The objectives of this research were as follows: First, to induce rules that classify farmland into crop suitability classes for 14 crops, with the aim of achieving accuracy rates of 70% or higher for each of the crops. These rules would then be used to develop spatial data layers of crop suitability for the study area. Second, to determine the contribution of various kinds of data to classification accuracy and interpretability, and third, to evaluate the usefulness of rough set theory for environmental classification and analysis.

To achieve these objectives, first, data tables of examples relating environmental attributes to crop yield or production level were constructed for each of the crops, as were exclusionary factors that precluded crop production. Next, different subsets of environmental attributes were used to define four learning algorithms. Then, the examples produced from each attribute subset were used by the learning system to generate rules predicting crop yield class. Accuracy estimates for each algorithm showed that all crops had at least one algorithm with an accuracy rate greater than 68%. Algorithms that contained both soil surface and profile data performed best, followed by soil surface data combined with topographic and climatic attributes.

Using these results, the algorithm based only on soil surface and profile data was selected for application to new cases. For each crop, unclassified cases were first screened for exclusionary factors and then the remaining cases were classified using the rules produced from the learning algorithm. Finally, a GIS was used to spatially relate the new crop suitability classes to the landscape.

The next section of this paper introduces the study area, the Willamette River Basin, Oregon, USA. Following this is an overview of rough set theory, a description of the attribute database, and the procedure used to induce rules. Then the results of the four learning algorithms are presented and compared, and the preferred algorithm selected and applied to new cases. Finally, the impact of data characteristics and attribute selection on classification accuracy is discussed, as is the overall utility of this approach for suitability assessment and classification.

2.3 Study Area

The Willamette River Basin is located in the northwest portion of Oregon, USA. It encompasses approximately 29,800 km^2 and contains the primary urban areas and agricultural lands of the state (Figure 2.1A). The basin has a Mediterranean climate, characterized by warm, dry summers and cool, wet winters. The Willamette Basin includes three Level III ecoregions, the Coast Range, Willamette Valley, and the Cascades (Omernik 1987; U.S. Environmental Protection Agency 1996). Agricultural lands cover approximately 17% of the basin area, nearly 500,000 ha, primarily in the Willamette Valley. The valley contains four Level IV ecoregions (Pater et al. 1998), covering one-third of the basin (Figure 2.1B). Significant crops grown in each ecoregion include nursery crops in the Portland/Vancouver Basin, fruits and vegetables in the gallery forest, grass seed and grain on the terraces, and Christmas trees, vineyards, and orchards in the valley foothills (Pater et al. 1998). However, these cropping patterns are not absolute, as the mild climate and fertile soils provide growers with a diverse array of potential crops that can be selected in response to changing land and market conditions.

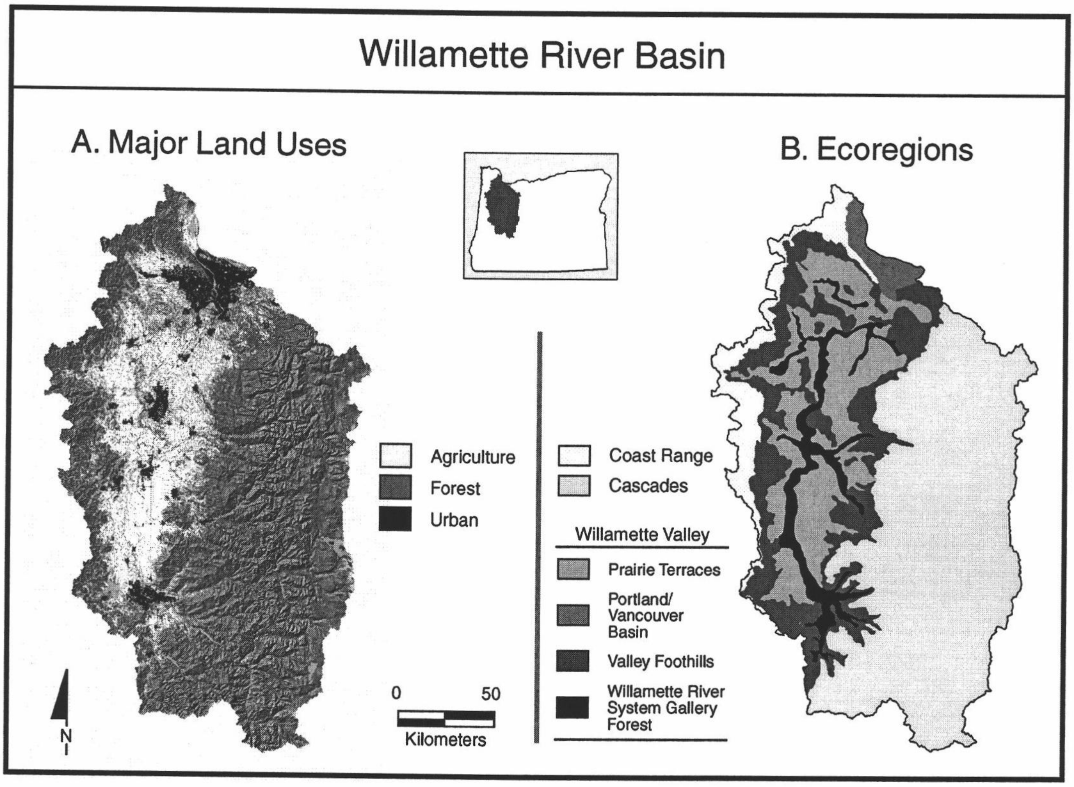

Figure 2.1. Maps of the study area showing: A. Land use distribution within the Willamette Rive Basin and B. Level III ecoregions contained with the Willamette River Basin and the Level IV ecoregions of the Willamette Valley.

2.4 METHODS

2.4.1 Concept Learning and Rule Induction

A concept is learned by acquiring information from a set of representative examples and then generalizing this information so the knowledge obtained can be applied to new situations. In machine learning, a supervised learning approach is usually employed to learn a concept. The learning system uses the information contained in a set of labeled examples to learn the relationship between the independent variables and the target concept. This set of examples is then divided into training data that is used to teach the learning system, and testing data that is used to evaluate the induced classifier. If the concept has been successfully learned, the classifier can be applied to unclassified cases from similar sources to predict the value of the concept.

For symbolic learning methods such as rough sets, the concept learned is expressed as propositional rules of the form IF c THEN d, denoted $c \rightarrow d$, where c is called the antecedent and d the consequent. The examples that form the training data used to elicit these rules are composed of a set of condition attributes (the independent variables) and usually a single decision attribute (dependent variable). The values of the condition attributes are discrete and represent either categories or intervals of continuous values, while the decision attribute holds the class value, which is the concept that is to be learned.

The data structure used for knowledge representation is the decision system or table, an example of which is shown in Table 2.1. The decision table, $\boldsymbol{S}$, is formally denoted as $\boldsymbol{S} = (U, C \cup \{d\})$ where U is a finite set of objects, such as examples, cases, or patients, C is a finite set of condition attributes with value set V_c for each attribute $c \in C$, and d is a decision attribute with m class values $V_d = \{r_1, \ldots, r_m\}$ (Pawlak 1991). This table stores each object's description in the rows of the table, while the columns hold the attribute values.

Table 2.1. An example of a decision table.

Universe	Condition Attributes			Decision Attribute
Object	c_1	c_2	c_3	d
u_1	No	Low	[1-3)	Good
u_2	No	Mod	[1-3)	Poor
u_3	No	Mod	[0-1)	Good
u_4	Yes	High	[1-3)	Good
u_5	Yes	Low	[0-1)	Good
u_6	Yes	High	[0-1)	Poor

The value of the decision attribute d partitions U into m disjoint classes, with each class containing the set of object in U having a given decision class value of r_1 through r_m. If the same condition attribute values are associated with the same decision class, then the decision table is called consistent and the rules induced will be certain, for example:

$$(c_i = v_i) \text{ and} \cdots \text{and } (c_k = v_k) \rightarrow (d = r_j) \tag{1}$$

where c_i is the ith condition attribute with value v_i, and d is the decision attribute for the jth class with value r_j. However, if any objects have the same condition attribute values associated with different decision class valued, the decision table is termed inconsistent and the rules are uncertain:

$$(c_i = v_i) \text{ and} \cdots \text{and } (c_k = v_k) \rightarrow (d = r_j) \text{ or} \cdots \text{or } (d = r_n) \tag{2}$$

Rough set theory provides a way to generate rules from inconsistent decision tables by using the ideas of concept approximation and object indiscernibility.

2.4.2 Overview of Rough Set Theory

Zdzislaw Pawlak (1982, 1984, 1991) developed rough set theory to deal with imprecise, vague, or uncertain information in the knowledge domain. Over the last decade, rough set theory has been successfully applied in the fields of medicine, economics, and engineering, and is finding increasing application in environmental and resource management (e.g., An et al. 1996; Furuta et al. 1998; Wilk et al. 1998).

An important assumption of rough set theory is that an object belongs to a single class; it is only because of incomplete or inaccurate data that class uncertainty exists. Thus, if complete knowledge were available there would be no uncertainty in the classification. This is in contrast to fuzzy set theory, where imprecision is expressed by a predetermined membership function assigned to an attribute. A benefit of rough set methods is that they operate on the base data, unlike many statistical techniques that require information on attribute independence or distribution.

Presented below is an informal overview of rough set theory, focusing on those issues important for classification: approximation spaces and indiscernibility. More information can be found in Pawlak (1991), which develops the classic theory of rough sets, and Komorowski, et al. (1999), which provides a detailed tutorial on rough set theory incorporating many recent developments.

2.4.2.1 Set Approximations

In classical set theory, an element either is or is not a member of the set, there is no ambiguity. This occurs because the information that describes each element is complete concerning membership, so it is clear to which set an element belongs. Similarly, if a decision table is consistent, then the decision class for any object is certain. However, if there is insufficient information available to accurately discern one object from another then the decision class membership is vague or uncertain.

To deal with this ambiguity, rough set theory defines two sets, the lower approximation and upper approximation of the vague concept (Pawlak, 1995). The lower approximation contains those objects that certainly belong to the decision class, while the upper approximation contains those objects that certainly or possibly belong to the decision class. Those objects that only possibly belong to the decision class are said to reside in the boundary, defined as the set difference of the upper and lower approximations. Any set of objects with a non-empty boundary is called a rough set.

To illustrate these definitions consider again the sample decision table shown in Table 1, and let the concept to be learned be "d = good" using condition attributes c_1 and c_2. Then, the lower and upper approximation and boundary are:

Lower Approximation = $\{u_1, u_5\}$

Upper Approximation = $\{u_1, u_2, u_3, u_4, u_5, u_6\}$

Boundary = $\{u_2, u_3, u_4, u_6\}$.

Objects u_2, u_3, u_4, and u_6 are in the boundary since for each pair, (u_2, u_3) and (u_4, u_6), the value of the decision class is different although the values of the condition attributes are the same. If the concept is characterized only by the single attribute c_1, there would be no objects in the lower approximation, while the upper approximation and boundary would contain the objects u_1, u_2, u_3, u_4, u_5, and u_6.

2.4.2.2 Indiscernibility and Attribute Reduction

As suggested above, different combinations of condition attributes may be used to characterize a concept. Thus, for the example decision table, there are seven (2^n -1, n = 3) combinations of condition attributes for each concept. However, not all the condition attributes may be needed to discern the objects. One of the characteristics of rough set analysis is that it identifies the minimal subset of attributes required to fully describe the information in the table. Such minimal subsets are especially useful in rule induction, where fewer attributes tend to promote higher rule quality by inducing more general and interpretable rules.

To create minimal attributes sets, condition attributes that are not required to distinguish the decision class are identified using an indiscernibility relation $I(B)$:

$$I(B) = \{(u_i, u_j) \in U^2 : c(u_i) = c(u_j) \text{ for every } c \in B \subseteq C\}. \tag{3}$$

and then removed from the attribute set. This indiscernibility relation defines when two objects u_i and u_j are indistinguishable by some subset of condition attributes B. For example, in the sample decision table (Table 1), the set of objects indiscernible by $B = \{c_2\}$ is $\{\{u_1, u_5\}, \{u_2, u_3\}, \{u_4, u_6\}\}$.

To preserve the same information content in the sub-table as in the entire decision table, the sub-table needs only to keep those attributes that preserve the indiscernibility relation. To illustrate, consider again the example decision table. Let $B = \{c_1, c_2, c_3\}$, then the set of indiscernible objects is $I(B) = \{u_1, u_2, u_3, u_4, u_5, u_6\}$ since each object is a unique combination of attribute values. If attribute c_1 is removed then:

$$I(B)\text{-}\{c_1\} = \{u_1, u_2, u_3, u_4, u_5, u_6\} = I(B) \tag{4}$$

therefore, attribute c_1 is superfluous and can be removed without changing the information content of the table. However removing either condition attribute c_2 or c_3 changes the indiscernibility:

$$I(B)\text{-}\{c_2\} = \{\{u_1, u_2\}, \{u_3\}, \{u_4\}, \{u_5, u_6\}\} \neq I(B) \tag{5}$$

$$I(B)\text{-}\{c_3\} = \{\{u_1\}, \{u_2, u_3\}, \{u_4, u_6\}, \{u_5\}\} \neq I(B) \tag{6}$$

so these attributes must be retained, otherwise knowledge is lost.

The attributes retained form a set called a reduct, the minimal set of attributes needed to uniquely identify an object. Reducts can be defined for the entire system or for a single object $u_i \in U$. In the latter case, an object-related reduct is the smallest set of attributes sufficient to identify object u_i from all other objects in U. Object-related reducts are useful in classification problems, as they generally contain fewer attributes and thus tend to generalize better than full reducts (Jenssen 1998).

2.4.2.3 Rule Generation

The reducts determined by the indiscernibility relation act as rule templates, whereby rules can be generated by associating the condition attribute values in a reduct with the corresponding decision class value. Rules generated from objects belonging to the lower approximation will be certain rules, while rules generated from the boundary will be uncertain rules. The accuracy or strength of a rule can be calculated as:

$$acc(c \to d) = \frac{|c \cdot d|}{|c|}, \tag{7}$$

where $|\cdot|$ denotes cardinality. Thus, Equation 7 gives the proportion of objects in the table that, given antecedent c, result in consequent d. A certain rule will have $acc(c \to d) = 1$, while an uncertain rule will have $0 < acc(c \to d) < 1$. For uncertain rules, the rule accuracy can be used as a threshold value to determine acceptable rules or to select between several possible decision classes, with the highest accuracy denoting the preferred rule.

2.4.3 Database Development

The concept to be learned in this study was the relationship between the crop yield class and the environmental characteristics of the land on which the crop was grown. To learn this relationship, a database of examples was created for each crop, where each example contained environmental and crop yield data for a soil map unit. The soil map unit, as defined by the National Resource Conservation Service (NRCS), delineates consistent and distinctive soil features at landscape scale (approximately 1:24000). A soil map unit usually consists of a single soil component but may include up to three components. In this latter case, the soil attributes of the most prevalent soil type that was also suitable for cultivation (capability class I-VI) were selected. Information on soil map units and their associated data is available in county soil manuals and as part of the Soil Survey Geographic (SSURGO) database (U.S. Department of Agriculture, NRCS 1998). Both data sources were used to determine the condition and decision attributes, as described below.

2.4.3.1 Condition Attributes

The SSURGO database COMPONENT and LAYER tables provide information about soil surface and profile characteristics, respectively. To be included in the decision table, an attribute contained in the database needed to be a categorical or continuously valued attribute that either directly affected crop growth (e.g., available water capacity) or that signified a condition that could affect crop production levels (e.g., capability class or hydric soil designation). Soil profile data was provided for varying soil depths, depending on soil type. To standardize this information, a maximum depth of 152.50 cm (60 in) was established, and then divided into six layers. The top two layers were 15.25 cm (6 in) in thickness and the remaining four layers were each 30.50 cm (12 in) thick. The weighted-average value of each profile attribute was then calculated for each layer.

In addition to soil data, climatic and topographic data were used to characterize each soil map unit. Climate information was represented by 2-km resolution grids of mean monthly precipitation for the year and the mean monthly number of growing degree days (50°C) for the growing season (March - October), which were produced by PRISM (Parameter-elevation Regression on Independent Slopes Model) (Daly et al. 1994). Elevation and aspect data were derived by using a 30-m U.S. Geological Service digital elevation model of the basin. The weighted-average value of each of the

Table 2.2. The final set soil, climatic, and topographic attributes. The check boxes at the end of each row indicate the algorithm subset containing the condition attribute.

