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Research Article

Generating Agricultural Landscapes for Alternative Futures Analysis: A Multiple Attribute Decision-Making Model

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Abstract
This paper describes the development of a multi-attribute decision model that generates depictions of the agricultural landscape for use in alternative futures studies. 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. The model first evaluates any changes in the land base due to conversion of farmland to non-agricultural uses, and then uses field descriptions, crop characteristics, and the decision paradigm of an agricultural producer to determine the preferred crop for each field under a particular policy scenario. By cycling over the fields for each time-step in the simulation, future depictions of the agricultural system that respond to various drivers of change are generated. 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.

1 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 resource management need a spatially explicit approach to define the characteristics of the system. The generation of such a spatially referenced

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landscape is challenging because of the data requirements and large spatial extent of most study regions. 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, frequently the only representation of a region's land cover, may not be of sufficient resolution or quality.

This last issue can be especially limiting, since agricultural land-use change models typically use a time-series of interpreted satellite 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 approach is implemented by loosely coupling ESRI's Arc/Info geographic information system to a C++ program that tracks the characteristics of each agricultural field over time and computes the subsequent MADM ranking. The model, called CropDM, provides access to decision and physical parameters that analysts can use to define and refine different crop selection and agricultural change scenarios. This 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. The use of the CropDM model in a regional, multiple-land-use, alternative-futures analysis is presented in Berger and Bolte (2004).

Carver (1991) is one of the first to describe the advantages of a coupled GIS-decision-making approach and the approach is further developed in Jankowski (1995) and Malczewski (1999). It has been applied in a variety of applications, including suitability analysis (e.g. Pereira and Dückstein 1993, Jankowski and Richard 1994, Joerin et al. 2001, Malczewski 2002), risk assessment (Chen et al. 2003), and group decision-making (e.g. Malczewski 1996, Jankowski and Nyerges 2001). In the realm of agriculture, GIS and decision-making methods have been used to study the change in agricultural landscape composition (Janssen and Rievelt 1990), assess the sustainability of alternative farming systems (Dunn et al. 1998), and evaluate the effect of different cropping patterns on water use (Abu-Zeid 1998). However, this is, to the authors' knowledge, the first time it has been used as the driving mechanism in a model of agricultural landscape change.

The next section of this paper contains an overview of MADM and a discussion of the decision-making 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 and challenges of using a decision-making approach for landscape generation concludes this paper.

2 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: non-compensatory methods and compensatory methods. Non-compensatory 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 non-compensatory 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 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.

Compensatory methods allow the decision maker to examine the trade-offs among alternatives, so strong attributes can compensate for weak attributes. These methods are computationally and conceptually more complex than non-compensatory 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 permits 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 based on 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 $m \times n$ 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:

$$V = v_{ij} = \boldsymbol{\omega}_j \, r_{ij}, \; i = 1,\ldots,m, \; j = 1,\ldots,n \tag{3}$$

4. Identify the positive-ideal solution, A^* and the negative-ideal solution, A^-. Let J represent the set of benefit attributes and J' the set of cost attributes, where a benefit attribute increases in value with increasing preference (i.e. the attribute provides an advantage), while a cost attribute decreases in value with increasing preference (i.e. the attribute is a liability). Then:

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

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

Thus A^* is a vector holding the maximum value of each benefit attribute and the minimum value of each cost attribute, while A^- holds the minimum value of each benefit attribute and the maximum value of each cost attribute. These values define an n-cube that bounds the set of attribute values. Note that the positive- 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- and negative-ideal solutions, respectively, using the Euclidean distance metric:

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

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^*.

