

Concept Paper

# Evaluation of Deterministic and Complex Analytical Hierarchy Process Methods for Agricultural Land Suitability Analysis in a Changing Climate

Harmen Romeijn <sup>1,\*</sup>, Robert Faggian <sup>1,\*</sup>, Vasco Diogo <sup>2,\*</sup> and Victor Sposito <sup>1,\*</sup>

<sup>1</sup> Faculty of Science Engineering and Built Environment, Centre for Regional and Rural Futures, Deakin University, Melbourne 3125, Australia

<sup>2</sup> Department of Spatial Economics, SPINlab, Vrije University Amsterdam, Amsterdam 1081 HV, The Netherlands

\* Correspondence: harmen.romeijn@deakin.edu.au (H.R.); r.faggian@deakin.edu.au (R.F.); vdiogo@feweb.vu.nl (V.D.); v.sposito@deakin.edu.au (V.S.); Tel.: +61-3-9244-5224 (H.R.); +61-3-9251-7327 (R.F.); +31-20-598-9898 (V.D.); +61-3-9251-7717 (V.S.)

Academic Editor: Wolfgang Kainz

Received: 11 March 2016; Accepted: 13 June 2016; Published: 20 June 2016

**Abstract:** Land suitability analysis is employed to evaluate the appropriateness of land for a particular purpose whilst integrating both qualitative and quantitative inputs, which can be continuous in nature. However, in agricultural modelling there is often a disregard of this contiguous aspect. Therefore, some parametric procedures for suitability analysis compartmentalise units into defined membership classes. This imposition of crisp boundaries neglects the continuous formations found throughout nature and overlooks differences and inherent uncertainties found in the modelling. This research will compare two approaches to suitability analysis over three differing methods. The primary approach will use an Analytical Hierarchy Process (AHP), while the other approach will use a Fuzzy AHP over two methods; Fitted Fuzzy AHP and Nested Fuzzy AHP. Secondary to this, each method will be assessed into how it behaves in a climate change scenario to understand and highlight the role of uncertainties in model conceptualisation and structure. Outputs and comparisons between each method, in relation to area, proportion of membership classes and spatial representation, showed that fuzzy modelling techniques detailed a more robust and continuous output. In particular the Nested Fuzzy AHP was concluded to be more pertinent, as it incorporated complex modelling techniques, as well as the initial AHP framework. Through this comparison and assessment of model behaviour, an evaluation of each methods predictive capacity and relevance for decision-making purposes in agricultural applications is gained.

**Keywords:** land suitability; Analytical Hierarchy Process; Fuzzy Analysis; Fuzzy AHP; agriculture; climate

## 1. Introduction

There is a growing consensus in natural resource management that agricultural policy will need to address likely impacts foreseen by climate change science and suggest and support adaptation actions [1]. Effective decisions, in relation to agricultural land use, suitability and capability, are fundamental to achieve and maintain ideal land productivity and to ensure future sustainability [2]. Decisions taken can influence not only agricultural or environmental practices, however, other linked components, such as infrastructure and transportation. These impacts will potentially occur across all spatial domains and have ramifications on the adaptive capacities of all linked components. The determination of productive land for agricultural systems, which can take into account projected climatic changes, is an important tool in the planning sphere.

Land Suitability analysis, which is the evaluation of how well the qualities of a unit of land match the prerequisites of a specific type of land cover or use [3], can be employed as one such tool. Suitability analysis can evaluate the appropriateness of the land for a particular purpose whilst integrating both qualitative and quantitative inputs. Evaluation of suitability is principally done to assess an area, or region, for optimal crop production and involves the interpretation of agricultural based data, such as soils, landscape, climate and water, in an effort to match land characteristics with crop requirements [4,5]. However, in an agricultural frame, the determination of what areas of land are deemed suitable for a particular use can be complex due to the multiple, and often disparate, streams of data. Multi Criteria Analysis (MCA) is a suite of methodologies that are primarily used for making decisions from complex input data and has been used numerous times for modelling suitability, where the main concern is how to combine multiple points of biophysical related data to arrive at a suitability decision [6–8]. Two main distinguishing features of a MCA is that it can combine objective and subjective inputs, as well as absolute or relative criteria, and it is flexible in terms of adjustment [9].

Initial undertakings in suitability analysis can, broadly, be traced to transparency overlaying techniques, such as those formalised by McHarg [10]. These hand-drawn methods have been replaced by computer based GIS systems and systems for assessing suitability have evolved and been formalised in frameworks and models. A widely accepted modelling framework is the Analytical Hierarchy Process (AHP) [11–13], which has been extensively applied for MCA purposes and utilised in many decision-making problems [14]. However, any methods that are employed to make these suitability determinations can be subject to uncertainties in both the scope and quality of outputs.

Boolean-based methodologies in the assessment of land suitability, which includes the AHP, consider both the input criteria and the categorisation of such, as clearly defined units [15]. Suitability assessments account for multiple factors that possess a continuous nature, such as soil properties or climatic variables. The disregard of these continuous factors in standard Boolean methods can lead to misallocation of land area within the segmented suitability classification [2]. These methods can overlook differences and inherent uncertainties found in the modelling inputs and outputs, as well as imposing new uncertainties relating to the defined suitability classes.

The application of fuzzy set theory or fuzzy logic [16,17] allows for the concept of these continuous factors to be modelled within a suitability assessment [18] within a GIS or spatial domain [4]. In a standard approach, membership with a set, or class, is clearly and crisply defined as either in the class or not in the class. In a fuzzy set, membership in the class can be apportioned a factor that ranges from not in to completely in the class. In comparison to standard Boolean models, which impose crisp boundaries and clearly defined geographical spaces that result in homogenised land units with single value suitability classes [19], fuzzy sets and fuzzy logic extends a method to process the continuous nature and uncertainty to produce a more realistic suitability classification system [18,20]. Fuzzy set modelling of spatially orientated data has been documented and exhibited for suitability assessments within the literature [2,5,14,15,18,19,21–23].