Categorical Attributes			Algorithm			
Attribute	Classes	Class Values	A1	A2	A3	A4
Surface Texture	23	C, CL, FSL, L, MUCK, S, SIC, SICL, SIL, SL, CB-L, CB-SICL, CB-SIL, CBV-L, CBV-SIL, GR-L, GR-SICL, GR-SIL, GR-SL, ST-CL, ST-SICL, ST-SIL, STV-SIL	√	√	√	√
Drainage Class	7	excessively, somewhat excessively, well, m_well, somewhat poorly, poorly, v_poorly	√	√	√	√
Root Depth	3	shallow, moderate, deep	√	√	√	√
Hydrologic Group	4	A, B, C, D	√	√	√	√
Frost Action	3	none, low, moderate	√	√	√	√
Hydric Soil	2	yes, no	√	√	√	√
Capability Class	6	I, II, III, IV, V, VI	√	√	√	√
Capability Subclass	4	C, E, S, W	√	√	√	√
Aspect	8	N, S, E, W, NE, NW, SE, SW	√		√	
Surface Organic Material	6	v_high, high, moderate, m_low, low, v_low			√	√
Surface Acidicity	6	e_strong, v_strong, strong, m_strong, slight, neutral			√	√
Surface Permeability	6	rapid, m_rapid, moderate, m_slow, slow, v_slow			√	√

Numerical Attributes				Algorithm			
Attribute	Type	Range	Units	A1	A2	A3	A4
Average Slope	integer	0 - 55	degrees	√	√	√	√
Available Water Capacity	real	0-0.5	cm cm^{-1}	√	√		
Bulk Density	real	0.13-1.68	gm cm^{-3}	√	√		
Permeability	real	0-20	in $hour^{-1}$	√	√		
Cation Exchange Capacity	real	0-60	meq $100g^{-1}$	√	√		
Percent Organic Material	real	0-60	unitless	√	√		
pH	real	4.3-7.2	unitless	√	√		
Percent Clay Content	real	0-65	unitless	√	√		
Average Elevation	integer	3 - 673	meters	√		√	
Growing Degree Days	integer	0-581	degree-days	√		√	
Monthly Mean Precipitation	real	5.34-8135.13	mm	√		√	

e-extremely, v-very, m-moderately

climatic and topographic values was then calculated for each soil map unit. Table 2.2 describes the final set of soil, climatic, and topographic attributes.

2.4.3.2 Decision Attribute Ranks

Fourteen crops were selected for this study (Table 2.3), including major crops such as vegetables and grass seed, and newer crops such as hybrid poplar. Yield data for hybrid poplar was provided by Withrow-Robinson et al. (1995), while yield data for every other crop was found in county soil survey manuals or in SSURGO MUYLD and WOODLAND tables, which report yield data for crops grown under a high level of management (Soil Survey Staff 2001). For two crops, the yield data was the average of multiple crops: Caneberries contained data for raspberry and blackberry yields, while Grass Seed represented annual ryegrass and perennial ryegrass crops.

Table 2.3. The crops selected for this study together with the total number of examples for each yield class and the percentage of farmland covered by the examples.

Crop	No. of Examples by Yield Class						Farmland
	1	2	3	4	5	Total	Coverage (%)
Irrigated							
Caneberries	73	56	69	25	0	223	21
Peppermint	21	21	8	0	0	50	3
Snap Beans	112	49	56	11	0	228	25
Strawberries	100	116	78	0	0	294	27
Sweet Corn	210	57	62	5	8	342	35
Non-irrigated							
Alfalfa	51	66	25	25	0	167	14
Christmas Trees	88	23	38	0	0	149	11
Douglas Fir	7	174	120	8	0	309	32
Filberts	26	53	84	27	13	203	24
Grass Seed	137	38	39	11	0	225	23
Hybrid Poplar	66	103	30	16	0	215	28
Pasture	22	97	139	218	111	587	55
Sweet Cherries	29	7	64	0	0	100	14
Winter Wheat	147	99	89	130	61	526	47

For all but two crops, the yield value was reported as a continuous value for each soil map unit. For these crops, yield classes were defined by calculating the ratio of each soil map unit's yield to the basin's maximum crop yield for that crop. Then natural breaks in the ratio distribution were used to define five yield classes: very good (1.0 to 0.85), good (0.85 to 0.70), moderate (0.70 to 0.55), moderately low (0.55 to 0.40), and low (0.40 to 0.10).

The remaining two crops, Christmas Trees and Hybrid Poplar, were already assigned a crop production class. These classes were brought into alignment with those defined above based on the qualitative class description (Christmas Trees) or their statistical characteristics (Hybrid Poplar). Table 3 shows the distribution of the crop yield data for the agricultural soils of the basin and within each yield class. Most of the crops lack representation in the lower crop yield classes, reflecting the higher yields needed for commercially viable crop production for high-value or specialty crops such as fruits, vegetables, or peppermint.

2.4.3.3 Negative Examples

Any rules induced by using the above condition and decision attributes will be overly inclusive, as the rules will represent only the positive knowledge in the database, i.e., the locations where crops are known to be at least minimally productive. Nor is the absence of a soil unit from a crop's database an indication of a nonproductive location, because the information in the SSURGO database is not exhaustive. To add negative information to the classification, recommendations contained in older soil survey manuals were used to form a set of exclusionary factors consisting of slope, capability class, and the amount of coarse fragments. The final set of values for the exclusionary factors (Table 2.4) was then determined by assuring that the exclusionary attribute values exceeded the limits of the condition attributes. This was done to account for technological or market developments occurring after the soil survey's publication that encouraged the cultivation of more challenging landforms.

Table 2.4. The final set of exclusionary values for each crop.

Crop	Maximum Slope (%)	Capability Class	Coarse Fragments
Alfalfa	25	5	CBV, STV
Caneberries	25	5	CB, CBV, ST, STV
Christmas Trees	45	5	CBV, STV
Douglas Fir	55	5	CBV, STV
Filberts	40	5	CBV, STV
Grass Seed	25	5	CB, CBV, ST, STV
Hybrid Poplar	18	5	CB, CBV, ST, STV
Pasture	53	5	None
Peppermint	8	5,6	CB, CBV, ST, STV
Snap Beans	18	6	CBV, ST, STV
Strawberries	25	5,6	CB, CBV, ST, STV
Sweet Cherries	55	5	CBV, STV
Sweet Corn	25	None	CBV, ST, STV
Winter Wheat	55	5	CBV, STV

CB-Cobbley ST-Stoney
CBV-Very Cobbley STV-Very Stoney

2.4.4 Implementation

The rule induction procedure (Figure 2.2) was implemented within the ROSETTA software system; a rough set tool-kit for knowledge discovery and data mining (Øhrn et al. 1998). The primary steps in the procedure, discretization of the continuous variables, rule generation and filtering, and algorithm evaluation, are discussed below.

2.4.4.1 Definition of the Learning Algorithms

A learning algorithm induces a concept from the training examples by constructing a classifier from a given set of examples, and then the induced classifier assigns a decision class to a new example (Dietterich 1998). In this study, the four learning algorithms are

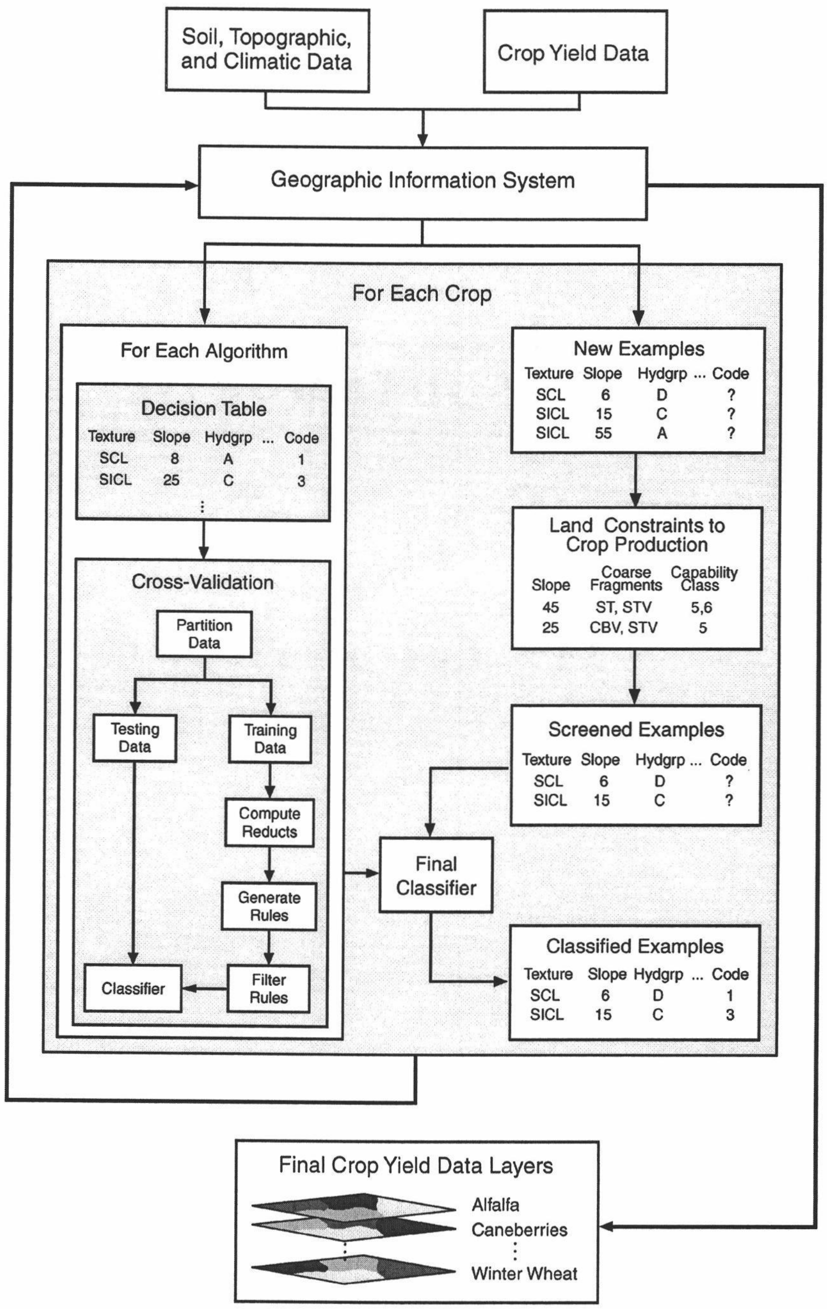

Figure 2.2. Program flow and procedures used to induce rules.

denoted as RS(A1), RS(A2), RS(A3), and RS(A4) where RS represents the learning method, rough set theory, and A1 through A4 represents the different condition attribute subsets:

A1: Soil surface, soil profile, topographic, and climatic attributes

A2: Soil surface and soil profile attributes

A3: Soil surface, topographic, and climatic attributes

A4: Soil surface attributes

The exact attributes used are noted in the check boxes of Table 2.2. The three classes of attributes: surface soil data, soil profile data, and topographic and climatic data, were selected because they each represent typical classes of data available to environmental modelers, and each requires different capabilities for their acquisition and manipulation. Since crop yield is known to be highly dependent on soil characteristics, some level of soil data was included in each learning algorithm.

2.4.4.2 Attribute Discretization

All continuous attributes were discretized using a supervised, entropy-minimization technique described in Dougherty et al. (1995) and contained in the ROSETTA program. This technique evaluates each condition attribute separately in concert with the decision attribute value. The algorithm recursively partitions the set of attribute values until a stopping criterion based on information content is satisfied. Thus, an attribute will have the same interval break points for each of a crop's four algorithms, but the break points will vary for each crop. Any condition attribute that provided negligible information with respect to the decision class was removed from the crop's decision system before rule generation.

2.4.4.3 Rule Generation and Filtering

The reduction algorithm by Johnson (1974) as implemented in ROSETTA was used to calculate object-related reducts. The rule sets produced by using these reducts were then filtered by enforcing a lower bound on a rule's quality, q (Agotnes 1999):

$$q(c \rightarrow d) = 0.7\, acc(c \rightarrow d) \; + 0.3\, cov(c \rightarrow d) \;\; > \;\; 0.5 \tag{8}$$

where

$$cov(c \rightarrow d) = \frac{|\, c \cdot d \,|}{|\, d \,|} \tag{9}$$

is the rule coverage or true positive rate and $acc(c \rightarrow d)$ is the rule accuracy defined in Equation 7. A bias toward accuracy was used in Equation 8 because it tends to improve the classification accuracy for this quality measure (Bruha 1997).

When a new object is presented to a classifier, three outcomes are possible: no rule is found, signifying no predicted decision class; a single rule is found, specifying a single decision class; or multiple rules are found, indicating several possible decision classes. To decide among multiple decision classes, a voting procedure was used to rank the predicted decision classes. For each rule, the number of objects that support the rule were counted and then divided by the total number of votes cast, providing a measure of certainty for each rule. The rule with the highest certainty was then used to predict the decision class.

2.4.4.4 Evaluation of the Classification Algorithms

If data is plentiful, a subset of the classified objects can be used to generate the rules, while the remainder of the data is used to determine the accuracy of the algorithm. However in this study, examples were scarce; thus, all of the classified objects were used for training, and cross-validation (CV) procedures used to evaluate algorithm accuracy. A k-fold cross-validation procedure partitions the data into k disjoint subsets of nearly equal size. One of the subsets is reserved for testing the induced classifier, while the rest of the data trains the classifier. This procedure is repeated k times, each time using a different subset as the test set, thus providing an estimate of the predictive accuracy while using all the available data.

Two cross-validation techniques were used to evaluate the algorithms: a 10-fold CV procedure and the 5x2 CV paired F-test developed by Alpaydin (1999). The 10-fold CV procedure was used to estimate the accuracy rate of each algorithm. The expected accuracy rate, μ, was calculated by performing ten 10-fold CV accuracy estimates and then applying the t-test at the α=0.05 level of significance.

The 5x2 CV paired F-test provides a pair-wise comparison of the accuracy rates of the algorithms, accepting the null hypothesis that the two algorithms have the same accuracy rate tests at the α=0.05 level of significance if (Alpaydin 1999):

$$F_{10,5} \sim \frac{\sum_{i=1}^{5} \sum_{j=1}^{2} \left(p_i^j\right)^2}{2\sum_{i=1}^{5} s_i^2} \leq 4.74 \tag{10}$$

where p_i^j is the difference between the error rates of the two classifiers for the ith replication on the jth fold.

2.5 Results

Algorithm performance was measured by accuracy rates and rule counts, with an ideal algorithm displaying high accuracy and low rule counts for each of the crops. The results of the 5x2 *F*-test (Table 2.5) showed no significant difference in accuracy rates between algorithms RS(A1) and RS(A2) for all the crops. In contrast, algorithm RS(A3) had significantly lower accuracy rates than RS(A1) for two crops (Snap Beans and Strawberries) and RS(A2) for four crops (Alfalfa, Caneberries, Pasture, and Strawberries). The RS(A4) algorithm suffered the most in comparison with the other algorithms, with lower accuracy rates in comparison with RS(A1) or RS(A2) for six crops, and lower rates than RS(A3) for four crops.

Table 2.5. The results of the 5x2 paired F-test by crop for each pairing of the four algorithms. Rejection of Ho, evaluated at the $\alpha = 0.05$ level of significance, is denoted by bold values within brackets.

Pair	Reject H_0	Alfalfa	Cane-berries	Christmas Trees	Douglas Fir	Filberts	Grass Seed	Hybrid Poplar	Pasture	Pepper-mint	Snap Beans	Straw-berries	Sweet Cherries	Sweet Corn	Winter Wheat
RS(A1) RS(A2)	0	1.82	1.39	0.88	0.90	1.09	0.98	0.92	3.57	0.91	0.64	4.10	1.23	2.54	1.10
RS(A1) RS(A3)	2	1.80	2.03	1.05	0.85	0.82	2.37	0.71	2.11	0.81	**[30.28]**	**[5.76]**	1.29	0.87	2.27
RS(A1) RS(A4)	6	**[17.44]**	2.48	**[10.34]**	2.59	0.79	**[5.74]**	4.59	**[5.01]**	2.55	3.17	**[8.90]**	0.71	**[16.70]**	1.22
RS(A2) RS(A3)	4	**[26.86]**	**[8.13]**	1.51	0.71	1.95	1.10	1.03	**[11.71]**	0.67	1.69	**[9.77]**	2.42	0.59	2.86
RS(A2) RS(A4)	6	**[6.65]**	**[103.88]**	1.02	1.84	1.37	**[5.92]**	**[7.12]**	3.76	1.78	2.54	**[7.83]**	1.06	**[7.64]**	2.57
RS(A3) RS(A4)	4	0.91	0.89	**[9.51]**	2.08	1.02	1.47	**[9.74]**	1.20	1.20	0.75	**[4.83]**	0.56	**[4.89]**	1.15

The results from the 10-fold CV experiments (Table 2.6) showed that all crops had at least one algorithm with a classification accuracy rate above 68%, while 11 of the 14 crops had accuracy rates of 70% or higher. The number of rules induced was a function of the number of objects in the decision table, with higher rule counts associated with more objects (Table 2.5). However, for a given crop, rule counts varied significantly by algorithm. Algorithms RS(A1) and RS(A3) had nearly identical rule counts for all crops, while the RS(A2) algorithm averaged 30% fewer rules than RS(A1) and the RS(A4) algorithm averaged about one-half the rules of RS(A1).

Table 2.6. Results of the 10-fold CV experiments and the rule count for each algorithm.