To evaluate trade-offs, compensatory methods require a decision maker 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 decision-maker 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 decision maker. 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):

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

where

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

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:

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

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

3 Model Description

The CropDM model was implemented as a loosely coupled MADM-GIS model, with a database acting as a conduit between the GIS and the simulation model (Nyerges 1993). Spatial data were 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 Agarwal et al. (2002), 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 calculation of the irrigation requirements for each crop.
- 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 defines 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 over time. First, biophysical and decision attributes were used to characterize the agricultural system (Table 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. Events that trigger a crop selection decision include changes in the status of a field (e.g. acreage reduction due to land conversion) or the conclusion of a crop rotation. If a field requires a new crop, the decision model evaluates the field's biophysical characteristics, the requirements of each potential crop and the

Table 1 Properties of the agricultural system used to characterize the agricultural landscape

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

attributes of the decision maker to make a final crop selection (Figure 1). 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, the next section presents an implementation of CropDM for a small study area located in Oregon's Willamette Valley.

4 Implementation of an Alternative Futures Simulation

A demonstration of an alternative-futures-scenario exercise is provided below to show how this method can be used to examine the impact of different policy or management options. This example focuses on a small portion of the Willamette Valley agricultural land. Figure 2 shows the steps in a typical alternative futures analysis. 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 scenario elements, develop new policy alternatives, select an alternative, or suggest ancillary studies. The sample implementation described below covers all but the last step in the analysis. The subsection describing each step is noted in Figure 2.

4.1 Scenario Description

The policy under investigation concerns a long-term program to restore riparian areas by converting selected farmland back into riparian forest. The CropDM program is to be used to gain insight into the degree of change the policy may provide and allow experimentation with different parts of the policy. This policy, termed Restoration, is to be carried out over a 50-year period (1990–2040) and uses a two-tier restoration scheme (Hulse et al. 2004). Tier 1 lands are managed with priority given to achieving a

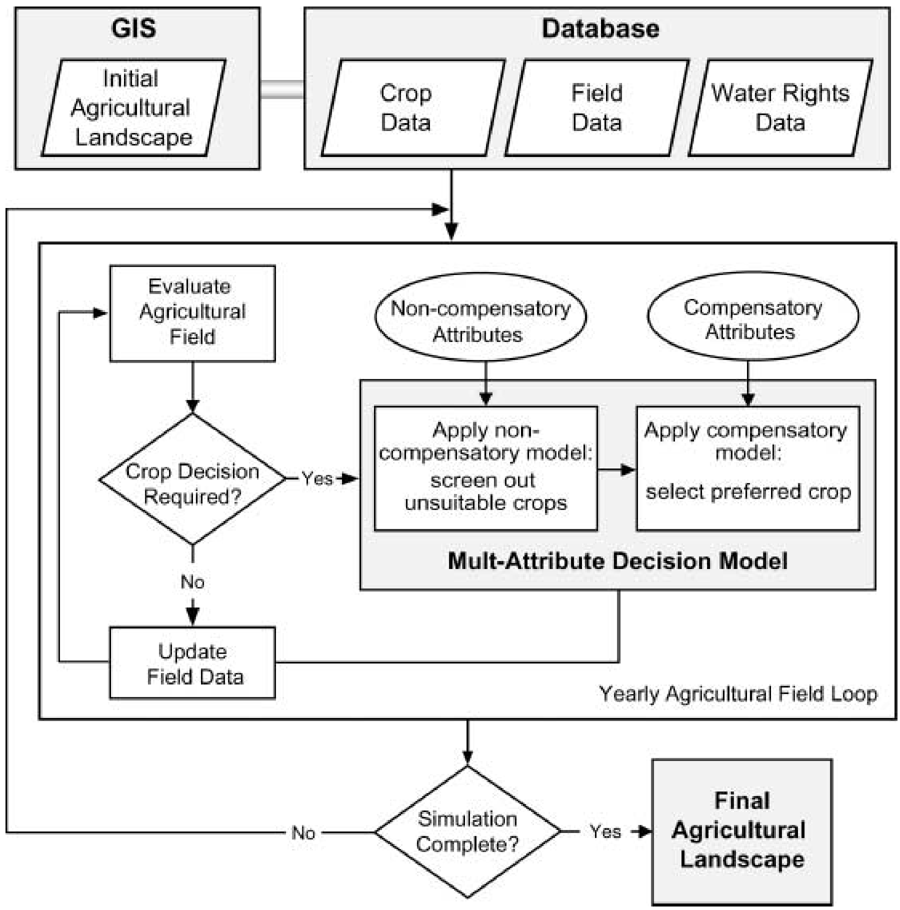

Figure 1 Schematic of CropDM model

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 at some time within the 50-year period.