The principal objective of this research is to compare these parametric and continuous modelling approaches to land suitability analysis. Boolean methodologies will be demonstrated using the AHP technique, whilst fuzzy logic approaches will be covered under two differing fuzzy set models; a Fitted Fuzzy AHP and a Nested Fuzzy AHP. Secondary to this objective is to assess how each land suitability method behaves in a projected climate scenario and the possible variations that may exhibit between models into a climate future. All three methods will evaluate the biophysical agricultural land suitability for pear production in the Goulburn Broken Region of the state of Victoria, Australia. Through this comparison and assessment of suitability model behaviours into a climate future, an evaluation of each methods predictive capacity, validity and relevance for decision-making purposes can be garnered. This can potentially highlight the role of uncertainties in the modelling framework and outputs, in particular how the imposition of crisp boundaries can define and amplify uncertainty.

## 2. Methods

### 2.1. Study Region

The area of focus for this analysis is centred upon the Goulburn Broken Region of the state of Victoria in Australia (Figure 1). The defined geographic area for the study comprises of the boundary extent for seven Local Government Areas; Moira, Shepparton, Benalla, Campaspe, Murrindindi and Mansfield. Hereafter, this area will be referred to as the Study Region. The region is located to the north of the state capital, Melbourne. It is bordered to the south by the Great Dividing Range and to the north by the Murray River and the state of New South Wales. It has an area of approximately 24,000 km<sup>2</sup> (2.4 million hectares) and has a mixture of land uses within its boundaries. The dominant amongst these uses is land turned over for agricultural production including dryland and irrigated agriculture, which account for almost two thirds of the area in the Study Region. The largest agricultural enterprise, in terms of area, in the Study Region are pasture systems set aside for dairy and beef cattle and other pasture based livestock. However, the predominant industry, in terms of gross revenue, is horticultural production, which includes stone fruit and pome fruit. Pear production in this region alone accounts for over 85% of Australian output.



**Figure 1.** The Goulburn Broken Region, showing local government areas, Victoria, Australia.

### 2.2. Land Suitability Analysis

The United Nations Food and Agricultural Organisation (FAO) has an established framework structure for the assessment of suitability for any type of land use and cover [3]. This structure is hierarchical in design and comprises of Orders, Classes, Subclasses and Units. There are two primary suitability orders, which indicate if a unit of land is suitable or not suitable. Suitability classes are used to reflect degrees of suitability; for example the suitable order can be divided into high, moderate and low suitability classes. Furthermore, the not suitable order can be defined into two classes; ‘temporarily’ not suitable and ‘permanently’ not suitable. If necessary, in a given analysis, the classes can be divided

into subclasses, which reflect types of limitation in a class, and subclasses can be divided into units, which are used to show production characteristics or other requirements.

This framework has been modified slightly for use in Goulburn Broken Region. The core of the framework is maintained for application in this study region. The two principle suitability orders are maintained; Suitable and Not Suitable (NS). NS is further defined into Permanently Not Suitable (PNS) and Temporarily Not Suitable (TNS). There are four suitability classes utilised; High, Moderate, Low and Very Low. However, further breakdowns into suitability subclasses and units are not part of the framework established.

### 2.3. Analytical Hierarchy Process

For the analysis of land suitability across the Study Region, a Multi Criteria Analysis (MCA) is utilised. This was done across a regional spatial realm with the use of a Geographic Information System (GIS). A MCA is a useful tool for dealing with complicated problems [24], in particular those with seemingly disparate streams of data points. A common technique applied in a MCA is the Analytical Hierarchy Process (AHP) [11–13,25].

The framework of the AHP is that of a hierarchical decision tree. The top tier of this hierarchy is the primary objective. From this primary objective the AHP can be divided into primary criteria groupings and further into secondary and tertiary criteria groupings, where needed. At the base of the decision tree at the lowest level criteria, alternatives are established. These alternatives are critical indexed ranges and determine limitations within the criteria groupings. Ratings are established to rank the intensity of these ranges from best to worst. This is where the determined suitability classes, with assigned numerical values, can be applied.

In the determination of primary criteria groupings for agricultural production in the Study Region, there can be many criteria established. Given the Regional Scale of the Study Region there are three principal biophysical variables, which form the primary criteria; climatic factors, landscape features and soil characteristics. These are used as a base to determine growth and production for agricultural land use. Based on expert input and knowledge, these three main criteria are divided into secondary criteria that are critical for the growth of the commodity being modelled. Where necessary, further divisions can be made.

Once the criteria are specified and the base decision tree formulated, criteria weightings are then established. These are calculated for each criterion and indicate the relative importance to one another and to the overall output. This is done by a pairwise comparison. This involves working with relevant experts to indicate their subjective input about the relative importance of the criteria by comparing each criterion against one another individually. This importance is scored via an intensity rating as seen in Table 1.

**Table 1.** Pairwise comparison decision importance scores.

Intensity Rating	Definition
1	X is of equal importance to Y
3	X is slightly more influential than Y
5	X is more influential than Y
7	X is highly more influential than Y
9	X is definitely more influential than Y

These decisions are placed into a pairwise comparison matrix [11]. Weights are determined through this matrix by normalising the pairwise comparisons; each value in the matrix column is divided by the sum of the column. The weights for each criterion are then calculated by taking the mean of each matrix row. The output values are the criteria weightings, which are absolute numbers with values between 0 and 1 and it is expected that across one criteria level, or grouping, that these

weightings add up to 1. Chen [26] and Zhang [27] are noted to further expand on the use of the pairwise comparison matrix.

Alongside this pairwise comparison and the calculated weights, a consistency ratio is also calculated, which is an indicator of the quality of the subjective assessments made by the experts involved [5,11,27]. If the calculated CR is below the set threshold of 0.1, then the pairwise comparisons are relatively consistent and fit for use in the AHP. If not, then the subjective judgements are not consistent and there is need for a re-evaluation of the pairwise comparison and the decisions made within.

Pairwise comparison can be a rigorous technique for capturing expert preferences or opinions, as comparisons of each factor is done against one another, thus making more reliable judgements [28]. This technique improves consistency amongst criteria weights.