Crop	Method	Accuracy	No. of Rules	Crop	Method	Accuracy	No. of Rules
Alfalfa	RS(A1)	88.646	66	Pasture	RS(A1)	64.839	216
	RS(A2)	92.440	36		RS(A2)	68.748	168
	RS(A3)	74.689	66		RS(A3)	55.363	211
	RS(A4)	71.771	27		RS(A4)	58.270	162
Caneberries	RS(A1)	83.683	105	Peppermint	RS(A1)	83.468	19
	RS(A2)	81.992	67		RS(A2)	93.711	14
	RS(A3)	62.595	92		RS(A3)	78.256	19
	RS(A4)	63.102	53		RS(A4)	33.570	13
Christmas Trees	RS(A1)	66.259	73	Strawberries	RS(A1)	84.245	121
	RS(A2)	67.438	58		RS(A2)	89.519	76
	RS(A3)	68.400	75		RS(A3)	74.407	125
	RS(A4)	50.543	43		RS(A4)	72.614	56
Douglas Fir	RS(A1)	81.518	114	Snap Beans	RS(A1)	79.626	97
	RS(A2)	80.144	75		RS(A2)	79.169	75
	RS(A3)	77.613	120		RS(A3)	74.109	102
	RS(A4)	66.440	70		RS(A4)	67.015	46
Filberts	RS(A1)	79.626	86	Sweet Cherries	RS(A1)	81.965	48
	RS(A2)	81.654	55		RS(A2)	87.769	27
	RS(A3)	72.340	84		RS(A3)	77.535	48
	RS(A4)	76.266	50		RS(A4)	79.423	23
Grass Seed	RS(A1)	74.916	94	Sweet Corn	RS(A1)	79.718	120
	RS(A2)	73.133	76		RS(A2)	83.159	86
	RS(A3)	66.857	94		RS(A3)	80.730	122
	RS(A4)	66.177	61		RS(A4)	73.723	59
Hybrid Poplar	RS(A1)	84.995	76	Winter Wheat	RS(A1)	62.158	191
	RS(A2)	83.657	59		RS(A2)	68.596	154
	RS(A3)	85.262	78		RS(A3)	57.603	173
	RS(A4)	77.791	45		RS(A4)	51.717	104

Based on the results of the cross-validation experiments and the rule counts, the RS(A2) algorithm – rough set induction using soil surface and soil profile data – was selected as the preferred algorithm for the study area, since for each crop it had a high accuracy rate coupled with a relatively low rule count. Figure 2.3 shows the relationship between the accuracy rate and rule count of this algorithm for each of the crop types. The data formed four clusters: Cluster 1, containing crops with many objects (average = 557) but low accuracy rates (average = 69%), Cluster 2 containing crops with relatively few objects (average = 187) and lower accuracy rates (average = 72%), Cluster 3 containing crops with a moderate number of objects (average = 254) and moderate accuracy (average = 82%), and Cluster 4 containing crops where a smaller number of objects (average = 153) produced classifiers with high accuracy (average = 91%).

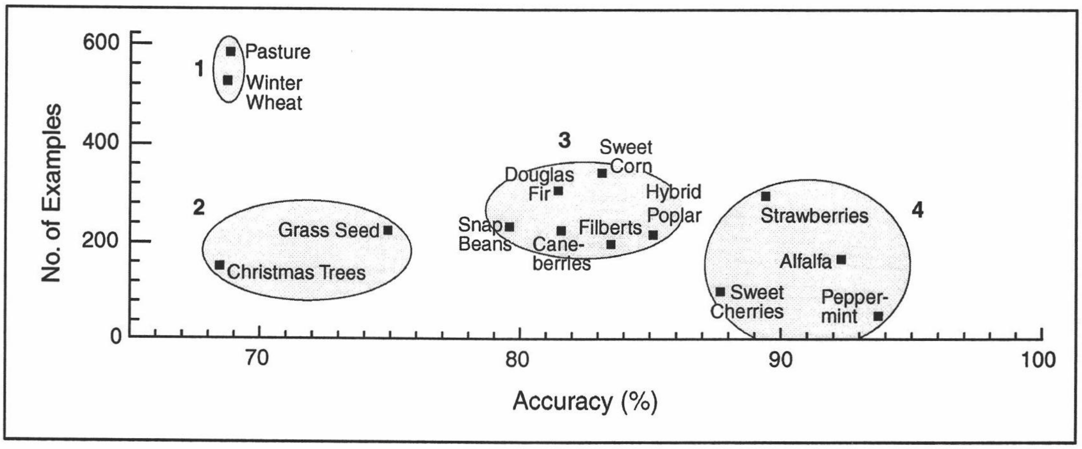

Figure 2.3. The relationship between the accuracy rate and the rule count of the RS(A2) algorithm for each of the crops.

Finally, new, unclassified objects were screened using the exclusionary values listed in Table 2.4, and then the RS(A2) algorithm was applied to the remaining objects. Table 2.7 displays the yield class distribution and general characteristics of the induced rules, while Figure 2.4 shows the spatial distribution of both the original data and the classified data for four crops, one from each of the four clusters.

Table 2.7. The yield class distribution and general characteristics of the induced rules for each of the crops shown in Figure 2.4.

Crop	Class 1	2	3	4	5	Undefined	Uncertain Rules (%)
Alfalfa	113	186	94	3	-	84	32
Caneberries	124	35	188	104	-	39	32
Grass Seed	225	92	45	12	-	120	35
Winter Wheat	19	24	3	95	97	14	46

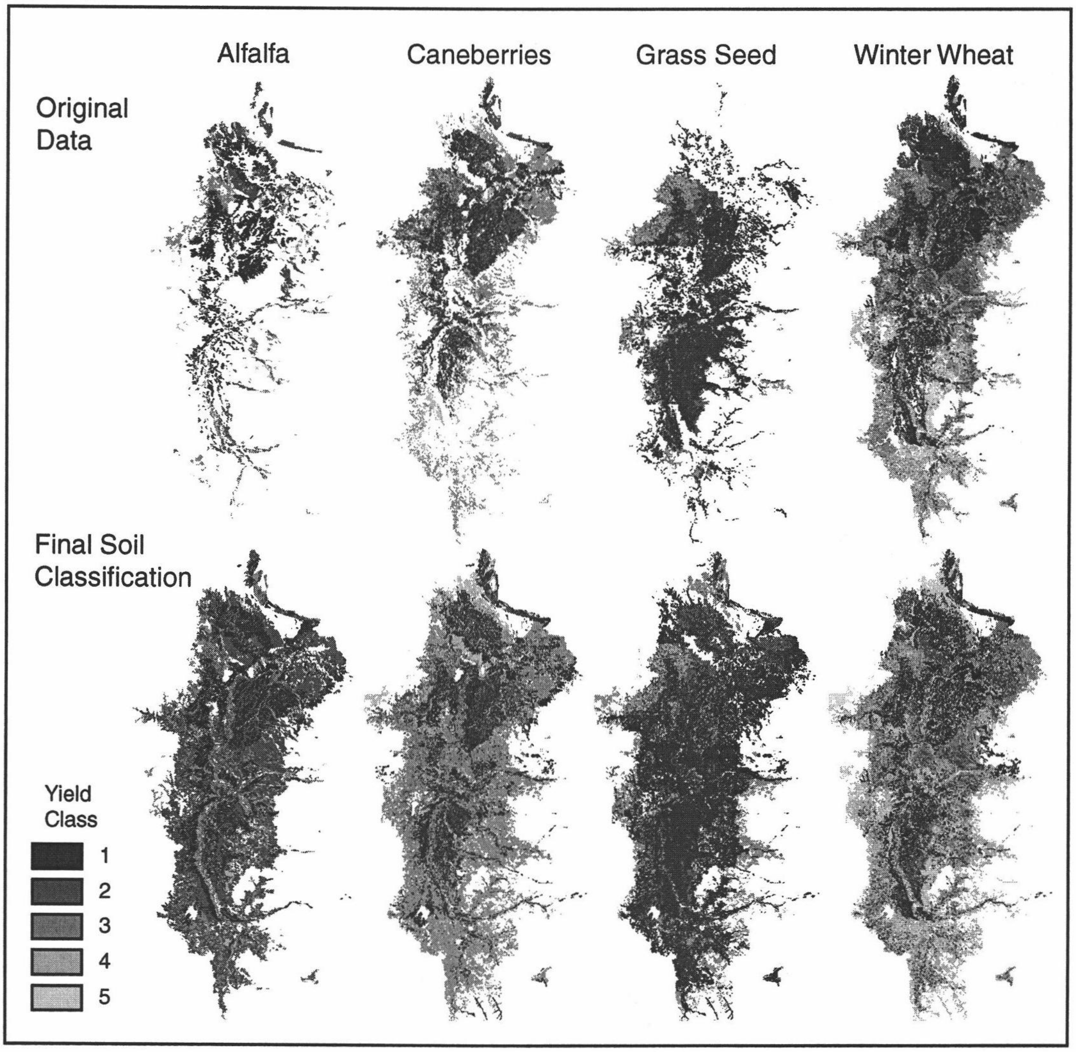

Figure 2.4. The spatial distribution of the original data and all classified data for four crops, one from each of the four clusters.

2.6 DISCUSSION

The result of the algorithm comparison shows that the algorithms that contained soil profile data, RS(A1) and RS(A2), had significantly higher accuracy rates than algorithms without such data for up to six crops. Adding climatic and topographic data to the soil profile data (RS(A1)) provided no significant increase in accuracy, but did have the negative effect of increasing the number of rules generated. However, adding climatic and topographic data to the soil surface data (RS(A3)) did provide a significant increase in accuracy rates over surface soil data alone for 5 of the 14 crops. The importance of climatic data to classification accuracy would likely increase in a less homogeneous environment, for example, if the region spanned several Level III (rather than Level IV) ecoregions.

For every crop, there was a clear trade-off between accuracy and interpretability (measured by rule counts) among the algorithms, although this characteristic was less noticeable in the case of the RS(A2) algorithm. This trade-off provides some flexibility in the selection of the algorithm to achieve a given goal. For example, if accuracy were the predominant characteristic required of the classifier, the high accuracy of the RS(A2) algorithm would be preferred. However, if interpretability were considered as important as accuracy, which could occur if knowledge discovery rather than prediction was the goal, then the RS(A4) algorithm would be preferred for many of the crops, followed by the RS(A2) algorithm. As accuracy was the primary goal of this study, the RS(A2) algorithm was selected as the final algorithm.

For all algorithms, there was no relationship evident between the irrigation status of a crop and the accuracy of the classification. Especially, the use of precipitation data did not improve the classification accuracy for dry-land crops, which depend on rainfall to fulfill the crop's water requirement. However, there is a relationship between accuracy rate and both the value of the crop and the number of examples available, which is illustrated for the RS(A2) algorithm in Figure 2.3. This is probably due to the differences in management between high- and low-value crops, leading to different levels of variability in crop yield evaluation. High-value crops like berries and vegetables tend to be managed more carefully, and so there is less variability among the examples and consequently less uncertainty in the rules. In contrast, crops like grain or pastureland experience more varied management approaches; wheat may be planted on highly productive or marginal lands, or pasture may be managed or unmanaged, leading to increased yield variability. Thus, although the Winter Wheat and Pasture crop types have the greatest number of examples, their classification accuracy is among the lowest.

Christmas Trees also suffered from a low (< 70%) accuracy rate. In this case, there are fewer examples, which may be a contributing factor, but the lower rate is probably due to the nature of the yield estimate, which was of a qualitative nature in contrast to the other crops. (Hybrid Poplar also had categorical yield estimates, but these were derived from continuous data.) Hence, there was more subjectivity involved in the initial classification of production level, and so lower accuracy in the final set of rules.

These ideas are apparent in the classification of new cases displayed in Figure 2.4. In each case, the newly classified examples strengthen the pattern of crop distribution in the original data. However, there are differences in class distribution among the crops, as shown in Table 2.7. Winter Wheat displays an opposite trend with respect to the other crops, with most of the new cases falling into the lower yield classes. This occurs because the original data already included the better soils, since data for Winter Wheat was available throughout the basin. Thus, the new, unclassified, examples tend to be of less productive land. This is in contrast to the other three crops, which had examples from limited portions of the valley, and thus exhibit more diversity in the unclassified cases. In addition, the lands classified are of moderate to high production levels, as the examples in the decision tables did not contain information on marginally productive soils.

The number of unclassified cases varied by crop as well. Both Winter Wheat and Caneberries have far fewer unclassified cases, at 6% and 8%, respectively, than either Grass Seed (24%) or Alfalfa (18%). For Winter Wheat, this is a result of the high number of rules. In the case of Caneberries, which had only a moderate number of rules, this effect could be a reflection of the exclusionary rules or low variability in the original data.

2.7 Conclusions

The primary goal of this study was to construct spatial data layers of crop yield distribution in the Willamette River Basin. Rough set theory provided a way to generate rules from inconsistent data, while the rules induced were used to generate basin-wide data sets from limited sample data. The results obtained are encouraging, not only did the selected algorithm nearly meet or exceed the 70% accuracy threshold but, since the parameters used in the reduction calculations and rule filtering were not optimized for a particular crop, it is likely that accuracy rates for some of the crops could be improved.

A secondary goal of this study was to determine how different types of data contributed to classification accuracy by defining learning algorithms formed from commonly available classes of data. This is important since the selection of condition attributes affects the quality of a supervised learning application. If the attributes selected do not contain sufficient information to distinguish the decision classes, the rules induced will be of little value. However, in environmental applications, it is not always possible to obtain data sets that contain potentially significant attributes. To investigate this situation, this study compared the performance of several algorithms differentiated by their attributes. It was found that while the combination of soil surface and profile data was the preferred algorithm, other combinations of attributes performed well for a variety of the crops, and for six crops any of the algorithms would have provided accuracy rates > 70%. This suggests that more readily available data could be used to provide useful information, especially for crops with management characteristics similar to those of Clusters 3 and 4. For example, the RS(A3) algorithms containing soil surface, climatic and topographic data could be applied in a regional-scale assessment where coarse-scale climate data is often available from public or private research organizations, but detailed soil data of the region is incomplete.

The third goal of this study was to assess the general usefulness of rough set theory in environmental applications. In this application, rough-set rule induction proved a useful technique for crop suitability assessment, suggesting its use in any suitability assessment evaluated through attributes, for example habitat suitability for a particular species. Such applications and the comparison of results with other classification techniques are needed to further assess the strengths and weaknesses of this approach.

The use of rough sets for rule induction was aided by the availability of the ROSETTA program and the detailed documentation that accompanied it. This program provided an accessible way to experiment with the different algorithms and parameter options; it also provided data preparation and analysis functions that aided the creation and assessment of the algorithms. This type of product frees environmental modelers to consider the particular qualities of their study rather than the details of programming and software engineering. The continued development of such systems, together with the increasing utility of information derived from knowledge discovery and classification, should provide a useful aid to the task of environmental problem solving.

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3. A MULTI-ATTRIBUTE DECISION MODEL FOR AGRICULTURAL LANDSCAPE GENERATION

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3.1 ABSTRACT

This paper describes the development of a multi-attribute decision model to simulate agricultural land-cover change. Field descriptions, crop characteristics, and the decision paradigm of an agricultural producer are all entered into a decision model. The model first screens out unsuitable crops and then uses the attribute values and weights of each remaining crop alternative to select a preferred crop for a field. This decision-making method is particularly suitable for the modeling of alternative futures, as it provides a variety of parameters that can be used to define and refine scenario elements. An example implementation of an alternative futures model is provided to show how this method can be used to examine alternative policy or management options.

3.2 INTRODUCTION

Alternative future scenario modeling provides a way for policy-makers and stakeholders to explore the long-term impacts of different management strategies. These models produce representations of possible future outcomes based on different drivers of change. Once the alternative representations are generated, analysts can evaluate and compare them using appropriate metrics or models. These results provide decision-makers with information on the impact of policy options, or give the community a broader perspective on potential future outcomes (Schoonenboom 1995).

Future scenarios focusing on natural resource management need a spatially explicit approach to define the characteristics of the system. The generation of such a spatially referenced landscape is challenging because of the data requirements and spatial extent of the study region. Developing alternative agricultural landscapes provides some special challenges. First, crop types and management techniques often vary from year to year, with each combination differentially affecting the surrounding landscape. Second, farmland may be converted to a non-agricultural land use, resulting in shifting production patterns as the remaining farmland adjusts to the changing land base. Finally, data describing the initial or past state of the agricultural system is often lacking or restricted; and classified, remotely sensed data, which is often the only representation of a region's land cover, is of varying quality and accuracy, if they exist at all.

This last issue can be especially limiting, since agricultural land-use change models typically use a time-series of historical data to develop transition probabilities or statistical models to explain the observed pattern of land use (Lambin et al. 2000), which are then used to generate future landscape patterns. This paper describes an alternative approach to agricultural change modeling that uses multi-attribute decision-making (MADM) methods and spatially explicit biophysical data to generate future representations of agricultural land cover. The model, called CropDM, provides a variety of decision and spatial parameters that analysts can use to define and refine different crop selection and agricultural change scenarios.