The study area (Figure 3) is located along the main stem of the Willamette River. The area covers 6,689 ha of farmland divided into 483 agricultural fields. The initial distribution of crop types was determined by using the Oregon Department of Fish and Wildlife (ODFW) land use/land cover data (Klock et al. 1998), county crop statistics (Oregon State University Agricultural Extension 1992), and crop suitability rankings (Berger 2004). Table 2 shows how land and water rights were distributed over the study area for each of the land designations (ordinary farmland, Tier 2 farmland, Tier 1 land).

This futures study explored two questions: (1) How does the conversion of farmland to Tier 1 or Tier 2 land affect agricultural land cover relative to current policy; and (2) To what extent does Tier 2 farmland provide improved habitat compared with ordinary farmland. The impacts arising from these policies was determined by comparing the Restoration land cover with both the initial land cover and that resulting from

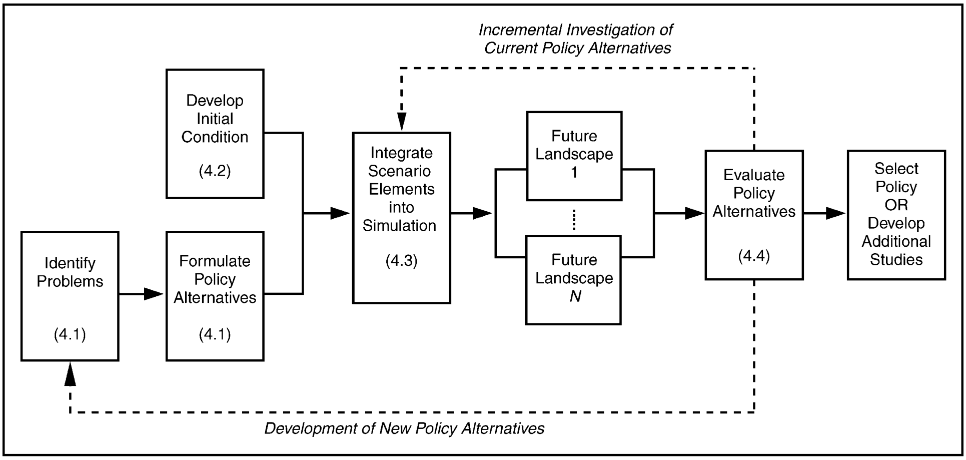

Figure 2 Steps in a typical alternative futures analysis. The dotted lines show different analysis paths, while the numbers appearing below each step reference the section that covers that portion of the analysis