#### 2.4. Fuzzy Set Modelling

It can be noticed in the establishment of the AHP framework, that as alternatives, or suitability classes in this instance, are set, there are defined memberships formed. That is, an input variable in any given criteria grouping belongs to one alternative, or class, and not another. This Boolean approach in the framework establishes crisp boundaries on decisions. But given the continuous nature of some input variables, this true or false approach can impose severe restrictions on the outputs and any analysis derived from such.

Fuzzy set logic, developed by Zadeh *et al.* [16,17] works on the principal that the boundaries between classes, for various reasons, cannot be clearly defined [20]. This can be due to vagueness or uncertainty in the inputs [29], or related to constant nature of some variables. Hence, fuzzy set logic removes the crisp boundaries and defines for each criteria class alternative, a degree of membership. This statement of fuzzy membership is not related to a statistically defined probability, but rather it is a statement of possibility that a variable is a member of a class [20,21,30]. Through a membership function calculation, a variable can be given a grade of membership to a set, whereby the membership grade always relates to a given proposition [27]. For example in this study, that a unit of land, in regards to the three primary biophysical criteria, is suitable for agricultural production.

Just as there can be in probability studies differing distributions, in fuzzy set analysis there can be a range of fuzzy membership functions [20]. These can include Boolean, linear, parabolic and sinusoidal functions, to more complex function calculations. For this study a bounded transition zone sinusoidal membership function is used, initially described by Burrough [20] as 'model 2' (Figure 2).

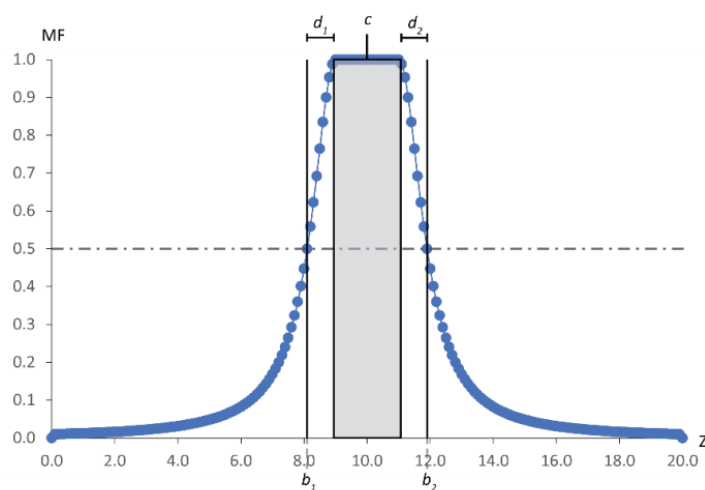


Figure 2. Bounded transition zone sinusoidal membership function.

In this Membership Function (MF), the behaviour of the positive and negative sinusoidal curves are set by the parameters  $d_1$  and  $d_2$ , which control the width and the transitional point of the curve where  $MF = 0.5$ . This model is defined by three equations:

$$MF(z) = \frac{1}{1 + \left(\frac{z-b_1-d_1}{d_1}\right)^2} \quad \text{if } z < b_1 + d_1 \quad (1)$$

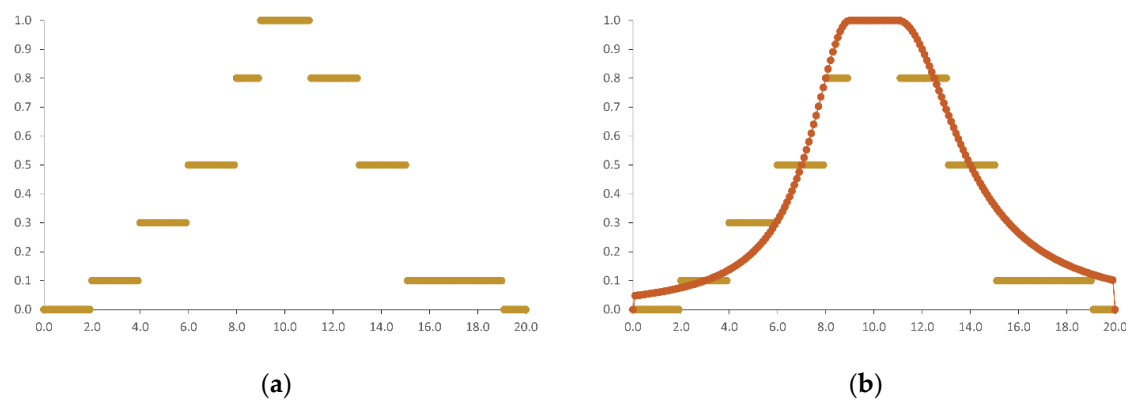
$$MF(z) = 1 \quad \text{if } b_1 + d_1 \leq z \leq b_2 - d_2 \quad (2)$$

$$MF(z) = \frac{1}{1 + \left(\frac{z-b_2+d_2}{d_2}\right)^2} \quad \text{if } z < b_2 - d_2 \quad (3)$$

where  $MF(z)$  is the value of the membership function corresponding to the variable value of  $z$ ,  $d_1$  and  $d_2$  are transitions zone widths with  $d_1$  relating to the positive curve and  $d_2$  to the negative curve, and  $b_1$  and  $b_2$  are the transitional cross-over points where the variable  $z$  has a  $MF(z) = 0$ .

These equations can be used together as a singular model to form a complete curve, or as distinct separate functions, depending on the nature of the variable being input into the function. When relating this back to an established AHP model, values of  $z$  and  $b$  can be ascertained. However, the transitional zone width of  $d$  in this curve is principally defined by the user. Hence, it is dependent on the users' knowledge and can be subjective in nature. This can be alleviated by fitting the curve to the AHP.

The AHP framework can be expressed within this membership function grading (Figure 3a), which depicts the crisp boundaries imposed by the criteria alternative classes. These boundary issues can be alleviated by overlaying and fitting a sinusoidal membership function model, as seen above (Figure 2), into a Fitted Fuzzy membership function (Figure 3b).