The CropDM model was developed as part of a broader modeling and analysis effort by the Pacific Northwest–Ecosystem Research Consortium, which studied the effects of different management options on Oregon's Willamette River Basin (Baker et al. in press). The use of the CropDM model in a regional, multiple-land-use, alternative-futures analysis is presented in Berger and Bolte (in press).

The next section of this paper contains an overview of MADM and details of the methods used in this study, followed by a description of the CropDM model. Then a sample implementation of an alternative futures model is presented to illustrate the definition and use of decision variables in the CropDM model. Finally, a discussion of the utility of the decision-making approach for landscape generation concludes this paper.

3.3 Multi-Attribute Decision Making

Decision analysis formalizes rational decision-making by using a set of procedures to analyze complicated decision problems. MADM is used when the decision problem is characterized by a finite set of alternatives that are described by multiple, often conflicting, attributes (Hwang and Yoon 1981). Typically, there is not a clearly preferred alternative, but rather several competing alternatives, each with its own strengths and weaknesses. By using the attribute values of each alternative and the attribute's importance to the decision, the various MADM techniques provide either a set of suitable alternatives, a single preferred solution, or a preference ranking of the set of alternatives.

MADM methods are divided into one of two classes: noncompensatory methods and compensatory methods. A description of each method is given below, together with details of the particular methods used in this study. A survey of MADM methods can be found in Yoon and Hwang (1995).

3.3.1 Noncompensatory Methods

Noncompensatory methods can be thought of as screening devices, with all feasible solutions consisting of those alternatives that fulfill certain standards. These methods do not allow trade-offs among attributes; thus, a single weak attribute may be sufficient to exclude an alternative. The noncompensatory method used in this research was the conjunctive method, which acts to divide the alternatives into acceptable and unacceptable categories. An alternative is found to be unacceptable if the value of one of the alternative's attributes falls outside of a prescribed value or set of values (Chen and Hwang 1992). Thus, this method can be used to enforce non-negotiable constraints on alternative selection.

3.3.2 Compensatory Methods

Compensatory methods allow the decision-maker (DM) to examine the trade-offs among alternatives, so strong attributes can compensate for weak attributes. These methods are computationally and conceptually more complex than noncompensatory methods, as they use ranking procedures to determine the preferred alternative or preference order based on some measure of optimality. The compensatory method used in this study is a variation of the ideal point method called the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Hwang and Yoon 1981). This method was selected as it makes full use of attribute information, provides a cardinal ranking of alternatives, and does not require preference independence of the attributes (Chen and Hwang 1992, Yoon and Hwang 1995). To apply this technique, the attribute values must be numeric, monotonically increasing or decreasing, and have commensurable units.

The monotonicity requirement provides for the definition of two extreme points called the positive-ideal solution and the negative-ideal solution. These points consist of the best (positive-ideal) and worst (negative-ideal) attribute values for a set of alternatives. The TOPSIS method calculates the distance of each attribute from the positive- and negative-ideal solutions, and then ranks the alternatives on the basis of these distance measures. The following procedure from Hwang and Yoon (1981) is used to calculate the preference order for m alternatives described by n attributes:

1. Form an m x n decision matrix **D:**

$$\mathbf{D} = \begin{bmatrix} d_{11} & \cdots & d_{1j} & \cdots & d_{1n} \\ \vdots & & \vdots & & \vdots \\ d_{i1} & \cdots & d_{ij} & \cdots & d_{in} \\ \vdots & & \vdots & & \vdots \\ d_{m1} & \cdots & d_{mj} & \cdots & d_{mn} \end{bmatrix}, \tag{1}$$

where each row describes an alternative and each column contains the values of an attribute. Then an entry d_{ij} is the value of alternative i with respect to attribute j.

2. Calculate the normalized decision matrix **R**:

$$\mathbf{R} = r_{ij} = \frac{d_{ij}}{\sqrt{\sum_i d_{ij}^2}}, i = 1,\ldots,m, \; j = 1,\ldots,n. \tag{2}$$

3. Calculate the weighted normalized decision matrix **V** where ω_j is the decision weight:

$$\mathbf{V} = v_{ij} = \omega_j \, r_{ij} \, , i = 1,\ldots,m \, , j = 1,\ldots,n. \tag{3}$$

4. Identify the positive-ideal solution, A^* and the negative-ideal solution, A^-. Let J represent benefit attributes and J' represent cost attributes, where a benefit attribute has increasing attribute values with increasing preference, while a cost attribute has decreasing attribute values with increasing preference. Then:

$$A^* = \left\{ \left(\max_i v_{ij} : j \in J\right), \left(\min_i v_{ij} : j \in J'\right) : \, i = 1,\ldots,m \right\} = \left\{ v_1^*,\ldots,v_n^* \right\}, \tag{4}$$

$$A^- = \left\{ \left(\min_i v_{ij} : j \in J\right), \left(\max_i v_{ij} : j \in J'\right) : \, i = 1,\ldots,m \right\} = \left\{ v_1^-,\ldots,v_n^- \right\}. \tag{5}$$

Note that the positive-ideal and negative-ideal solutions are not perfect solutions, but rather the best and worst solutions provided by a given decision matrix.

5. Calculate the separation measures S_i^* and S_i^- from the positive-ideal and negative-ideal solutions, respectively, using the Euclidean distance metric:

$$S_i^* = \sqrt{\sum_j \left(v_{ij} - v_j^*\right)^2} \; , \; S_i^- = \sqrt{\sum_j \left(v_{ij} - v_j^-\right)^2} \; , \; i = 1,\ldots,m \; , j = 1,\ldots,n. \tag{6}$$

6. Calculate the relative closeness to the positive-ideal solution, C_i^*, of each alternative:

$$C_i^* = \frac{S_i^-}{S_i^* + S_{i-}}, \; i = 1,\ldots,m. \tag{7}$$

The alternatives can then be ranked in descending order of C_i^*.

3.3.3 Attribute Weighting

To evaluate trade-offs, compensatory methods require a DM to provide the relative measure of importance, or weight, of each attribute to the final decision. Two popular methods of weight assignment are subjective weights and entropy-based weights (Hwang and Yoon 1981). User-defined subjective attribute weights incorporate DM knowledge into the final decision. A default case would be assigning the same weight for each attribute, signifying that each attribute has the same importance to the DM. As user-controlled values, the subjective weights provide one way for a range of alternatives to be investigated by exploring how the preferred alternative varies with changing decision weights.

Entropy weights measure the information content in the attribute values of the alternatives, thereby evaluating each attribute's usefulness in detecting differences in the data. For example, if an attribute has the same value for each of the alternatives, then that attribute provides no information that distinguishes the alternatives. On the other hand, an attribute that has different values for each alternative has a high information content and is useful when comparing and contrasting the alternatives. The entropy weight, w_j, is calculated as (Hwang and Yoon 1981):

$$w_j = \frac{1-E_j}{\sum_j (1-E_j)}, \; j = 1,\dots,n \tag{8}$$

where

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^{m} p_{ij} \ln p_{ij}, \; j = 1,\dots,n \tag{9}$$

is the entropy and p_{ij} is calculated by dividing d_{ij} by the sum of all the values for the j^{th} attribute. The term $1 - E_j$ describes the contrast intensity for attribute j, with larger values denoting a more information-rich attribute.

Either of these weights may be used alone, or they can be combined to form a composite weight ω_j:

$$\omega_j = \frac{\lambda_j \, w_j}{\sum_j \lambda_j w_j}, \quad j = 1, \ldots, n \tag{10}$$

in effect, weighting the importance of the attribute to the decision by the information content of the attribute.

3.4 Model Description

The CropDM model was implemented as a loosely coupled MADM-GIS model, which used a database as a conduit between the GIS and the simulation model. Spatial data was stored and manipulated within a GIS, while the simulation model used process-models and decision attributes to evaluate each field's condition and make crop selection decisions. Following the framework provided by Agawar et al. (in press), the current implementation of the CropDM model has the following characteristics:

- Spatial Resolution: Vector-based with a minimum two-hectare polygon.
- Temporal Framework: Yearly time-step, with monthly computation of irrigation requirements
- Agent: Agricultural field's decision-maker
- Domain: Basin
- Spatial Complexity: Spatially representative
- Temporal Complexity: Moderate, with many time-steps and a long duration

- Human Decision-making Complexity: High, the model provides for the definition of one or more decision-makers
- Representation of Land Uses: The model provides for detailed agricultural land-cover representations. If land-cover types are indiscernible with respect to the decision attributes and constraints, they may be aggregated.

The fundamental assumption of the model is that changes in agricultural land-cover are due to rational decisions made by an agricultural producer that are based on the attributes of the producer, the crops, and the field. Using MADM, the model generates future land-cover by simulating the crop-selection process through time. Biophysical and decision attributes were used to characterize the agricultural system (Table 3.1). Then for each year in the simulation, the program cycles through every field and tests to see if a crop decision needs to be made. If a decision is required, the characteristics of the field, each crop, and the DM are entered into the decision model, which makes the final crop selection (Figure 3.1).

Table 3.1. Properties of the agricultural system used to characterize the agricultural landscape.

Properties of the Agricultural System			
Crop	Field	Water Right	Decision-Maker
Crop ID	Field ID	Water Right ID	Field Suitability
Maximum Age	Water Right ID	Priority Date	Water Availability
Planting Date	Crop ID	Rate	Market Conditions
Harvest Date	Crop Age	Duty	Profit Margin
Root Depth	Field Area	Source	Crop Suitability
MAD	AWC per Foot		Management Factors
Monthly ETc	Average Root Depth		Price Variability
Maximum ETc	Monthly Precipitation		Yield Variability
Month of Max. ETc	Crop Suitability		
Field Area Range			

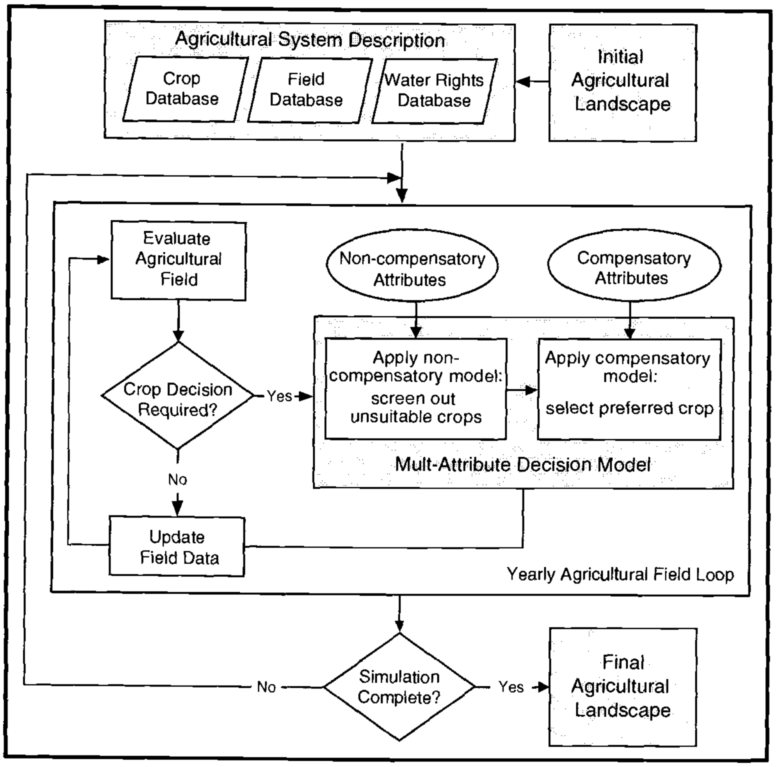

Figure 3.1. The schematic of the CropDM model.

While most of the biophysical attributes that describe the agricultural system are common to any agricultural landscape, the decision attributes and values will be specific to the particular scenario under study. To illustrate the generation and use of both the biophysical and the decision attributes, an implementation of CropDM for a portion of the Willamette River Basin is presented in the following two sections.

3.5 Implementation of an Alternative Futures Simulation

The steps in a typical alternative futures analysis are shown in Figure 3.2. Usually stakeholder groups or policy-makers identify problem areas and develop alternatives that explore these issues. Next, models such as CropDM can be used to place the scenario information into a modeling framework and create depictions of future outcomes. This information can then be used to refine the current scenario elements, develop new policy alternatives, select an alternative, or suggest ancillary studies. The sample implementation described in the following sections covered all but the last step in the analysis. The section or sections describing each step are noted in Figure 3.2.

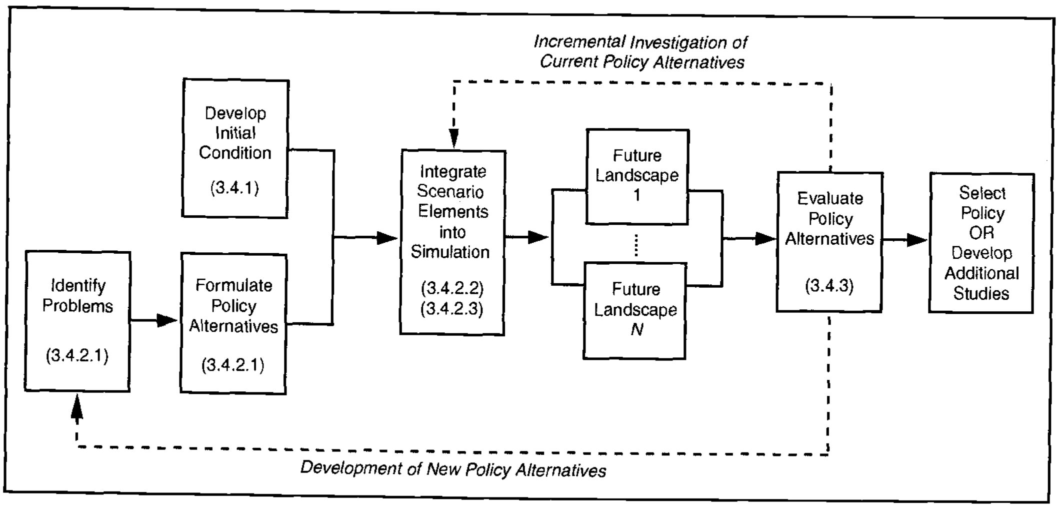

Figure 3.2. Steps in a typical alternative futures analysis. The dotted lines show different analysis paths, while the numbers appearing below each step reference the section that covers that portion of the analysis.

3.5.1 Development of an Initial Representation of the Agricultural System

To generate future agricultural landscapes requires a representation of the current agricultural system that includes characteristics that influence, or are influenced by, the drivers of change. The components used to describe the agricultural system will depend on the environmental setting and the agronomic uses of the farmland under study. For this study, the following data were used to characterize the physical status of the agricultural system: the physiological and management characteristics of the crops, the biophysical characteristics of the agricultural fields, and the irrigation requirements and availability for a particular field-crop combination. Described below is the process used to develop these data sets for the farmland of Oregon's Willamette River Basin.

3.5.1.1 Crop Descriptions

The fertile soils and mild climate of the basin support a diverse selection of crops, with over ninety kinds of agricultural crops currently under production. Twelve types of crops were selected for this study, including both the currently prominent crops and new crops that are experiencing increased acceptance in the basin (Table 3.2). A crop type can include a single crop, a combination of crops that have similar management and resource requirements, or a rotation of multiple crop types.

Table 3.2. The crop types used in this study and their primary attributes.

Crop Type	Rotation Period (yrs)	Field Area (ha)	Market Change (%)	Irrigation Period		*MAD* (%)	RD_{eff} (cm)
				Start	End		
Orchards	40	2-40	0.2	-	-	-	-
Irrigated Caneberries	15	2-40	-0.5	4-15	7-5	50	14.0
Christmas Trees	8	2-80	0.2	-	-	-	-
Irrigated Perennial Crop							
(Large)	5	8-80	-2.0	4-15	8-20	35	9.5
(Small)	4	2-20	-0.5	4-15	6-15	50	9.5
Irrigated Nursery Crop	20	2-40	2.0	4-15	9-30	40	9.5
Irrigated Annual Rotation							
(Early)	3	6-120	-0.4	4-15	6-30	50	9.5
(Late)	3	6-120	-0.4	7-1	9-30	50	9.5
Grain	1	6-200	-3.0	-	-	-	-
Grass Seed Rotation	7	10-200	1.0	-	-	-	-
Hay	1	6-160	-1.0	-	-	-	-
Pasture	1	2-200	0.0	-	-	-	-
Hybrid Poplar	15	2-25	0.5	-	-	-	-
Wood Lot	70	2-25	0.5	-	-	-	-

Each crop was assigned a rotation period defining the interval between crop selection decisions, a field acreage range, and a yearly market trend. It was necessary to place bounds on the size of a field that can grow a particular crop, as many crops require extensive acreage to produce an economically viable crop, while other crops typically use smaller fields. For example, it would not be economically productive to grow a grass seed crop on five hectares of land, although this is not an unusual size for a caneberry crop. To determine bounds on acreage size, farm acreage data from the 1992 Agricultural Census (U.S. Department of Agriculture, National Agricultural Statistics Service 1994) was used to provide an estimate on suitable field sizes for each of the crop types. The yearly percentage change in crop acreage was determined from statistical data (Oregon State University Agricultural Extension 1981-1998), which was modified to reflect near-term changes in the agricultural system that appear to be affecting the long-term trends, such as the recent reduction in vegetable production due to the closing or relocation of food processing facilities.