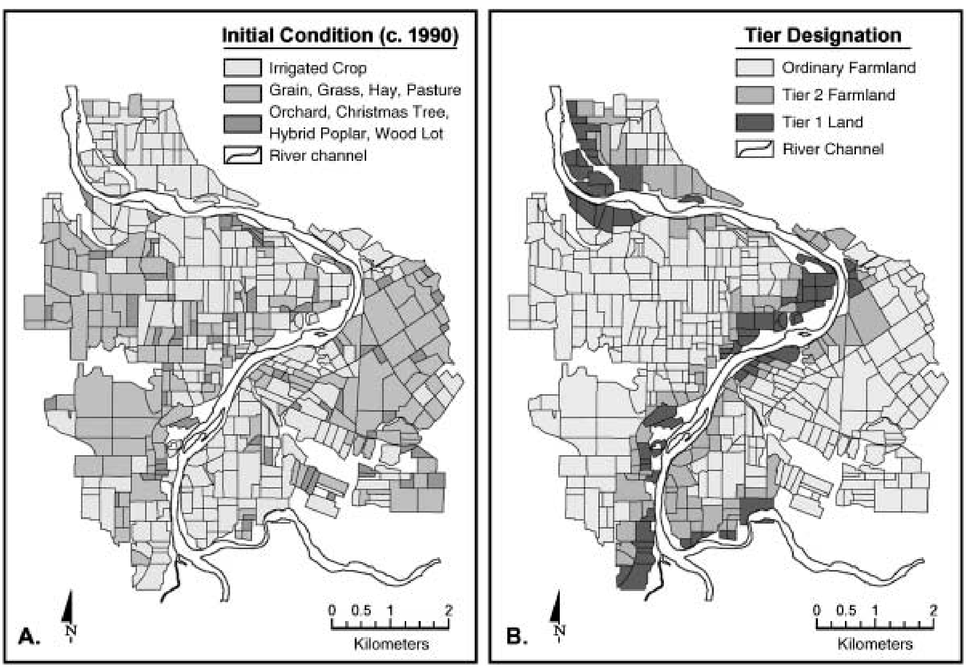

Figure 3 The study area showing: (A) the distribution of general crop classes and (B) the location of each land designation and its relationship to the river system

a continuation of current trends (Continuing Trends) over the same 50-year period. To address the second question the Restoration scenario was divided into two alternatives based on water rights: one alternative (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

Table 2 Characteristics of the agricultural fields for each of the land designations and for the entire study area

Land Designation	Number of Fields	Fields with 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

exercised at least once within a five-year period. The second option (Restoration-WR), allows the decision maker to select the most appropriate crop without this constraint.

Given these scenario descriptions, the next step was to construct an initial description of the agricultural system and then 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 non-compensatory or compensatory attributes, and suitable cut-off points or values determined.

4.2 Development of an Initial Representation of the Agricultural System

To generate future agricultural landscapes requires a representation of the initial agricultural system, including characteristics that influence, or are influenced by, the drivers of change defined by the scenario. 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 components consisted of the physiological and management characteristics of each crop, the biophysical characteristics of the agricultural fields, and the irrigation availability and crop water requirements for a field-crop combination.

4.2.1 Crop Descriptions

The fertile soils and mild climate of the Willamette Valley support a diverse selection of crops, with over 90 kinds of agricultural crops currently under production. Twelve types of crops were selected for this study, including both currently prominent crops and new crops that are experiencing increased acceptance in the region (Table 3). 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.

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 some crops require extensive acreage to produce an economically viable crop, while other crops typically use smaller fields. To determine bounds on acreage size, farm acreage data from the 1992 Agricultural Census (U.S. Department of Agriculture, National Agricultural Statistics Service 1994) were used to provide an estimate on suitable field sizes for each of the crop types.

Table 3 The crop types used in this study and their primary attributes

Crop Type	Rotation Period (years)	Field Area Range (ha)	Irrigation Period Start mm-dd	Irrigation Period End mm-dd	*MAD* (%)	Rd_{eff} (cm)
Orchards	40	2–40	na	na	na	na
Irrigated Caneberries	15	2–40	04–15	07–05	50	14.0
Christmas Trees	8	2–80	na	na	na	na
Irrigated Perennial Crop (large acreage)	5	8–80	04–15	08–20	35	9.5
Irrigated Perennial Crop (small acreage)	4	2–20	04–15	06–15	50	9.5
Irrigated Nursery Crops	20	2–40	04–15	09–30	40	9.5
Irrigated Annual Rotation (early planting)	3	6–120	04–15	06–30	50	9.5
Irrigated Annual Rotation (late planting)	3	6–120	07–01	09–30	50	9.5
Grain	1	6–200	na	na	na	na
Grass Seed Rotation	7	10–200	na	na	na	na
Hay	1	6–160	na	na	na	na
Pasture	1	2–200	na	na	na	na
Hybrid Poplar	15	2–25	na	na	na	na
Wood Lot	70	2–25	na	na	na	na

MAD: management allowable depletion, Rd_{eff}:effective root depth, na: not applicable

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. (1998) 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.