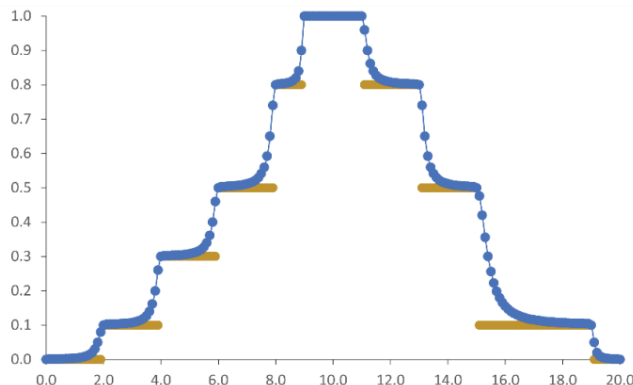


**Figure 3.** (a) Membership function representation of a Standard Boolean Analytical Hierarchy Process framework; (b) A sinusoidal membership function that is fitted to an AHP membership function—Fitted Fuzzy Curve.

Here, the values for  $b$  are derived from the alternative classes where the suitability class value is 0.5, which equates to a membership function value of 0.5. Then values for the transition zone width,  $d$  can be calculated by determining the difference between the values where  $MF(z) = 1.0$  and  $MF(z) = 0.5$ .

An alternative to this Fitted Fuzzy curve is to establish curves within the AHP, forming multiple nested membership functions between each AHP criteria alternative class (Figure 4). The establishment and formation of any AHP model utilises multiple experts to define objectives, criteria and alternatives. By using a fuzzy membership curve, even one that is fitted to an AHP, there can be some obfuscation of expert decisions and input. A Nested Fuzzy AHP still makes use of the overall structure and values of the original framework established by the Standard AHP. By fitting the membership functions

within the AHP, original decisions and expert inputs are, more or less, wholly maintained, but crisp boundaries are eliminated and fuzzy transitions are introduced in their place. However, in the use of this approach the width of the transition zone in each nested curve is set by the user and cannot be fitted to pre-existing knowledge.



**Figure 4.** Multiple sinusoidal membership functions fitted within an AHP membership function—Nested Fuzzy AHP.

### 2.5. Model Inputs and Application

The land suitability model was applied for pear production across the Study Region for both current and future climate conditions. Relevant data inputs were sourced from the representative Local Councils within the Study Region. Climatic information is both provided in a current timeframe and as future projections for the year 2050, whereas soils and landscape data remain static between each timeframe. For current values of climate, a climate normal has been established. This is referred to as the baseline climate. This baseline is calculated for all climatic variables using climatic data from 1961 to 1990. This thirty year period is long enough to include and account for year to year variations, but not that long to allow it to be influenced by longer term climate trends. This period of 1961 to 1990 is also used as a baseline by a number of other meteorological organisations including the World Meteorological Organisation and the Australian Bureau of Meteorology. Future climate scenarios for the year 2050 were created by use of the CSIRO's Global Circulation Model (GCM) CSIRO Mk 3.5 [31] and the A1FI emissions scenario [32]. The atmospheric content of the Mk 3.5 model has been used to generate monthly-based data. Both the baseline and projected climate data are provided Victoria-wide for the necessary climatic variables and is furnished at a spatial resolution of a 5 km<sup>2</sup> in a grid format.

The AHP model for pear production is presented in a tabular format in Table 2. Only the highest and lowest suitability classes are detailed in this particular table due to the complexity and size of this particular AHP decision tree model. Further presentations of a simpler AHP decision tree model as applied to suitability analysis in Victoria, Australia, can be found in Sposito *et al.* [28]. For actual application of the model there are several defined suitability classes, from high to very low, not documented within the table. The three main biophysical criteria are represented in this model. Each of these criteria has associated weights attached to them, which are presented as percentages for ease of interpretation and add up to 100% in any given grouping. For example, landscape had a weight of 15%, soil 25% and climate 60%. These values reflect the respective significance of each criterion for the growth of the commodity in question. In the next level down, within climate, rainfall is the most important criteria with a weight of 60%. All primary and secondary criteria divisions, weights, suitability classes and index values are determined and defined by expert judgement and subjected to a pairwise comparison. All these calculated values have been tested for consistency using a consistency ratio calculation and have been found to be under the threshold of 10%.

Table 2. Land suitability model for pear production.

Criteria			Weight (%)			Suitability Class		Index Value		Membership Function	
1st	2nd	3rd	1st	2nd	3rd	High	Low	High	Low	Equations	Curve Behaviour
Landscape			5								
Slope			90			<1.8°	>18°	1.0	−1.0 (Perm)	(3)	Negative
Aspect			10			N, E, W	S	1.0	0.6	(1)–(3)	Full
Soil			30								
pH			10			5.8–7.0	<4.0 and >8.5	1.0	−1.0 (Temp)	(1)–(3)	Full
Sodicity			10			Not Sodic	Sodic	1.0	0.6	n.a.	n.a.
Useable Depth			25			>45 cm	<10 cm	1.0	−1.0 (Perm)	(1)	Positive
Texture			25			CL, L, LC, SL	S, HC	1.0	0.1	n.a.	n.a.
Drainage			10			Well, Moderate	Very Poor	1.0	0.1	n.a.	n.a.
ECe			20			Very Low	Very High	1.0	−1.0 (Perm)	n.a.	n.a.
Climate			65								
Temperature			45								
Minimum Temperature			50								
September–October			70			4–20 °C	<−2 °C	1.0	0.0	(1)–(3)	Full
November–March			30			15–20 °C	<10 °C, >25 °C	1.0	0.0	(1)–(3)	Full
Maximum Temperature			50								
September–October			70			4–20 °C	<−2 °C, >25 °C	1.0	0.0	(1)–(3)	Full
November–March			30			<25 °C	>32 °C	1.0	0.0	(3)	Negative
Wind			5			<5 km/h	>30 km/h	1.0	0.5	(3)	Negative
Chill Units			5			>500 CU	<300 CU	1.0	0.0	(1)	Positive
Water Availability			45								
June–August			40			50–120 mm	<35 mm, >120 mm	1.0	0.0	(1)–(3)	Full
September–October			10			<40 mm	>120 mm	1.0	0.0	(3)	Negative
November–January			30			20–45 mm	>135 mm	1.0	0.0	(1)–(3)	Full
May			20			20–150 mm	>200 mm	1.0	0.0	(1)–(3)	Full