Planting and harvest dates (Oregon Agricultural Statistics Service 1995) were used to determine the period during which a crop might require irrigation. To estimate a crop's water requirement, Smesrud et al. (1997) provided values for the management allowable depletion (MAD), which is the percentage of water that a plant can remove from the root zone before causing soil moisture stress in the plant, the effective root depth (RD_{eff}), defined as the depth of the root zone where a crop extracts most of its water, and the crop evapotranspiration (ET_c), which is the amount of water transpired by a crop or evaporated from the soil surface.

3.5.1.2 Field Description

In this model, the fundamental physical unit of the agricultural landscape is the field, considered here to be a plot of land containing a single crop-type. Initial delineations of agricultural fields were provided by the Oregon Department of Fish and Wildlife (ODFW)

Land Use/Land Cover map (Klock et al. 1998) and Oregon Water Resources Department (OWRD) irrigation place-of-use data. These boundaries were then amended and extended by manually digitizing field boundaries from false-color satellite images. To differentiate commercially viable agricultural fields from hobby farms and gardens, an agricultural field was required to have an area of at least two hectares.

The suitability of a crop, defined here as the potential crop yield, was determined by using a supervised classification to generate rules relating soil characteristics to crop yield for each of the crops in this study (Berger 2002). Each field was assigned a crop suitability rank for each crop, with values of 9-very good, 7-good, 5-moderate, 3- moderately low, 1-low, to 0-unsuitable.

To calculate the crop water requirement, each field must have information on rainfall amounts and soil characteristics. Mean monthly precipitation was provided by PRISM (Parameter-elevation Regressions on Independent Slopes Model) data layers (Daly et al. 1994), while maximum root depth and available water capacity per foot of depth were derived from the Soil Survey Geographic (SSURGO) database (U.S. Natural Resources Conservation Service 1998). Area-weighted averages of rainfall, maximum root depth, and available water capacity per foot were then calculated for each field.

3.5.1.3 Water Rights and Irrigation Scheduling

Oregon's water law is based on the principle of prior appropriation, where access to water is controlled by the priority date of the water right, with older water rights having seniority in times of water scarcity. A water right may be associated with a single field or with multiple fields, as in the case of an irrigation district. A water right may also be lost if the right is not exercised at least once during a five year period. The water right specifies the maximum volume of water per unit time withdrawn (rate), and the maximum annual volume of water that can be diverted (duty). The OWRD place-of-use data layer contained the priority date, rate, and duty for each water right in the study.

Whether the amount of water provided by the water right is sufficient to grow a crop depends on the characteristics of the crop, the field, and the irrigation method. The amount of irrigation water applied must also be sufficient to compensate for system losses due to effects such as evaporation or wind drift. Most well-designed sprinkler systems have on-farm efficiencies of 60% to 75%, while drip irrigation has efficiencies ranging from 80% to 90% (James 1993). In this model, the irrigation efficiency was set to 90% for irrigated nursery crops to reflect the use of drip irrigation systems and 70% for all other irrigated crops

A soil-water accounting method was used to calculate the irrigation interval I_t (days) and depth I_d (in) needed to refill the soil profile to field capacity before the plant experiences moisture stress (Smesrud et al. 1997):

$$I_t = \frac{AWC\ MAD\ RD_{eff}}{max\, ET_c} \tag{11}$$

$$I_d = \frac{I_t\ ET_c}{I_{eff}} - P \tag{12}$$

where AWC (in/in) is the soil's available water capacity, ET_c (in/day) is the average daily crop evapotranspiration for a month, I_{eff} is the irrigation efficiency, RD_{eff} (in) is the minimum value of the effective root depth of the crop or soil root depth, and P (in) is the rainfall occurring over the irrigation interval. Equations 11 and 12 assume that the initial soil moisture was at field capacity, a reasonable assumption for this region, which experiences heavy winter and early spring rainfall.

3.5.2 Alternative Scenarios Definition and Implementation

Once the initial agricultural system is defined, the scenario description needs to be translated into elements suitable for use in a modeling environment. To illustrate these steps, a sample policy study was implemented that investigates the effects on farmland of a long-term riparian restoration program.

3.5.2.1 Scenario Description

The purpose of the riparian restoration program is to convert selected farmland back into riparian forest. The Restoration policy is to be carried out over a fifty-year period and uses a two-tier restoration scheme (Husle et al. in press). Tier 1 lands are managed with priority given to achieving a naturally functioning landscape by converting agricultural land to riparian forest. Tier 2 lands are managed for sustainable agricultural production compatible with habitat conservation values. Farmland enrolled as either Tier 1 land or Tier 2 farmland will convert to that particular tier-type sometime within the 50-year simulation period. The impacts arising from these policies will be deduced by comparing the Restoration land cover with both the initial land cover and that resulting from a continuation of current trends (Continuing Trends) over the same 50-year period. In the Continuing Trends scenario, the only driver of change is the market demand for each crop.

This futures study explores two questions: 1) How does the conversion of farmland or the adoption of Tier 2 farmland change the distribution of crops, and 2) To what extent does Tier 2 farmland provide improved habitat relative to ordinary farmland. To address this second question the Restoration scenario was divided into two options: one option (Restoration) treats Tier 2 farmland the same as any other farmland, with the possibility of a field losing its water right if it is not exercised at least one within a five-year period. The second option (Restoration-WR), allows the DM to select the most appropriate crop without this constraint.

The study area (Figure 3.3) is located along the main stem of the Willamette River. The area covers 6689 ha of farmland divided into 483 agricultural fields. The initial distribution of crop types was determined using the ODFW land use/land cover data (Klock et al. 1998), county crop statistics (Oregon State University Agricultural Extension 1992), and crop suitability rankings. The distribution of land and water rights for each of the land designations (ordinary farmland, Tier 2 farmland, Tier 1 land) is shown in Table 3.3.

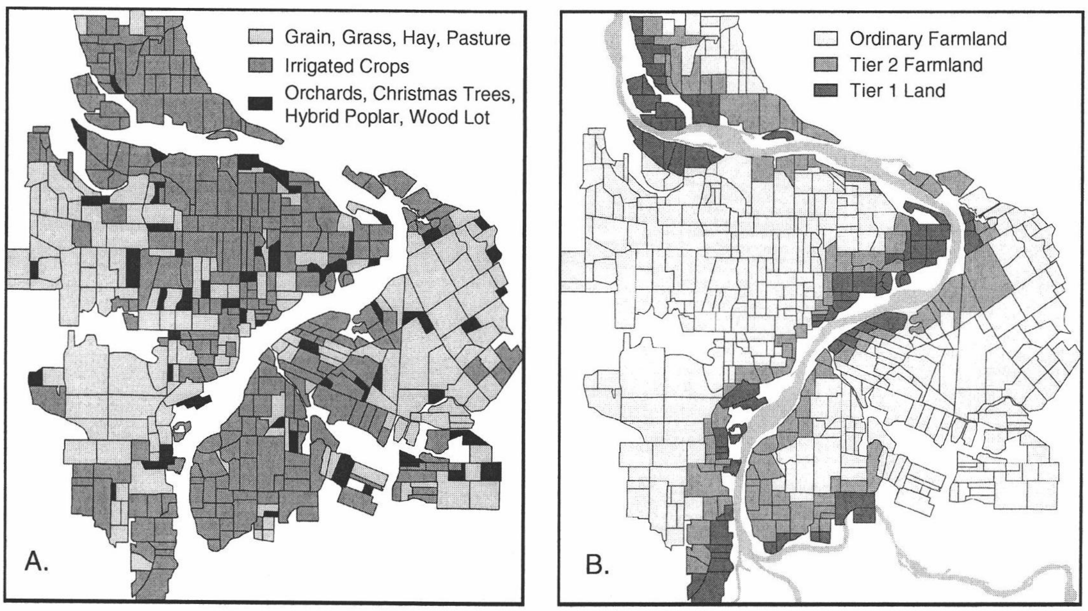

Figure 3.3. A) Distribution of general crop classes. B) Location of each land designation and its relationship to the river system.

Table 3.3. Characteristics of the agricultural fields for each of the land designations and for the entire study area.

Land Designation	No. of Fields	Fields w/ Water Rights	Hectares		
			min	max	average
Tier 1 Land	71	48	2.3	38.2	10.6
Tier 2 Farmland	95	62	2.8	85.7	13.1
Ordinary Farmland	317	157	2.3	104.0	14.8
All Land	483	267	2.3	104.0	13.9

Given the above scenario descriptions, the next step is to identify the attributes that contribute to the crop selection decision or that reflect particular scenario constraints. Once identified, these attributes must be classified as either noncompensatory or a compensatory attributes, and suitable cut-off points or values determined.

3.5.2.2 Noncompensatory Attributes

The attributes selected for the noncompensatory method were used to identify unsuitable crops, so that they could be removed from the list of crop alternatives before applying the compensatory method. For all scenarios, the attributes selected for the conjunctive method were: crop suitability, field acreage, market factors, and irrigation availability. Cut-off values for each of these attributes were developed as follows.

Any crop with a crop suitability rank of zero was excluded from further consideration. Similarly, if the field area fell outside the crop's field-acreage range given in Table 3.2, that crop type was excluded.

Market factors were modeled by constraining the number of hectares growing each crop type. First, the initial *market acreage* of each crop type was defined as either 110% of the initial total crop acreage or the initial total crop acreage plus the maximum field size for that crop, whichever was greatest. This provided needed flexibility during the initial period of the simulation. Then, for each year in the simulation, the market acreage was increased or reduced by the percentage change shown in Table 3.2. The compensatory method used this information to determine whether selecting the crop type would increase the yearly crop acreage total beyond that of the market acreage for that year, in which case the crop was considered unsuitable.

Finally, irrigation availability for irrigated crops was determined by first requiring that a field held a water right. If no water right was held, the crop was excluded. If a field did hold a water right, then Equations 11and 12 were used to estimate the rate of water needed and the total amount of water used over the growing season. If these calculations showed that sufficient water could be supplied without violating the rate or duty constraints of the water right, irrigation availability was classified as suitable; otherwise, it was classified as unsuitable for that crop type.

In the Continuing Trends and Restoration scenarios, fields with water rights could not select non-irrigated crops that have a rotation period of five years or more. This constraint was lifted in the Restoration-WR scenario. Both Restoration scenarios had an extra attribute–the number of years until a field converted to Tier 1 restoration land. The rationale for this attribute was that it would be irrational for a DM to select a crop that could not be established and at least minimally harvested before the field converted to another land use. The minimum number of years required before a field converts to Tier 1 land was: Orchards - 30 years, Irrigated Caneberries - 10 years, Christmas Trees - 6 years, Irrigated Perennial Crop - 4 years, Irrigated Nursery Crop - 10 years, Hybrid Poplar - 8 years, and Wood Lot - 40 years. All other crop types were unconstrained.

3.5.2.3 Compensatory Attributes

Attributes used in the compensatory method should provide information on the trade-offs involved in crop production. The following compensatory attributes, which were used in each of the scenarios, represent the economic and management attributes of the crops: crop suitability, price variability, yield variability, profit margin, and management requirements. Price variability, yield variability, and management requirements were identified as cost attributes, while profit margin and crop suitability were designated as benefit attributes. Each attribute was ranked on a scale from one to nine. Crop suitability was already expressed as a rank, while the initial rankings for the remaining compensatory attributes were developed from county economic reports (Oregon State University Agricultural Extension 1981-1998) and enterprise data sheets, and then refined after discussion with agricultural extension agents about current grower attitudes and future market expectations. With the exception of the management requirements attribute, the values of the compensatory attributes did not change over the course of the simulation. For the management requirements attribute, the value of the attribute was a function of the previous crop. If a crop had difficult or costly management requirements, but had been grown during the prior selection period, the subsequent management requirements rating were lower, reflecting a grower's experience.

The CropDM model used Equation 10 to calculate a composite attribute weight for use in the TOPSIS model. The following rationale determined the order of the subjective weights: a grower would first want to secure a return on the crop, followed by reducing risk by having the appropriate management skills and field conditions. Finally, these circumstances would be modified by price and yield variability. Yield variability was the lowest concern, as this can be mitigated with appropriate cultivar selection.

The Restoration alternatives prescribed a different management strategy for Tier 2 farmland, since growers managed a field to obtain a reasonable economic return while growing crops compatible with habitat conservation values. To represent this new factor in the decision process, an attribute reflecting the relative wildlife habitat quality of a crop was derived from habitat suitability scores (Schumaker et al. in press), and the subjective weight of the attribute was set equal to that of the crop's profit margin. Table 3.4 shows the type, attribute values, and subjective weights assigned to each crop alternatives for ordinary farmland or Tier 2 farmland.

Table 3.4. Decision attributes and their associated values for each crop type and the subjective weights for each type of decision-maker.

Crop Type	Profit Margin (Benefit)	Crop Suitability (Benefit)	Management New / Exper. (Cost)	Yield Variability (Cost)	Price Variability (Cost)	Habitat (Benefit)
Orchards	5	1-9	9 / 1	1	3	3
Irrigated Caneberries	3	1-9	9 / 1	3	1	3
Christmas Trees	5	1-9	4 / 1	9	7	5
Irrigated Perennial Crop						
(Large)	3	1-9	5 / 1	5	3	1
(Small)	5	1-9	9 / 5	1	1	1
Irrigated Nursery Crop	9	1-9	9 / 1	5	3	1
Irrigated Annual Rotation	7	1-9	4 / 1	5	3	1
Grain	2	1-9	2 / 2	5	1	5
Grass Seed Rotation	7	1-9	3 / 1	3	2	5
Hay	3	1-9	2 / 2	7	3	5
Pasture	1	1-9	1 / 1	5	5	5
Hybrid Poplar	3	1-9	2 / 2	5	7	3
Wood Lot	9	1-9	1 / 1	7	7	9
Subjective Weights						
Ordinary Farmland	0.250	0.200	0.225	0.150	0.175	0.000
Tier 2 Farmland	0.200	0.160	0.180	0.120	0.140	0.200

3.5.3 Comparing the Future Outcomes

The decision attributes and scenario elements for the Continuing Trends, Restoration, and Restoration-WR scenarios were each incorporated in turn into the CropDM model, which generated three future outcomes. The resulting landscapes were then evaluated to determine the impact on the agricultural system of converting farmland to restoration land and the value of Tier 2 farmland in supporting Tier 1 conservation areas.

Table 3.5. Distribution of land cover for the Continuing Trends and Restoration scenarios, for all land and for Tier 2 farmland.

Crop Type	Distribution of Land Cover (%)							
	All Land				Tier 2 Farmland			
	Initial Condition	Continuing Trends	Restoration	Restoration -WR	Initial Condition	Continuing Trends	Restoration	Restoration -WR
Orchards	2	3	2	3	4	3	1	1
Irr. Caneberries	2	2	2	2	5	5	7	3
Christmas Trees	3	4	4	4	2	4	7	8
Irr. Perennial Crop	10	5	2	1	16	5	2	0
Irr. Nursery Crop	2	5	2	2	0	0	0	0
Irr. Annual Rotation	37	36	34	25	46	55	55	2
Grain	4	1	1	2	5	1	2	2
Grass Seed Rotation	33	38	36	47	17	23	23	79
Hay	4	3	2	3	3	0	0	1
Pasture	0	1	1	0	0	1	1	0
Hybrid Poplar	1	1	1	1	0	1	1	1
Wood Lot	1	1	1	1	1	1	1	2
Riparian	0	0	11	11	0	0	0	0

The result from Continuing Trends shows how the landscape responded to decision factors over the simulation period (Table 3.5), displaying the expected acreage reductions in Grain and Hay and the increases in Irrigated Nursery Crops and Grass Seed Rotation. In contrast, Restoration had acreage reductions in all crops except for Christmas Trees and Grass Seed Rotation. This difference is due to several factors. First, converting agricultural fields to Tier 1 restoration land reduced the agricultural land base by 11% in both

Restoration options. Compared with Continuing Trends, the largest acreage loss was in Irrigated Annual Rotation (370 ha), since many of the fields along the river had fertile soil and a convenient source of irrigation, ideal conditions for high-value vegetable crops. Smaller losses occurred from Irrigated Perennial Crops (121 ha) and Grass Seed Rotation (89 ha).

About 20% of the agricultural fields in Restoration and Restoration-WR were Tier 2 fields managed to support wildlife habitat. This Tier 2 farmland behaved differently from ordinary farmland, with increases in Irrigated Caneberries, Christmas Trees, Irrigated Annual Rotation, and Grass Seed Rotation. Note that these crops had the higher habitat values and profit margins, with Irrigated Caneberries and Christmas Trees selected for smaller fields, and Irrigated Annual Rotation and Grass Seed Rotation selected for larger fields. Overall, the effect of the Restoration scenarios on the agricultural system was to remove highly productive soils from agricultural production. The economic impacts resulting from this reduction include county and state revenue losses and commercial losses because of the decrease in agricultural and consumer purchases.