4.2.2 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 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. Since the decision rules and scenario elements are operating on commercial agricultural operations, a minimum area of two hectares was used to differentiate these agricultural operations from hobby farms and home gardens.

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 2004). Each field was assigned a crop suitability rank for each crop, with values of very good, good, moderate, moderately low, low, or 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. Department of Agriculture, 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.

4.2.3 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, and can be transferred to adjacent fields or for in-stream uses. 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 (cm) needed to refill the soil profile to field capacity before the plant experiences moisture stress (Smesrud et al. 1998):

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

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

where AWC (cm/cm) is the soil's available water capacity, ET_c (cm/day) is the average daily crop evapotranspiration for a month, I_{eff} is the irrigation efficiency, RD_{eff} (cm) is the minimum value of the effective root depth of the crop or soil root depth, and P (cm) 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.

4.3 Alternative Scenarios Definition and Implementation

After defining the initial agricultural system, the next step was to translate the scenario descriptions from Section 4.1 into either non-compensatory or compensatory attributes, together with suitable cut-off values or ranks.

4.3.1 Non-compensatory Attributes

For all scenarios, the attributes selected for the conjunctive method were: crop suitability, field acreage, total crop acreage, and irrigation availability. These attributes identify unsuitable crop-field pairings based on the physical limitations of the field or regional market limits. Unsuitable conditions for each attribute were:

- A crop suitability rank of unsuitable
- A field area that fell outside the crop's field acreage range (Table 3)
- The total regional crop acreage that exceeded maximum crop acreage determined from historical production data (Oregon State University Agricultural Extension 1981–98)
- For irrigated crops, inadequate irrigation because the field lacked a water right or had insufficient water availability based on Equations (11) and (12).

For 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 for Tier 2 farmland in the Restoration-WR scenario. Both Restoration scenarios had an additional 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 decision maker 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.

4.3.2 Compensatory Attributes

Attributes selected for use in the compensatory method provided information on the trade-offs involved in crop production. In each scenario, the compensatory method used attributes of crop suitability, price variability, yield variability, profit margin, and management requirements to represent the economic and management attributes of a crop. 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. Except for 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 was 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 by cultivar selection.

The Restoration and Restoration-WR alternatives prescribed a different management strategy for Tier 2 farmland, since growers managed these fields 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 ranking (denoted as the habitat ranking) of a crop was derived from habitat suitability scores (Schumaker et al. 2004). Then the subjective weight of the habitat ranking was set equal to that of the crop's profit margin. In the present application, all species are treated equally; however, habitat conditions that impact at-risk species could be formed as an attribute and weighted accordingly. Table 4 shows the type, attribute values, and subjective weights assigned to each crop alternative for ordinary farmland and Tier 2 farmland.

4.4 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 (Figure 4). The result from Continuing Trends showed the expected acreage reductions in Grain and Hay and the increases in Irrigated Nursery Crops and Grass Seed Rotation (Table 5). In contrast, Restoration had acreage