At base, the defined criteria are classified into suitability classes and are given a numerical index value. These numerical values are based on the suitability framework, as established by the FAO [3]. There are two main suitability orders; Not Suitable (−1.0) and Suitable (0.0 to 1.0). Not Suitable is further detailed into Temporarily Not Suitable (TNS), which indicate areas that can be remediated and Permanently Not Suitable (PNS) for areas completely off-limits. Four suitability classes are utilised; High (0.8 to 1.0), Moderate (0.5 to 0.7), Low (0.2 to 0.4) and Very Low (0.0 to 0.1).

For analysis of agricultural land suitability for pear production within the Goulburn Broken Study Region three approaches will be utilised. These will be a Standard AHP approach and two variations of fuzzy set modelling, namely Fitted Fuzzy curves and Nested Fuzzy AHP. This will be done over two differing climate periods, the climate normal baseline and the future projected year of 2050.

In translation to fuzzy membership functions for each of the two applied fuzzy set models, each input criteria will exhibit different behaviours. This will be in relation to the membership function curves and Equations (1)–(3), and will present as a positive curve, a negative curve or a combination of both. Table 2 outlines how each of the input criteria will be modelled by their respective membership functions.

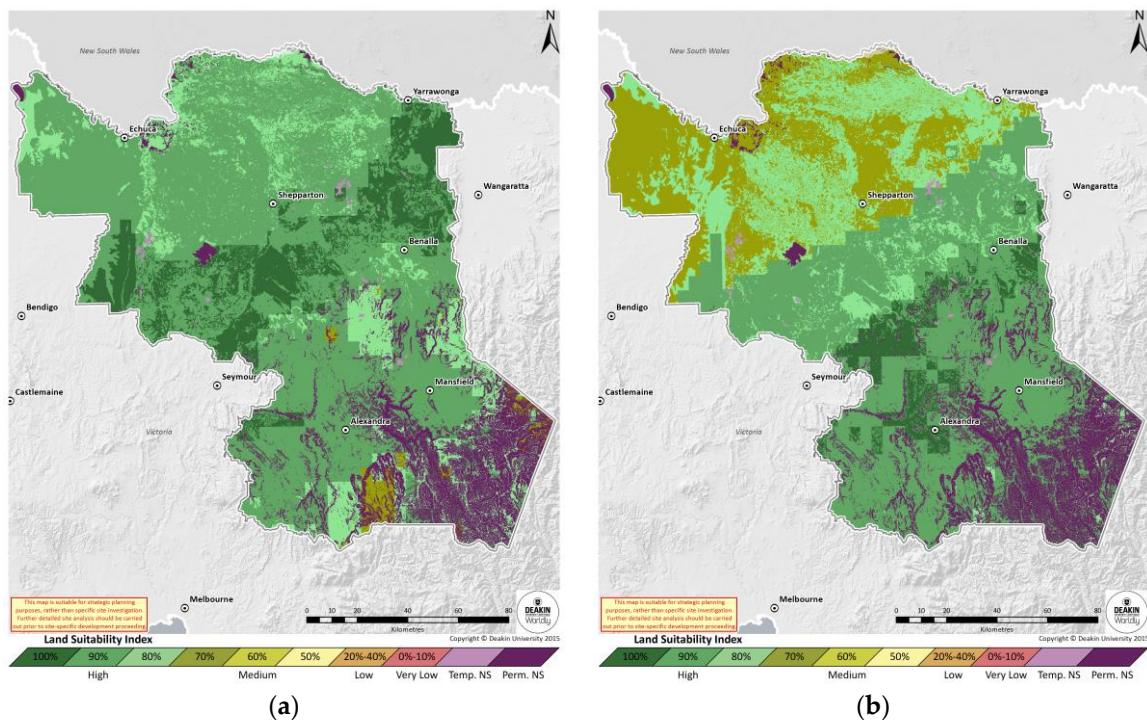
The land suitability model was implemented using Python Scripting Modules and Tools embedded within ESRI ArcGIS v10.1© (Redlands, CA, USA). Each data input for the biophysical factors are reclassified and overlaid, as according to the suitability index value and weighting. The final output is a composite map detailing the suitability for growth for perennial ryegrass across the study region.

### 3. Results

The execution of the model produces a composite map that ranks areas in terms of suitability for the growth of perennial ryegrass; it has an index range of 0.0 to 1.0, where 0.0 means a site which is deemed to have no potential and 1.0 represents a site deemed ideal for growing perennial ryegrass/sub-clover. For interpretation purposes these values have been converted to percentages, which correspond to, and can be grouped into, the defined suitability classes. For the purposes of this study, all area within the Study Region will be considered for analysis in spatial analysis and total area counts. In reality a portion of the study region is deemed public land or for urban use, such as national or state parks or residential settlements.

#### 3.1. Standard AHP Outputs

Figure 5 depicts the suitability outputs for the climate normal baseline year and the year 2050 in the Standard Boolean AHP Model. In the baseline years (left panel) the majority of the Study Region shows high suitability, primarily in the 90% suitability index value, with some areas in the southeast and north in the lower 80% values. Across the central region, northeast to west, is a distribution detailing a suitability of 100%. There are some minor distributions into the southern areas showing suitability in the moderate ratings at 80%. Large areas in the south detail land that is determined to be PNS, which is related to landscape and soil factors that inhibit pear cultivation. Other areas into the north have been determined to be PNS since they are large water bodies. Into 2050 (right panel), the majority of the region still shows high suitability at 80%, and above. However, towards the north there are some declines into more moderate suitability classes. The central band of high suitability has shifted into the south, with this central region now showing suitability at 90%.