The effect of the scenario assumptions on habitat quality was determined by calculating the mean wildlife habitat rating for the Tier 2 farmland. The habitat rating went from 2.4 for the initial landscape to 2.6 in Restoration and to 4.9 in Restoration-WR. The higher habitat value in Restoration-WR is a result of the DMs selecting crops without concern for losing the field's water right. As Table 3.5 shows, crop selection moved away from irrigated crops, especially Irrigated Annual Rotation, to Grass Seed Rotation. In addition, the acreage of Irrigated Caneberries is reduced by half, while the acreage of Wood Lot doubles. These results suggests that the success of the Tier 2 component of the riparian restoration policy rests on decision-makers developing policies that address the water rights issue for these fields. To determine which policies would be most beneficial, additional scenario studies could be undertaken in tandem with other analyses, such as econometric models.

3.6 Conclusions

This paper has presented a new method to generate future agricultural landscapes. It combines both spatial and aspatial biophysical characteristics of fields and crops with human factors related to crop selection. The use of the approach for future scenario studies was illustrated by a sample implementation that compared two policy alternatives for farmland located along Oregon's Willamette River. The model results showed how changes in different drivers of the agricultural system influenced crop selection decisions. These results support the continued study of decision-making methods for integrating biophysical features with human factors in agricultural systems. The final stage of the analysis would include the use of metrics and models to compare and contrast various agronomic, ecological, and socio-economic aspects of the different landscapes.

The structure of the model provides for an array of modifications depending on the requirements of the investigation, the scale of the project, and the data available. An analyst can run different scenarios by changing the attribute weights, by adding or deleting attributes or alternatives or by altering the spatial character of the landscape. For example, different types of growers could be distinguished by using surveys to solicit decision-attribute values and weights; a GIS could provide the model with the spatial pattern of urban encroachment into farmland; or climate change scenarios could be explored using weather generators. In each case, the field's DM integrates this information and makes the final crop selection or land-use decision. The strength of such simulations is not in there predictive use, but in providing a sense of the trends or trade-offs due to the different future conditions.

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4. EVALUATING THE IMPACT OF POLICY OPTIONS ON AGRICULTURAL LANDSCAPES: AN ALTERNATIVE FUTURES APPROACH

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4.1 ABSTRACT

Alternative futures analysis was used to analyze different scenarios of future growth patterns and attendant resource allocations on the agricultural system of Oregon's Willamette River Basin. A stakeholder group formulated three policy alternatives: a continuation of current trends, an increased reliance on market forces to determine land use, and an increased emphasis on environmental restoration programs. To model the alternative scenarios first required the development of a spatial representation of the current agricultural system. Next, rules and constraints based on the three policy scenarios were formulated. Then a spatially explicit, multi-attribute decision-making model was used to model changes in agricultural land-cover and land-use. This procedure generated three future landscapes, each depicting an alternative state of the agricultural system in the year 2050. Finally, the agronomic and environmental condition of each agricultural system was evaluated by using landscape metrics and screening models. The results show that the type and amount of farmland conversion were the scenario elements that most distinguished the future agricultural landscapes. By continuing current land-use policies, nearly all of the existing farmland was conserved for future agricultural use, while both the market-driven and environmental restoration scenarios converted 15% or more of the agricultural land to other uses. The use of farmland for vegetation restoration activities was particularly successful in improving riparian habitat, while habitat quality over the region showed widespread improvement. The patterns of crop selection in each future followed general trends, but with variations among scenarios as crop selection decisions adapted to changing field and basin conditions.

4.2 INTRODUCTION

Policy-makers and stakeholders are under pressure to promote both environmental restoration and land development plans that address present concerns, while having limited knowledge of the long-term impacts of these decisions on the regional system. Agriculture is an important part of most regional systems, interacting with both the urban and natural habitat portions of a region. Thus, methods that provide reasoned depictions of the spatial and temporal dynamics of agricultural landscapes should help inform decision-makers about the impacts and trade-offs of different management approaches.

To study the potential effects of different policy options on Oregon's Willamette River Basin, the Pacific Northwest-Ecosystem Research Consortium working with several stakeholder groups developed three alternative future scenarios for the basin, spanning 60 years: a continuation of current trends (Plan Trend 2050), an increased reliance on market forces to determine land use (Development 2050), and an increased emphasis on environmental restoration programs (Conservation 2050) (Hulse et al., this issue). The purpose of such long-term future scenarios is not to forecast future conditions, but to create depictions of future conditions based on a consistent set of assumptions (Veeneklass and van den Berg 1995). Once the future landscapes are generated, analysts can evaluate and compare the landscapes, providing decision makers with information on the potential outcomes of different policy alternatives and broadening the perspective of society (Schoonenboom 1995).

Most methods used to generate future depictions of land use and land cover require a time-series of historical land-cover maps. This information is used to create land transition probabilities (Berry et al. 1996), or regression models (Veldkamp and Fresco 1996;

Pijanowski et al. 2000) or to train neural networks (Pijanowski et al. 2002). However, these methods cannot be used if there is limited land-cover data or when the future trajectories of change that are to be explored do not follow from past trends. The Willamette River Basin's agricultural system is an example of such a data-limited situation. Historical data on agricultural land use in the Willamette River Basin is restricted to county-level statistics, with only a few representations of area land cover, of varying detail and extent.

This paper describes a method to generate spatial depictions of future land-cover patterns, using only an initial spatial configuration. Instead of employing a historical time-series of land-cover maps, the relationship between current and future land cover is derived by using information about the decision process of agricultural growers. The approach developed uses a spatially explicit, multi-attribute decision-making model to simulate land-cover change, and translates the effects of land-use and water-use change from other models by using decision constraints and change rules. Thus, the maps generated are a reflection of the scenario elements, and the potential impacts and trade-offs associated with each policy option can be determined by comparing and contrasting the different scenario outcomes.

The next section introduces the study area, followed by a description of the model and the derivation of its components. Then, various basin- and watershed-scale measures are used to evaluate the alternative landscapes. The final sections discuss the implications of these results to the Willamette River Basin and the effectiveness of this modeling approach.

4.3 STUDY AREA

The Willamette River Basin is located in the northwest portion of Oregon, USA. It encompasses approximately 29,800 km^2 and contains the primary urban and agricultural areas of the state (Figure 4.1).

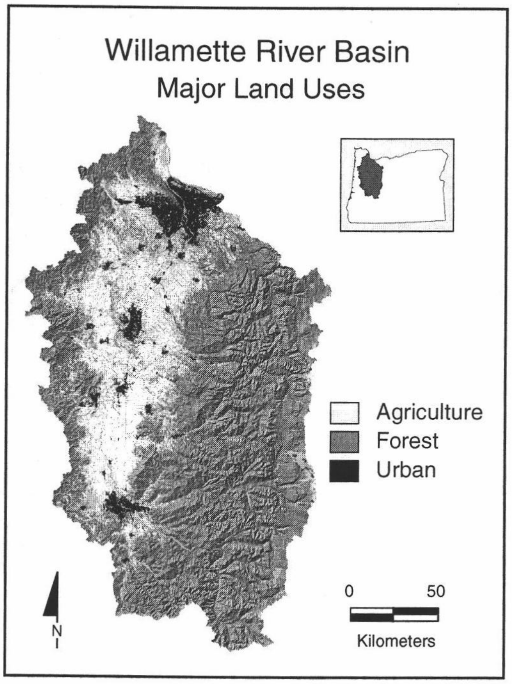

Figure 4.1. Major land-use classes of the Willamette River Basin.

The basin has a Mediterranean climate, characterized by warm, dry summers and cool, wet winters. Farmland covers over 5,260 km^2 (17%) of the basin, primarily located on the valley floor and lower foothills. The mild climate and fertile soils encourage the production of a diverse array of agricultural crops, including vegetables, nursery crops, Christmas trees, grass seed, and caneberries, with annual agricultural sales of approximately $1.5 billion (U.S. Department of Agriculture, National Agricultural Statistics Service 1999). Agricultural lands also provide important areas of open space and wildlife habitat, while the proximity of farmland to natural and urban areas challenges growers to use management techniques that decrease the negative impacts of farming.

4.4 METHODS

4.4.1 Agricultural Landscape Evolution Model

The modeling approach adopted had to determine both land-cover changes occurring within the agricultural sector as well as the effects of other resource allocation models on farmland. These requirements necessitated the development of an initial characterization of the agricultural system, an agricultural land-cover change model, and methods to integrate land conversion and changes in water resource allocation.

A representation of the final model is shown in Figure 4.2. Beginning with the initial depiction of the agricultural system, and for each consecutive year in the simulation, the model evaluated the state of every agricultural field, selecting new crops as needed. Every decade, the model integrated the land conversion and water allocation data from other resource models. The result was three land cover maps of 30-m spatial resolution, each of which reflected the elements of its respective scenario. The following subsections describe the development of each part of the agricultural landscape evolution model.

4.4.1.1 Characterization of the Agricultural System

To develop a field-scale depiction of the initial agricultural system for the Willamette River Basin required the assembly of crop production and management information and the creation of a spatial database containing the biophysical characteristics of the

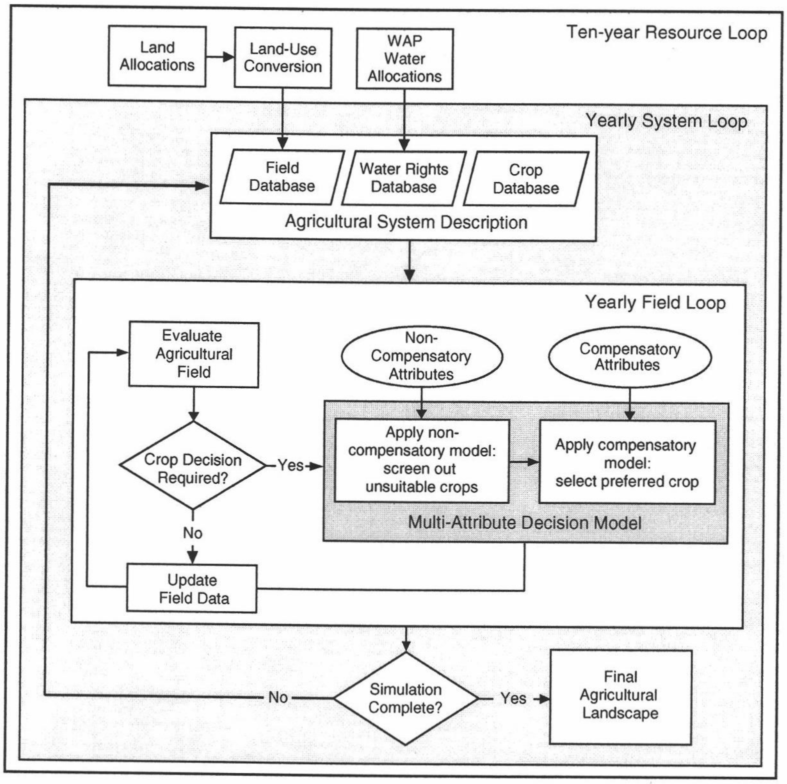

Figure 4.2. The program flow diagram for the agricultural landscape evolution model.

agricultural fields. This characterization was limited to agronomic production as there were insufficient data to describe animal operations. This deficiency is mitigated by the fact that the primary commodities of the basin are agronomic. Thus, the future landscapes should provide a reasonable depiction of the agricultural land cover.

The Willamette River Basin supports a diverse selection of crops, with over ninety commodities currently under production. To represent this agricultural diversity, twelve crop types were defined by grouping together crops that had similar economic and management characteristics or that were typically grown in rotation (Table 4.1). Each crop type was assigned a minimum and maximum field size and the number of years before a new crop selection takes place (U.S. Department of Agriculture, National Agricultural Statistics Service 1994; Oregon State University Agricultural Extension 2001). In addition, irrigated crop types were assigned planting and harvest dates (Oregon Agricultural Statistics Service 1995), management allowable depletion, crop root depth, and monthly crop evapotranspiration (Smesrud et al. 1998), which were used to estimate monthly crop water requirements.

Table 4.1. The twelve crop types used to represent the agricultural products of the Willamette River Basin. Subcategories were implemented by imposing different planting-time or field-size constraints. The Pasture class includes both land actively managed for livestock use and unmanaged pasture as described in Klock et al. (1998).

Irrigated Crops	Non-irrigated Crops
• Caneberries	• Orchards
• Nursery Crops	• Christmas Trees
	• Grain
• Perennial Crops small fields large fields	• Grass Seed Rotation • Hay
	• Pasture
• Annual Rotation early planting late planting	• Hybrid Poplar • Wood Lot

The spatial unit of analysis for the agricultural system was the agricultural field, which represented that portion of a land parcel undergoing cultivation. The Oregon Department of Fish and Wildlife Land Use/Land Cover map (Klock et al. 1998) and Oregon Water Resources Department (OWRD) irrigation place-of-use data provided the initial field boundaries. Then digitized boundaries from false-color satellite images were used to amend and extend the field boundaries to the entire basin. This procedure created 46,470 agricultural fields covering 441,670 ha, which ranged in size from 2 ha to 280 ha, with a mean area of 12 ha. A minimum field area of 2 ha was established to differentiate commercially viable agricultural fields from hobby farms.

For each field, a GIS computed an area-weighted average of the mean monthly precipitation (Daly et al. 1994), available water capacity per foot of soil depth (U.S. Department of Agriculture, Natural Resources Conservation Service 1998) and the suitability ranking for each of the crop types. This ranking is a relative measure of the level of crop production occurring under normal management. The rankings were determined by using a supervised classification scheme that created rules relating crop yields to the biophysical characteristics of the soil (Berger 2002).

For those fields that hold a water right, the amount of water that can be withdrawn is constrained by two factors: the rate, which sets the maximum volume of water per unit time that can be withdrawn, and the duty, which is the annual volume of water that can be diverted. The OWRD supplied data on irrigation water rights place-of-use, rate, duty, and priority date for both surface water and groundwater rights. The priority date was used to create a seniority ranking system, with the oldest water right having the first opportunity to use the available water.

To determine surface water availability, each water right with a surface water point-of-withdraw was associated with a Water Availability Polygon (WAP). Thus, the ability to exercise a surface-water right was dependent on the rate and duty of the water right, and amount of irrigation water available in the WAP, which was determined by the WaterMaster program (Dole et al. this issue). Thus, the water must first be physically available as defined by the WAP, and non-appropriated as defined by the priority date of the water right, before a surface water right can be exercised. As no water availability data were available for groundwater rights, no similar constraints on groundwater availability were imposed. Finally, the irrigated fields adjacent to waterways located downstream of federal dams were allowed to supplement their irrigation with diverted water, within the constraints of the field's water right.

Four land cover maps (Table 4.2) were used to define the initial (circa 1990) crop distribution, hereafter denoted as the Circa 1990 agricultural landscape. The crop classes from each map were associated with one of the twelve crop types and assigned confidence levels. The data from Anderson et al. (1997) and the test polygons used to train the Oetter et al. 2001 classification had a high confidence for all crop classes because the classes were verified during the data collection process. For the remotely sensed data (Oetter et al. 2001; Klock et al. 1998), the associated error matrix provided the confidence level for the crop class. County-level crop statistics (Oregon State University Agricultural Extension 1992; U.S. Department of Agriculture, National Agricultural Statistics Service 1994) were then used to calculate the percentage of each crop type in every county. Next, using information on a field's irrigation availability and crop suitability, the crop type with the highest confidence was assigned to each agricultural field until each county's crop acreage requirement was fulfilled. The age of the crop type was determined by randomly selecting a number within the crop type's age range.

Table 4.2. Characteristics of the four land-use/land-cover maps used to define the initial crop distribution. The date gives the year or years during which the data was collected. The minimum mapping unit for the Anderson et al. 1997 data was estimated based on the description of the data and by comparison with similar data sets.

Source	Date	Number of Crop Classes	Minimum Mapping Unit	Area Coverage (%)
Oetter et al. 2001 (satellite image)	1992	17	25m	100
Oetter et al. 2001 (test polygons)	1992	23	0.25 ha	1
Klock et al. 1998	1993-1996	5	0.12 ha	79
Anderson et al. 1997	1996	39	0.25 ha (est.)	4

4.4.1.2 Rules for Agricultural Field Conversion

Spatial data layers containing the location of restoration lands and of rural residential and urban development were supplied for each 10-year interval in the simulation period (Hulse et al. this issue). All three future scenarios included the conversion of farmland to built uses, while Conservation 2050 also included the use of farmland for vegetation restoration. The restoration policy implemented two tiers of conservation and restoration lands. Tier 1 lands were lands managed with priority given to achieving a naturally functioning landscape, while Tier 2 lands were managed for sustainable production of goods and services compatible with habitat conservation values (Hulse et al., this issue). Circa 1990 agricultural fields could thus end up in one of three different states in Conservation 2050: normal farmland, Tier 2 farmland, or Tier 1 conservation land. In addition, a woody or shrubby field border was placed around all Tier 2 agricultural fields, while the adoption of field borders around normal farmland increased over the simulation period.