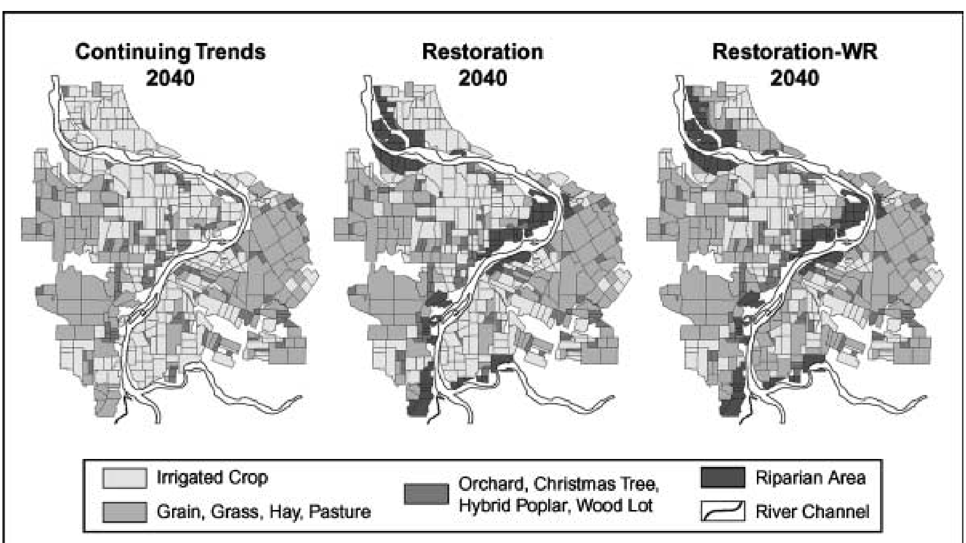

Figure 4 The spatial distribution of cropland and restoration areas for each of the future scenarios

Table 4 Decision attributes and their associated values for each crop type and the subjective weights for each type of decision maker. Numerical ranks span values from 1-very low to 9-high

Crop Type	Profit Margin (benefit)	Crop Suitability (benefit)	Management (cost)		Yield Variability (cost)	Price Variability (cost)	Habitat (benefit)
			New	Exper.			
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 acreage)	3	1–9	5	1	5	3	1
Irrigated Perennial Crop (small acreage)	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

Table 5 Distribution of land cover for the Continuing Trends and Restoration scenarios, for all land and for Tier 2 farmland

	Distribution of Land Cover (%)							
	All Land				Tier 2 Farmland			
Crop Type	Initial Condition	Continuing Trends	Restoration	Restoration-WR	Initial Condition	Continuing Trends	Restoration	Restoration-WR
Orchards	2	3	2	3	4	3	1	1
Irrigated Caneberries	2	2	2	2	5	5	7	3
Christmas Trees	3	4	4	4	2	4	7	8
Irrigated Perennial Crop	10	5	2	1	16	5	2	0
Irrigated Nursery Crop	2	5	2	2	0	0	0	0
Irrigated 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

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 may 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 habitat ranking for the Tier 2 farmland. The habitat ranking 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 decision makers selecting crops without concern for losing the field's water right. As Table 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 suggest 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 hydrologic modeling to assess the impact of enhanced stream flows due to the transfer of irrigation water rights to in-stream use.

5 Conclusions

This paper has presented a new method to generate future agricultural landscapes by combining spatial and non-spatial characteristics of fields and crops with management factors related to crop selection. The use of this approach for future scenario studies was illustrated by a sample implementation that compared three policy alternatives for a small region of farmland located along Oregon's Willamette River. The model results showed how changes in different drivers of the agricultural system influenced crop selection decisions, generating new agricultural landscapes. Once developed, these landscapes can then be further analyzed using suitable metrics and models to compare and contrast the agronomic, ecologic, or 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 decision maker integrates this information and makes the crop selection or land-use decision.

The strength of alternative futures simulations is not in its predictive use, but in providing a sense of the trends or trade-offs due to the different future conditions. Such studies provide a way for policy makers and stakeholders to investigate the future impacts of different management strategies by providing representations of possible outcomes. Since the purpose of these 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), validation is less problematic than with short-term forecasts, where a greater veracity is expected. Even so, the results of long-term models must show some evidence of realism. If sufficient historical data are available, the earliest data set can be used to initialize the model, and the model results can then be compared with the known outcome. For this study, the lack of historical data at the appropriate spatial and thematic resolutions precludes this approach. In this and similar cases, "appropriate" behavior can to some degree be judged through a detailed knowledge of the application area and the type and duration of changes that might realistically occur.

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