**Figure 5.** Standard Boolean Analytical Hierarchy Process model output for (a) climate normal (b) 2050.

### 3.2. Fuzzy Set Modelling Outputs

The two panels in Figure 6 are fuzzy set modelling outputs in which the sinusoidal membership function curve is fitted to the determined values within the AHP, as depicted in Figure 3. These two panels represent outputs for the climate normal baseline year (left panel) and the year 2050 (right panel). Suitability index values, *i.e.*, membership function values, in the Standard AHP approach are presented as being in distinct classes. In comparison with this, the suitability index values in the fuzzy set models are continuous. Hence, the spatial outputs can be depicted with a gradated colour schema, similar to that in the Standard AHP spatial outputs, but more reflecting the complex modelling values.

In the climate normal baseline panel, the majority of the region depicts high suitability values, which are at 80% and above. Higher values are concentrated into the central sub-region from the northeast into the central west, with lower high values either found along the periphery of these distributions or interspersed in smaller minor distributions. Moderate ratings at 70% and below are also noted into the southern areas. Here also are patches of land determined to be PNS, which is principally due to landscape slope factors and other limiting soils criteria. However, in comparison to the Standard AHP outputs, these non-suitable distributions are smaller in area. Into the year 2050, these areas of higher suitability are seen to shift southward, with the majority of the south of the Study Region detailing values at approximately 80% and above. Moderate ratings in the south, noted in the baseline, are now replaced by these higher ratings. However, moderate ratings are now observed in the north, where higher suitability values decline into lower classes.

Spatial outputs for the secondary fuzzy set model, in which individual membership functions are nested within the Standard AHP framework, are detailed in Figure 7. Index values within these outputs are continuous and therefore, the output figures are presented with a gradated colour ramp. The two panels for the baseline climate normal (left panel) and the year 2050 (right panel), show very similar trends and patterns to the two previous modelling outputs, with high suitability ratings in the baseline that is noted to shift southward into 2050, with a general decrease in suitability in the north.

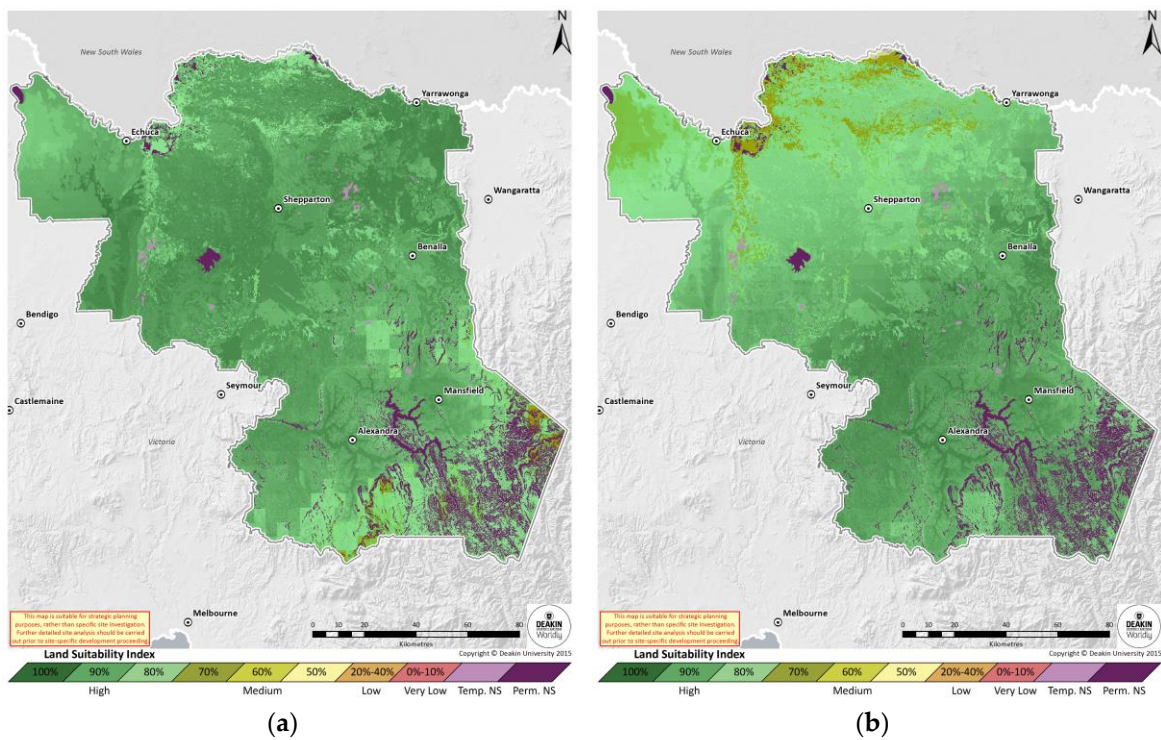


Figure 6. Fitted Analytical Hierarchy Process Fuzzy Set Membership model for (a) climate normal (b) 2050.