The effect of these land allocations on farmland was field fragmentation and acreage reduction. The nature and degree of this fragmentation, as well as acreage loss, signaled land use change; as commercially viable agriculture cannot take place when the geometry of the field hinders activities such as tillage or irrigation, or when the field becomes too small. The shape of a field was measured by the field's perimeter-to-area ratio and fractal dimension. Any shape value over four standard deviations beyond the mean value for the Circa 1990 agricultural fields was taken as an indication of conversion.

In Development 2050, fields undergoing built development tended to exhibit diffuse fragmentation. This type of field fragmentation was assessed using two texture measures, the angular second moment (an indicator of image homogeneity) and entropy (an indicator of image evenness) from the gray level co-occurrence matrix (Haralick 1979) derived from the field. Cutoff values for texture were defined experimentally by simulating field fragmentation on sample fields and relating indicator levels to visual determinations of the suitability of the field for continued farming.

In Conservation 2050, a field partially converted to Tier 2 farmland with at least 16 ha of the field remaining as normal farmland was subdivided, so the original field was treated with two different management approaches. Finally, a woody or shrubby field border was placed around all Tier 2 fields, while for each decade, 10% of the normal agricultural fields had field borders randomly placed along field boundaries.

In all the future scenarios, field fragments no longer farmed had an increased probability for conversion to built uses or natural vegetation in subsequent iterations of the land allocation models applied by Hulse et al. (this issue).

4.4.1.3 Decision-Making for Crop Selection

The CropDM model (Berger 2002) was used to simulate the crop selection process, thereby generating future agricultural land-cover. This model uses a two-step, multi-attribute decision-making process to represent the crop-selection decision process. The first step uses the conjunctive method, which as a non-compensatory method, does not allow trade-offs among attributes; therefore, a single weak attribute is sufficient to exclude an alternative. As used in crop selection, the conjunctive method evaluates the suitability of a crop type based on the attributes of the field and basin at the current time-step. The method screens out crop types that: do not produce a marketable yield, fall outside the crop type's acreage range or maximum basin acreage levels, or do not have sufficient irrigation water available. The Conservation 2050 model included an additional noncompensatory attribute: the number of years until a field converted to a Tier 1 restoration area. This attribute insured that the model would only select a crop that would produce a marketable yield before the field converted to a non-agricultural land use.

The second step in the crop selection process was the use of the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to select the final crop type from the set of suitable crop types. TOPSIS is a compensatory model, which allows the decision-maker to examine the trade-offs among alternatives; thus, a weakness in one attribute can be compensated for by strength in other attributes (Hwang and Yoon, 1981). This method was selected since it makes use of all attribute information, provides a cardinal ranking of alternatives, and does not require preference independence of the attributes (Chen and Hwang 1992).

TOPSIS used the values and decision weights of the noncompensatory decision attributes to rank the crop alternatives, with the most preferred crop selected for the field. In this manner, the agricultural fields were able to adjust to changes in their environment, selecting the preferred crop for current conditions. In contrast to the field and basin attributes used in the conjunctive method, the attributes used in TOPSIS focused on agronomic and economic characteristics. Estimated values for these attributes were determined from county-level agricultural statistics data, then modified in consultation with agricultural experts and reviewed by the stakeholder committee. The attributes, listed in order of importance to the decision-making process, were the profit margin, management requirements, crop suitability, price variability, and yield variability for each crop. The management requirements attribute was further refined by defining its value as a function of the field's previous crop. Thus, if a crop requires a high level of management expertise, prior experience with the crop improves the value of the management requirements attribute.

Plan Trend 2050 and Development 2050 used the same set of decision attributes, values, and weights since the rationale for crop selection was not dependent on the scenario elements. In contrast, Conservation 2050 included an additional attribute for Tier 2 farmland, the wildlife suitability rank (Schumaker et al. in press) of the crop type. By setting the decision weight for the crop's habitat quality equal to that of the crop's profit margin, the model reflected the importance of habitat quality to the crop selection decision. A summary of the decision methods and rules developed for each scenario is listed in Table 4.3.

Table 4.3. Decision variables and field conversion rules implemented for each future scenario.

Scenario Element	Plan Trend 2050	Development 2050	Conservation 2050	
			Normal Farmland	Tier 2 Farmland
Field Conversion Rules	None	Field conversion governed by field shape, size, and texture	Field conversion governed by field shape and size	Field conversion governed by field shape and size
				Large fields subdivide
			Increased use of field borders	Field borders required
Decision Attributes				
Conjunctive Method	Field Size Irrigation Availability Basin Crop Acreage Crop Suitability	Same attributes as Plan Trend	Same attributes as Plan Trend	Same attributes as Plan Trend plus addition of Time-to-Conversion to Tier 1
TOPSIS	Profit Margin Management Factors Crop Suitability Yield Variability Price Variability	Same attributes as Plan Trend	Same attributes as Plan Trend	Same attributes as Plan Trend plus addition of Habitat Suitability

4.4.2 Analysis of the Alternative Agricultural Landscapes

The following characteristics were used to measure the effect of the scenario elements on the agronomic and ecological conditions of the agricultural systems: farmland conversion, crop distribution, soil erosion, groundwater vulnerability, riparian cover, and wildlife habitat quality. The analyses of farmland conversion, riparian cover, and wildlife habitat quality were done for the entire Circa 1990 area, that is, the initial 46,470 agricultural fields. Evaluations of crop distribution, soil erosion, and groundwater vulnerability were limited to those areas still actively farmed in each scenario, as these measures related strictly to agricultural activity. To visualize the spatial pattern of change, a set of watersheds ranging in size from 25 to 100 km^2 were derived from fifth field watershed delineations and 30-m digital elevation data (Figure 4.3). Each watershed used in the analysis had at least 20% of its area in farmland in Circa 1990, with the entire set of 337 watersheds covering 90% of the Circa 1990 farmland.

4.4.2.1 Farmland Conversion

The impact of farmland conversion is dependent on both the quantity and quality of the converted farmland. High quality farmland was defined as farmland that met the criteria for National Resource Conservation Service (NRCS) prime agricultural land (Soil Survey Division Staff 1993). The NRCS designation of prime farmland is based on the soil attributes of the land and specific field conditions such as irrigation availability or drainage system installation. This definition was used to locate the prime farmland occurring within the agricultural land of the basin. Then the percentage of all farmland and prime farmland in each of the major land uses - Agriculture, Built, and Natural Vegetation - was calculated for each scenario.

4.4.2.2 Crop Distribution

Two indicators were used to quantify changes in crop distribution within the actively farmed land of each scenario. The first indicator was the basin-scale proportion of cultivated land covered by each crop type. The second indicator was the Shannon-Weaver evenness index:

$$E = \frac{-\sum_{i=1}^{n} p_i \ln p_i}{\ln n} \tag{1}$$

where n=12 is the total number of crop types, and p_i is the proportion of land growing each crop type with respect to the total cultivated land area. Increases in crop diversity indicate a system that is more resilient to change, and hence has greater economic stability, while decreases in diversity may indicate a more at-risk system. This index was calculated for each watershed and for the entire basin area.

4.4.2.3 Soil Erosion

The Universal Soil Loss Equation (USLE) was used to compute the rate of soil erosion taking place on the cultivated land of each scenario. The USLE is a widely used first-tier screening method for estimating sheet and rill erosion from empirical measures of climatic, topographic, and management values. The equation is calculated as (Wischmeier and Smith 1978):

$$E = R\,K\,LS\,C\,P \tag{2}$$

where E denotes the annual soil loss in tons per hectare per year, R is the rainfall erosivity factor, K is the soil erodibility factor, LS is the topographical factor, C is the cover management factor, and P is the erosion control practice factor. The National Resource

Inventory database (U.S. Department of Agriculture, Natural Resources Conservation Service 1995) provided *R*- and *C*-factor values. Cropping system *C*-factors were calculated by averaging each crop's *C*-factor over the basin, and, for crop types composed of two or more crops, computing a weighted average. *K*-factors for each soil type were contained in the NRCS SSURGO digital database for each county in the basin (U.S. Department of Agriculture, Natural Resources Conservation Service 1998). The topographic factor, *LS*, was calculated as (Moore and Burch 1986):

$$LS = \left(\frac{A}{22.13}\right)^{0.4}\left(\frac{\sin\theta}{0.0896}\right)^{1.3} \tag{3}$$

where A is the contributing upslope area and θ is the slope in radians. The *P*-factor, which describes the reduction in soil erosion from conservation farming techniques such as contouring or strip farming, was set to one, as no such strategies were implemented in this study. To apply the USLE to the topographically complex basin region, areas of soil deposition were identified by using an erosion/deposition model (Mitas and Mitasova 1998; Mitasova et al. 1996) and removed from the analysis. Then the USLE was used to calculate the erosion rate occurring on the remaining agricultural land.

Soil loss can reduce crop productivity when the rate of erosion is greater than the rate of soil formation. The maximum rate of soil loss that can occur while still permitting high levels of crop production is defined as the soil loss tolerance (Soil Survey Division Staff, 1993). After determining the rate of erosion, the ratio of soil erosion to the soil loss tolerance was calculated for each 30-m pixel, forming a measure of erosion risk E_{risk}, where $E_{risk} \leq 1$ indicates tolerable soil loss levels and $E_{risk} > 1$ denotes potential problem areas. Then, the mean value of E_{risk} for each scenario was calculated for both the basin and for each of the watersheds, together with the percentage of cultivated land in each scenario having $E_{risk} > 1$.

4.4.2.4 Groundwater Vulnerability

A first order groundwater vulnerability potential was calculated to assess if changes in crop distribution had altered the risk of groundwater contamination. First, information on the types and amounts of chemicals typically applied to crops in the area was obtained from Anderson et al. (1997). There were no data for the hybrid poplar or wood lot crop types, but as these crops do not generally require systematic chemical applications, their absence from the analysis should be negligible for a first-order estimate. Next, the Oregon Water Quality Decision Aid software (Huddleston 1998) was used to assign a pesticide-movement rating to each chemical and a soil-sensitivity rating to each soil type. These categorical values were converted to numeric values and used to compute a weighted average of the pesticide-movement rating for each cropping system, and an area-weighted average of soil sensitivity for each field. Then, the soil-sensitivity and pesticide-movement rating values were converted back to categorical values by rounding to the nearest integer value and assigning it the corresponding rating. Finally, each field's soil-sensitivity rating and its crop's pesticide-movement rating were used to determine the groundwater vulnerability potential by using a lookup table contained in Kerle et al. (1998), with values ranging from very low, to low, moderate, high, and very high vulnerability. The percentage of land in each groundwater vulnerability class for both irrigated and non-irrigated crops was then calculated for the cultivated area of each agricultural landscape. Note that as these values were determined only for land in agricultural production, they do not reflect potential groundwater contamination from sources such as septic systems or construction that may occur in the developed areas of agricultural fields.

4.4.2.5 Riparian Land Cover

To determine how changes in near-stream land-cover affected the quality of riparian habitat, a 30-m buffer was placed along the first- through seventh-order streams. A GIS computed the percentage of each land-use class occurring within the buffer zone. This classification was further refined into a grass, shrub, or wooded land-cover class for natural vegetation. The analysis was done only for riparian areas in agricultural lands; details of the influence of all riparian lands on stream condition are contained in Van Sickle et al., this issue.

4.4.2.6 Wildlife Habitat Quality

Habitat quality was measured as the number of native bird, herpetofauna, or mammal species that have a moderate to strong preference for breeding in that habitat (see Schumaker et al., this issue). The percentage of land that gained or lost two or more species relative to Circa 1990 conditions was then computed for each agricultural landscape. In addition, the net percent change in habitat quality was determined for each watershed, with interval cut-off values determined by natural breaks in the data.

4.5 RESULTS

The amount of farmland, including prime farmland, remaining in agricultural production varied significantly among scenarios (Table 4.4). Plan Trend 2050 had the smallest change in agricultural land acreage, with almost all (99%) of the Circa 1990 farmland remaining in agricultural production. The conversion of prime farmland was greatest (24%) in Development 2050; with one-third of the converted land used for built development and two-thirds comprising yards, gardens, and remnant fields associated with the development. In contrast, Conservation 2050 used the majority (87%) of its converted prime farmland for restoration activities and only 13% for built development. For both scenarios, prime farmland was the preferred land for urban and rural residential development, while Tier 1 restoration areas displayed no preference between ordinarily and prime farmland.

Table 4.4. Land-use distribution in each of the alternative landscapes for all agricultural land and prime farmland.

Scenario	All Farmland			Prime Farmland		
	Crop	Built	Natural	Crop	Built	Natural
Circa 1990	100%	0%	0%	100%	0%	0%
Plan Trend 2050	99%	1%	0%	99%	1%	0%
Conservation 2050	83%	1%	16%	85%	2%	13%
Development 2050	80%	6%	14%	76%	8%	17%

The pattern of farmland conversion also varied between scenarios (Figure 4.4). Conservation 2050 generally had moderate (0% to 40%) levels of conversion taking place throughout the basin, while Development 2050 had many watersheds with high levels (60% to 100%) of conversion. These watersheds were located in the upper portion of the valley surrounding the major metropolitan area.

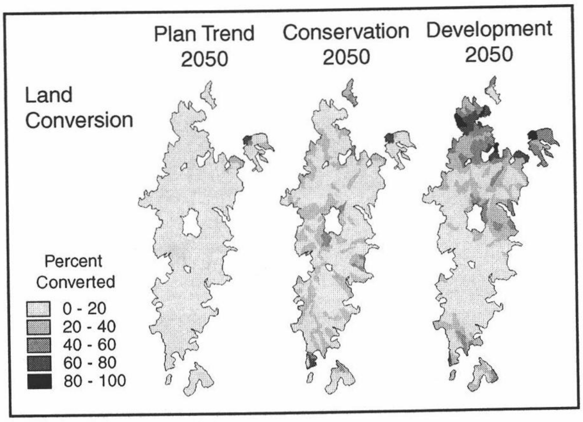

Figure 4.3. The percentage of agricultural land converted to other uses in each future landscape.

The percentage of farmland covered by each crop type in each of the scenarios is shown in Table 4.5. With respect to Plan Trend 2050, Conservation 2050 experienced shifts from Irrigated Perennial Crops to Irrigated Nursery Crops, and from Grass Seed Rotation and Hay to Pasture. There was little change overall in the preference for Christmas Trees, Orchards, Irrigated Caneberries, and Hybrid Poplar. However, Tier 2 farmland did show a preference for these crop types along with Pasture since each could be grown in smaller fields and tended to have the higher wildlife suitability rankings. Also, Hybrid Poplar and to a less extent Wood Lot were selected as they provided a low management alternative to Hay, Grain, and Pasture, especially for smaller fields with marginal soil quality. The reduction in Grass Seed and Hay acreage is probably a result of reduced field size caused by the partial conversion of fields to Tier 1 land. Pasture then became a more viable crop, particularly for Tier 2 farmland, where it provides some habitat benefits.

Table 4.5. The percentage of land in each agricultural land-cover class over all Circa 1990 farmland and for the cultivated portion of each future agricultural landscape.

	Scenario	Orchards	Irr. Caneberries	Christmas Trees	Irr. Perennial Crops	Irr. Nursery Crops	Irr. Annual Rotation	Grains	Grass Seed Rotation	Hay	Pasture	Hybrid Poplar	Wood Lot
	Circa 1990	2.7	0.9	1.1	3.1	1.2	6.0	12.8	32.4	15.3	24.4	0.1	0.1
All 2050 Cultivated and Converted Land	Plan Trend 2050	3.2	0.4	1.0	1.2	2.2	3.7	1.3	54.4	9.7	21.2	0.2	0.1
	Conservation 2050	2.9	0.4	1.0	0.6	2.5	2.7	1.0	41.8	7.0	22.5	0.2	0.1
	Development 2050	2.2	0.3	0.7	0.6	2.2	2.6	0.5	43.7	6.7	19.6	0.1	0.1
Only 2050 Cultivated Land	Plan Trend 2050	3.3	0.4	1.0	1.2	2.3	3.8	1.3	55.2	9.9	21.4	0.2	0.1
	Conservation 2050	3.5	0.5	1.3	0.7	3.1	3.3	1.2	50.5	8.5	27.2	0.2	0.1
	Development 2050	2.7	0.4	0.8	0.8	2.8	3.3	0.6	55.1	8.4	24.7	0.1	0.1

Relative to Plan Trend 2050, Development 2050 experienced shifts from Irrigated Perennial Crops and Irrigated Annual Rotation to Irrigated Nursery Crops and from Orchards, Grains, and Hay to Pasture. As in Conservation 2050, nursery crops were a preferred choice for fields with irrigation, as they had good profit margins and a market that grows with an increasing population. They also have a smaller acreage requirement than irrigated field or vegetable crops, and were often established on smaller fields with groundwater irrigation that did not suffer from the water availability constraints of surface water rights. Grass Seed Rotation was the preferred large acreage non-irrigated crop in Development 2050 because it can grow on poorer quality soils and provides better returns than Grain or Hay.