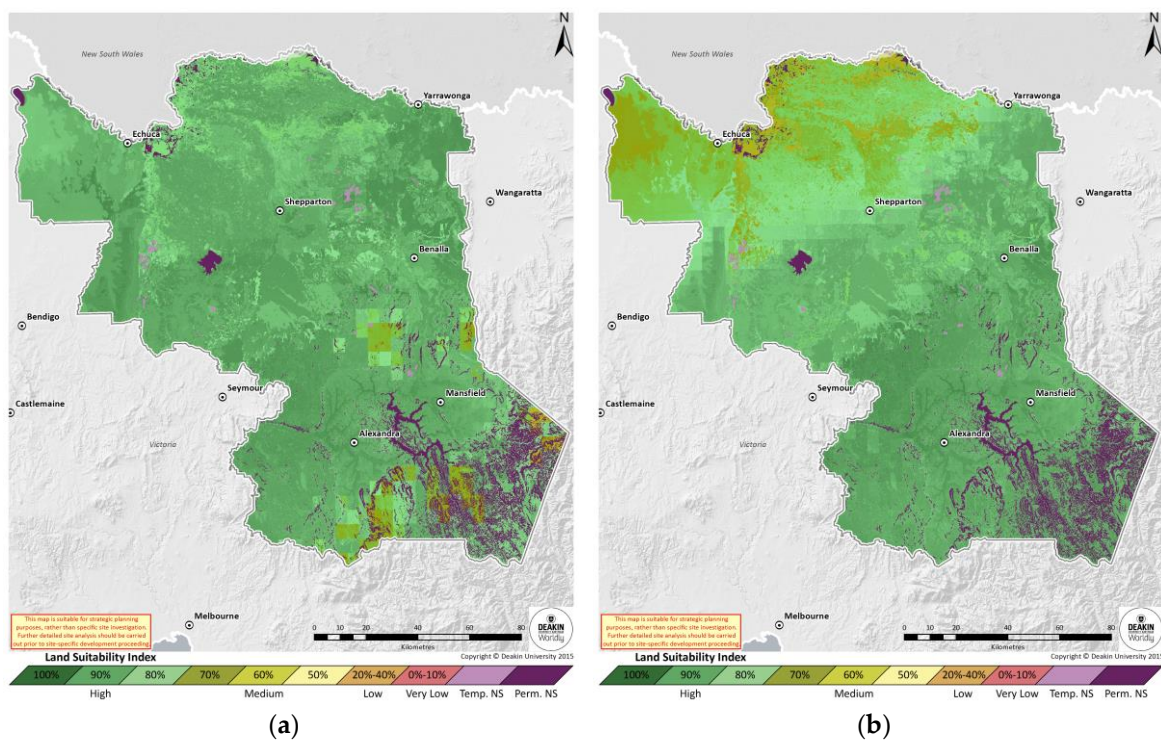


Figure 7. Nested Analytical Hierarchy Process Fuzzy Set Membership model for (a) climate normal (b) 2050.

However, outputs can be described as an amalgam of both the prior modelling techniques. These figures depict slightly more clearly defined distributions or regions of suitability, which reflects

the Boolean framework in the Standard AHP approach. But there is a more gradated and continuous flow between these areas, which is a characterisation of the membership curves fitted into and within the AHP. This is more clearly represented in the 2050 output, where there is a clear demarcation between the northern and southern areas with a northeast to west distribution of high suitability ratings. Additionally, moderate ratings in the north are more clearly defined and slightly larger in area, whilst still retaining the continuous and gradated pattern.

### 3.3. Output Comparisons

For each suitability class, the total hectare amount each class occupies within the Study Region, as well as their relative proportion can be obtained, which is shown in Table 3. For comparison purposes between the Standard AHP and both fuzzy set models, the suitability index values have been defuzzified, that is they have been grouped in their respective whole number broad suitability classes.

**Table 3.** Total hectare output for each suitability index value class in the study region for each of the three suitability modelling methods in a climate normal and a 2050 climate.

Suitability Index Value	Standard		Fitted		Nested	
	Normal	2050	Normal	2050	Normal	2050
Hectares (ha)						
TNS <sup>1</sup>	8045 (0.3%)	8045 (0.3%)	8045 (0.3%)	8045 (0.3%)	8045 (0.3%)	8045 (0.3%)
PNS <sup>2</sup>	320,632 (13.1%)	320,632 (13.1%)	178,508 (7.3%)	178,508 (7.3%)	178,508 (7.3%)	178,508 (7.3%)
60%	3 (>0.1%)	-	-	-	-	-
70%	29,674 (1.2%)	489,530 (20.0%)	3513 (0.1%)	24,129 (1.0%)	16,713 (0.7%)	67,159 (2.8%)
80%	340,934 (14.0%)	487,400 (20.0%)	277,150 (11.4%)	533,325 (21.8%)	226,459 (9.3%)	665,944 (27.3%)
90%	1,431,712 (58.6%)	1,008,898 (41.3%)	1,655,614 (67.8%)	1,576,833 (64.6%)	1,999,149 (81.9%)	1,508,904 (61.8%)
100%	310,643 (12.7%)	127,138 (5.2%)	318,813 (13.1%)	120,803 (4.9%)	12,769 (0.5%)	13,083 (0.5%)

<sup>1</sup> Temporarily Not Suitable; <sup>2</sup> Permanently Not Suitable.

General trends for each method indicate that between the climate normal baseline and 2050 there is an overall decline in suitability ratings, but the higher proportions always remain within the 90% suitability index value. Also of note is that the values for the TNS and PNS index values remain the same. However, from the Standard AHP and fuzzy set models, for these non-suitable classes, there is a reduction in the total occupied area in the Study Region. The differences between each modelling method can be discerned from these numerical outputs, in particular between the Standard AHP and the Fitted Fuzzy model.

Although these numbers cannot illustrate any of the spatial shifts seen in the outputs, they can demonstrate behaviours in suitability groupings between the impositions of crisp boundaries in the Standard AHP approach and the fuzzy memberships in both fuzzy set modelling approaches. Of particular note here is the large increment in the 70% rating in the Standard AHP between the normal and 2050 outputs. Likewise, another observation within these numerical outputs is the relatively minor changes in the 90% suitability index value in the Fitted Fuzzy approach.

The Nested Fuzzy approach, as an amalgam of the Standard AHP and Fitted Fuzzy, exhibits some behaviours of both models. This can be seen in how the 90% suitability class has a strong decline between the normal and 2050, which is comparable to the Standard AHP results, or the large

increment in the 80% suitability index value, which is analogous to results garnered from the Fitted Fuzzy approach.

#### 4. Results Discussion

Between each suitability modelling technique it is only the climatic criteria that are changed between the two timeframes, whilst both the soils variables and landscape factors are kept constant. The projected change in climate into the year 2050 invariably leads to a change in suitability. With a likely decrease of available water and increase in temperatures, the favourable climatic envelope for the production of pears in the Study Region is seen to shift. Each suitability analysis method witnesses these changes as a southward shift of higher suitability ratings, with an increase in lower suitability ratings in the north. This is principally driven by projected increasing inland temperatures coupled with a lowering of potential water supplies in the current irrigations districts and surrounds.