The mean crop diversity for Circa 1990 was 0.7, which declined to 0.6 for Plan Trend 2050 and Conservation 2050, and to 0.5 for Development 2050. Figure 4.4 shows that for Development 2050 most of this change occurred in the northern portion of the valley near the major metropolitan areas, suggesting the decline is due primarily to urban development. The reductions in Plan Trend 2050 and Conservation 2050 reflect the decrease in Grain and Hay acreage, while Conservation 2050 shows higher diversity values in those watersheds undergoing extensive restoration, which tends to results in a more diverse crop selection relative to Plan Trend 2050. The southern portion of the valley shows little change, as the soil limits crop selection and a very suitable crop for the larger fields is Grass Seed, which is favored in the future scenarios due to its economic and habitat values.

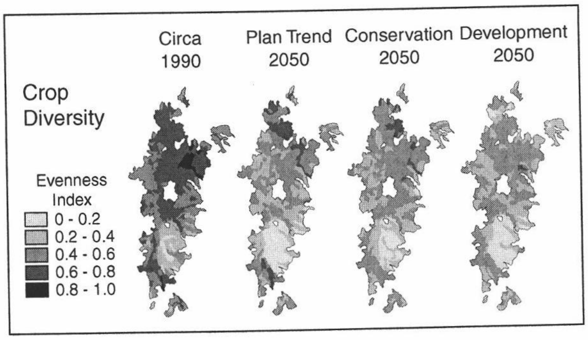

Figure 4.4. Crop diversity in each watershed measured by Shannon's evenness index.

The basin's mean erosion risk for cultivated land was 0.3 (tolerable soil loss) for both the Circa 1990 and future landscapes, and the proportion of cultivated land with $E_{risk} > 1$ was 3% for each scenario, nor did the spatial patterns of risk vary between scenarios. This is partially a reflection of the low erosion rate throughout most of the valley, and the conversion of farmland in the foothills to non-agricultural uses. This was especially true in Development 2050 where conversion of farmland to low-density development occurred in the foothills around major metropolitan areas.

Changes in groundwater vulnerability potential occurred mainly for irrigated crops, with little change for non-irrigated crops (Table 4.6). The largest change occurred in

Conservation 2050, with 15% of the cultivated land in irrigated crops shifting from moderate, high, or very high vulnerability to low vulnerability. Development 2050 also had reductions of 11% between the same classes, followed by Plan Trend 2050 with a reduction of 6%. The change in Plan Trend is due mainly to patterns of irrigated crop selection, while Development 2050 and Conservation 2050 have additional decreases due to the conversion of soils with higher sensitivity ratings to non-agricultural uses, especially those soils occurring along major waterways. This conversion shifted irrigated crops to lower sensitivity soils, reducing the groundwater vulnerability potential in these watersheds.

Table 4.6. The percentage of each scenario's actively farmed land occurring in each groundwater vulnerability potential class.

Scenario	Irrigated Crops					Non-irrigated Crops		
	Very Low	Low	Moderate	High	Very High	Very Low	Low	Moderate
Circa 1990	1%	50%	44%	3%	2%	3%	90%	8%
Plan Trend 2050	2%	57%	38%	1%	2%	3%	93%	4%
Conservation 2050	1%	64%	32%	0%	2%	3%	92%	5%
Development 2050	1%	61%	35%	1%	2%	2%	93%	4%

The changes in riparian land-cover occurring in each scenario are shown in Table 4.7. Extensive vegetation gains took place in Conservation 2050, with 99% of the Circa 1990 farmland within 30 m of a stream converted to some form of natural vegetation, one-third of which was woodlands. For Development 2050, vegetation increased 7%, nearly matching a 5% increase in built development.

Table 4.7. Land-cover distribution within the 30-m riparian area of each alternative agricultural landscape. Approximately 3% of the Circa 1990 farmland was located within 30 m of a stream.

Scenario	Riparian Land Cover				
	Crop	Built	Grass	Shrub	Wooded
Circa 1990	100%	0%	0%	0%	0%
Plan Trend 2050	97%	1%	1%	0%	1%
Conservation 2050	1%	0%	56%	10%	33%
Development 2050	89%	5%	1%	4%	2%

Changes in land cover also altered the value of the landscape as wildlife habitat. Table 4.8 shows the percentage of land that experienced gains or losses of two or more potential species relative to the Circa 1990 agricultural landscape. Plan Trend 2050 had modest improvement in bird (4%) and mammal (2%) classes, with little change (1%) in herpetofauna. Conservation 2050 experienced the largest area increase in each taxonomic class with net gains of 13% for birds and 11% for herpetofauna and mammals. In Development 2050, areas of bird richness increased a net amount of 11%, but little net change occurred for mammals (2%) and no change for herpetofauna.

Table 4.8. The percentage of land that experienced a loss or gain of two or more species with respect to the Circa 1990 agricultural landscape.

Scenario	Birds		Herpetofauna		Mammals	
	Loss	Gain	Loss	Gain	Loss	Gain
Plan Trend 2050	5%	9%	5%	4%	9%	11%
Conservation 2050	6%	19%	5%	16%	10%	21%
Development 2050	6%	20%	8%	8%	17%	19%

The spatial patterns of change in habitat quality are shown in Figure 4.5. In Plan Trend 2050, watersheds located along major waterways experienced modest levels of improvement in all three taxonomic classes, with the greatest variation occurring for mammals. For this class, the areas of both positive and negative change are located mainly in the mid-valley region and reflect changes in crop selection between irrigated and non-irrigated crops. Conservation 2050 showed strong improvements in all three taxonomic classes in watersheds along riparian areas, reflecting the increase in natural vegetation as farmland converted to Tier 1 areas. In contrast to both Plan Trend 2050 and Development 2050, the lower portion of the valley in Conservation 2050 has more watersheds with moderate improvement for all taxonomic classes, resulting from an increase in natural vegetation from agricultural field borders and Tier 1 lands.

In Development 2050, the patterns of gain and loss varied for each taxonomic class. Watersheds near urban areas in the upper portion of the valley experienced a significant net gain in habitat quality for native birds, as many bird species prefer the shade trees associated with low-density development. This same region saw a more varied change in mammalian habitat quality, with an inverse relationship occurring between the amount of development in a watershed and habitat quality. Little change occurred for herpetofauna in Plan Trend 2050 and Development 2050, with a few watersheds displaying a loss of species richness in watersheds adjacent to major metropolitan areas.

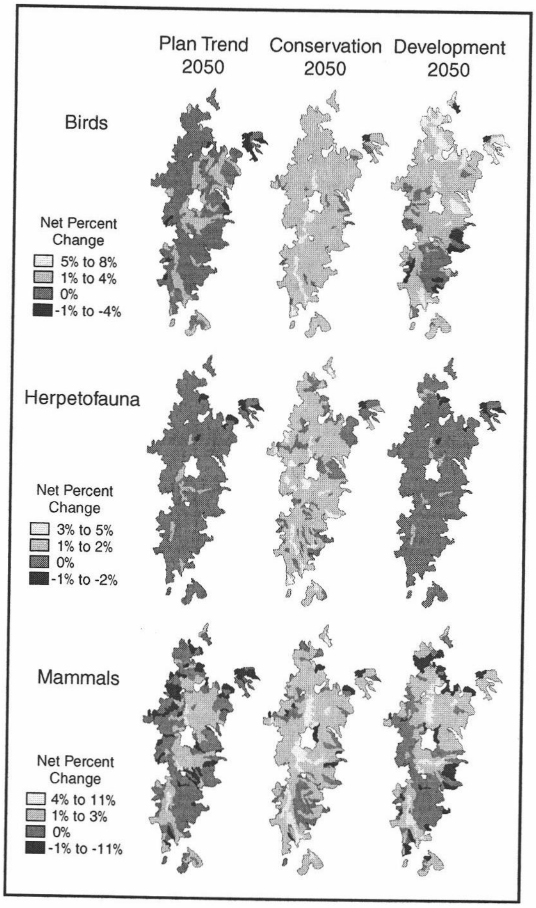

Figure 4.5. The net percent area that gained or lost two or more species for each alternative future relative to Circa 1990 conditions. The mapped intervals were determined by natural breaks in the data.

4.6 Discussion

4.6.1 Policy Implications

The type and amount of farmland conversion were the scenario elements that most distinguished the future agricultural landscapes. The loss of agricultural land, particularly prime farmland, reduces the economic benefit derived from crop production and its supporting businesses, and can alter the social fabric of an area. The results from the Plan Trend 2050 scenario suggest that current land-use policies, regulated by urban growth boundaries and restricted development on resource lands, would preserve almost all the current farmland for future agricultural use. In contrast, the less restrictive land-use policies of the Development 2050 scenario caused not only the direct conversion of farmland to residential development but, because of the diffuse spatial structure of the development, often rendered the remaining fields un-farmable even if sufficient acreage remained. In addition, since both Conservation 2050 and Development 2050 favored development on prime farmland, any relaxation of current land-use laws should include rules for decreasing the amount of prime farmland used for development purposes and encouraging the in-filling of partially converted agricultural fields before developing neighboring farmland. Increased residential development of farmlands could also create conflicts between growers and non-growers, especially in areas where little development has previously taken place. Establishing programs to introduce new residents to local farming practices may help reduce the social conflicts common in these areas (Chase and Hutcheson 1998).

The patterns of crop selection in each future followed modeled market trends, but with variations among the scenarios as crop selection decisions adapted to changing field and basin conditions. In Conservation 2050, the added decision constraints applied to Tier 2 farmland resulted in the selection of a broader array of crops in these areas, particularly those crops suitable for smaller field sizes such as Christmas trees, orchards, berries, and hybrid poplar. For Development 2050, declining crop diversity occurred in watersheds adjacent to metropolitan areas, where residential development tended to convert entire fields rather than just reducing the available acreage, as occurred in Conservation 2050.

Thus, these fields were able to select large-acreage crops such as grass seed rather than move to smaller-acreage crops.

The modest decline in crop diversity coupled with a shrinking land base suggests that the Willamette River Basin can continue to support a diverse selection of crops, although the resiliency of the agricultural system may decline, making it more susceptible to negative drivers of change (e.g., pest infestations, economic downturns). To succeed, agricultural producers, particularly smaller operations, will have to develop new strategies to mitigate risk and open alternative markets. Growers are already beginning to adopt new approaches, such as the use of niche crops and value-added farming (Gentle 1997).

Changes in crop selection can alter the risk of production-limiting soil erosion or groundwater vulnerability. In all three future agricultural landscapes, the level of risk was the same as, or less than, that of current conditions. Thus, changes in the agronomic component of the agricultural system should not increase erosion risk or groundwater vulnerability over current levels. This does not mean that the risk of erosion or groundwater contamination in all of the Circa 1990 farmland is negligible, since both soil loss and groundwater contamination can occur as a result of development activities in the converted portion of agricultural fields.

In Conservation 2050, farmland was the major source of land used for vegetation restoration. However, productive farming operations on Tier 2 farmland also contributed to habitat restoration by using field borders and selecting low-input crops. Therefore, Conservation 2050 saw not only material gains in habitat quality in areas undergoing watershed restoration, but also moderate improvements throughout many areas of the basin's farmland. There were also extensive gains in riparian vegetation, which improves water quality by decreasing the transport of sediment and agricultural chemicals into neighboring waterways (Lowrance et al. 1984), while wooded riparian areas provide added benefits to aquatic habitat through stream temperature regulation and organic material supply (Beschta et al. 1987; Gregory et al. 1991).

Development 2050 also had an increase in habitat quality. This was due partly to the increased use of riparian buffers, but primarily to increased woody vegetation that appeared as a byproduct of low-density development. While this vegetation proved attractive to many bird species, it held less appeal for herpetofauna and mammals. This suggests that planned areas of vegetation restoration provide the greatest benefit to a range of wildlife species. Nor do all such improvements require a change in the field's land use. For example, increased use of vegetated field borders, if suitably located, could provide habitat networks while requiring only a small concession of farmland. In addition, the expansion of current policies for conservation reserves and other set-aside programs could increase the use of marginal farmlands for native vegetation restoration, preserving the most productive farmland for future agricultural use.

4.6.2 Modeling Approach

Several methods were used to create the alternative future agricultural landscapes. First, a rule- and probability-based approach was successful in integrating diverse data sets into consistent spatial and thematic databases suitable for characterizing the current agricultural system. Next, the multiple-attribute CropDM model provided a way to include knowledge of growers' general decision-making processes while making full use of a limited data set. Finally, by linking the CropDM model with data from other resource models, system changes occurring over the course of the simulation could be incorporated into both the crop selection decisions and land conversion rules. This approach seems particularly suitable for the exploration of alternative futures, as scenarios can be defined and quickly refined by altering the selection of alternatives, their attributes or weights, and decision constraints. It does not require extensive historical data other than reported agricultural statistics for the area, and the modeling of processes such as irrigation or climate change can be done in a way suitable for the particular location and study requirements.

The successful application of any alternative futures model rests in part on the quality and completeness of the data describing the past and current state of the system under study. A complete description of the agricultural system is difficult, as land-cover change occurs frequently, water availability and chemical use data are often unavailable, and the factors that go into a land-use decision are manifold. Ideally, these data sets would include a spatially explicit time-series of crop selection and productivity, field-scale chemical and water use data, and grower attitudes and preferences. This information could then be used to create an accurate spatial description of the current agricultural system, providing better data extrapolations and a richer set of decision attributes that reflect different types of farming operations. Thus, for effective decision support, it is imperative to gain the cooperation of stakeholders, and especially agricultural producers, to gather the necessary data.

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5. CONCLUSIONS

5.1 RESEARCH CONTRIBUTION

The purpose of this research was to develop a simulation model that generates future agricultural landscapes in response to drivers of change, and then to analyze these landscapes and use the results to improve policy evaluation and stimulate community discussions. This research program was accomplished by creating new information about the agricultural system of the Willamette River Basin, developing models of land-cover and land-use change, and evaluating the final landscape representations with watershed- and basin-scale metrics. The major contributions from this research are:

- The use of decision making as the motive force for land-cover transitions rather than relying on historical records of land cover. This method explicitly includes human factors as well as biophysical conditions in the forces that lead to land-use change, a component missing in many land-cover change models.

- The application of rough-set rule induction to deal with data uncertainty while creating predictive if-then rules of crop suitability for the region. Rough-set methods in particular, and rule-induction approaches in general, have not been readily adopted for use in geographical or environmental modeling, even though they are well suited to the GIS-based analyses currently undertaken by a wide variety of researchers.

- The identification of data sources and the strategies used to integrate the diverse data sets to depict the current state of the agricultural system in the Willamette River Basin. The steps described should be useful to other researchers faced with these issues, since they are not particular to this portion of the county but common to any area with an agricultural component.

- An illustration of how an alternative futures analysis can provide information useful for policy evaluation. Besides providing information on trade-offs and impacts, alternative futures analysis can also help define the scope of further studies or identify areas where future data needs to be developed.

5.2 Future Research

This research employed a variety of techniques and modeling approaches. None of these approaches had been applied previously to its problem area, so there are many possibilities for future research projects. Several of the most interesting possibilities are discussed below.

Machine learning is an important field within computer science that continues to provide new analysis techniques, many of which could be readily applied to environmental problems. A general research focus should include the evaluation of these techniques versus more traditional methods such as linear or logistic regression. For the specific case of crop suitability classification, a follow-up study should be done at various scales to determine how the rules change with changes in scale. Another application of the rough-sets classification method may be as a first-order screening method to find suitable areas for new crops by using data from field plot studies or from similar geographical locations that currently grow the crop.

There are several ways to improve the CropDM land-cover model. First, the current implementation used a simple representation of an agricultural decision-maker. An interesting future study would use a survey to collect grower attitudes, creating a richer representation of decision-makers. Similarly, the collection of crop alternatives could be expanded, as could the types of management schemes such as double cropping or more realistic irrigation strategies. A weakness of the CropDM model is that it does not include representation for a farm, where multiple fields are considered in the decision. Such information would provide opportunities to include farm-level decisions–for example, the temporary transfer of water rights to another field or the selection of an optimal mix of crops instead of selecting the best crop for a given field. However, this approach was not adopted in the current study due to the confidentiality of ownership information, which is likely to remain an issue in the future. Thus, a farm-level model would have to be done at the local scale with the full cooperation of area producers.

Two tracks could be taken to enhance either the CropDM model or the agricultural evolution model. One track focuses on expanding the modeling approach to include other factors. For example, weather generators could be used to create alternative scenarios of climate change, or the model could focus more on the demographic characteristics of the population. Another track is the development of an integrated analysis framework that would provide both a user-interface to the decision values and modules that provide statistical and geographical visualization of the simulation results.

Moving beyond the academic qualities of this research, a further question is whether the results of the PNW-ERC futures study have proven useful to the communities and policy-makers of the Willamette River Basin. This is a difficult question to answer, as there is currently no way to measure the impact of the alternative futures study on decision-makers. However, it is notable that this information was provided to government and citizen groups, has been discussed in various printed publications, and remains available in books and over the Internet. The widespread availability of the information suggests that the futures study has contributed, and may well continue to contribute, to the continuing discussion about future conditions in the Willamette River Basin. Alternative futures models such as the one presented here are the necessary first steps toward the routine use of futures scenarios in regional planning, with the result of improved resource allocation and reduced environmental damage.

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