From a decision-making and planning perspective, it can be beneficial to examine these suitability changes between the climate normal baseline and projected climates for agricultural applications. One of the principal reasons intended for a multi-model analysis between two timeframes was to examine model behaviour between Boolean and Complex modelling techniques with changing variables.

As described, each method exhibits a similar change pattern between the two timeframes, albeit with their own idiosyncrasies. The standard AHP approach imposes a Boolean logic to the suitability index values. Ratings are either definitely part of one grouping, there are no possibilities that it could share membership with other neighbouring groupings. These crisp boundaries on the suitability index values enact an either/or on ratings. Hence, in some instances where an index value falls between two classes, it can be relegated to one class over another. This can occur even where a value is neither wholly a member of a particular class.

Instances of this can be evidenced within the PNS classes for both timeframes in each of the modelling techniques. In the Standard AHP approach this class is shown to occupy a higher amount of land, whereas in the fuzzy models these amounts are lower. This is an archetype of where index values can have a grade of membership between two classes and it is reflected in the fuzzy model spatial outputs, where more area is shown to fall within the suitable range. This is also evidenced in other classes, such as the 70% moderate class. Here, in the standard AHP approach, between the climate normal baseline and 2050 there is significant increase in the amount of area occupied by this class. However, for the Fitted Fuzzy and Nested Fuzzy approaches, this increase in this class is not as large.

#### 5. Concluding Comments

The base AHP framework on which all approaches have been built is an Expert Systems Model. That is, the models are informed by and built by agricultural experts. There are land use data layers that spatially indicate where agricultural enterprises exist in the landscape. But, as is often the case, the placement of agriculture across the Australian landscape has largely been informed by historic settlement patterns and tradition has maintained their placement. Suitability of the land is only now becoming a more established concept that is slowly being accepted across the Australian farm-*scape*. The suitability outputs, for all approaches, at best exhibit a representation, or snapshot, of reality at a particular point in time. This is dependent on the best available data at the time of modelling and the reliability of expert input and interpretation.

However, this expert systems modelling methodology can be subject to a range of uncertainties. The expert input that forms a core part of the framework is subjective in nature, it can be formulated on biased opinions or a narrow field of expertise. Also definitions of certain land factors derived by experts, which may be considered important in the determination of suitability, can be intrinsically vague [21]. These uncertainties can be diminished through certain actions, such as in an AHP where pairwise comparisons, use of multiple experts and consistency ratios all act in unison to reduce

subjectivity. Furthermore, Sicat *et al.* [21], through the application of fuzzy set modelling on expert knowledge, essentially controls and reduces this subjective uncertainty.

Moreover, uncertainties are seen within the AHP model framework. The Boolean design of an AHP imposes an either/or format on the suitability index values. In a natural system where there is often a gradual change in particular factors, such as climate or soils, over space and time, this categorical structure in attributing values introduces a range of uncertainties. This is clearly evident in the Standard AHP spatial output where there are distinct crisp boundaries across the Study Region. The complex modelling approach, seen in both fuzzy set methods, are useful in minimising these uncertainties as they more closely approximate the natural systems. Fuzzy set theory is able to depict this land continuity for differing classes, which provides a major advantage [2]. The spatial outputs for both the Fitted Fuzzy and Nested Fuzzy approaches illustrate this, with both outputs describing a gradation of suitability across the Study Region, with very little evidence of boundaries between suitability classes.

To this end, the fuzzy set approaches utilised provide an improved and more comprehensive final product over that produced by the Standard AHP. Similar conclusions were expressed, amongst others, by Burrough [18], Keshavarzi [2], Elaalem [15] and Zhang [27]. Between the Fitted Fuzzy and Nested Fuzzy methods, both have associated positives and negatives that inform their usage. The Fitted Fuzzy approach is beneficial in that the sinusoidal membership function curves are fitted to the AHP, that is, the curves transition zone is defined by the AHP framework. Hence, the curve structure is wholly defined by the AHP and any modeller-based subjectivity is removed. However, this singular curve used over the whole AHP framework smooths out the AHP, which overlooks the staggered or disparate suitability index value class categorisation of some AHP frameworks.

The Nested Fuzzy approach, as an amalgam of the Standard AHP approach and fuzzy set modelling, proffers some benefits over the Fitted Fuzzy approach, with minimal weaknesses. One drawback to this approach lies in the determination of the transition zone in membership function curve. Since there is not set parameter to guide the width of this zone, the value has to be set by the determination of the modeller. Hence, this does introduce some uncertainty back into the framework via the subjective input. Further to this, Elaalem [15] extends that in reality there can be overlap between classes. By nesting membership curves between suitability classes, some of this overlap, or continuity, can be lost. However, by retaining the original structure and suitability index value class categorisation found in the Standard AHP in the Fuzzy Nested AHP approach, the expert decisions and input are preserved. Secondly it introduces the complex modelling found in fuzzy sets, which is shown to replicate the continuous compositions found in natural systems.

Therefore, whilst both fuzzy approaches provide better outputs over the Standard AHP, it is expected that a Nested Fuzzy AHP approach will more soundly represent and integrate the continuous nature of the biophysical factors as input into the suitability framework, while producing a more astute and pertinent suitability output for decision making and planning purposes in agricultural applications. It allows the inherent vagueness of the landscape to be expressed by not imposing limits or breaks on the system [18], whilst still integrating expert based knowledge into the framework. Other illustrations of this approach of marrying expert knowledge and fuzzy set theory are observed in Sicat *et al.* [21] and Reshmidevi [22].

This comparison and subsequent assessment of the three suitability analysis techniques, from a climate normal baseline into a climate future, furnishes an insight into model behaviour. It provides a base for evaluation of each method's predictive capacity, validity and relevance. A principal application of the base outputs is that they will be used to inform decisions in agricultural and natural resource management and shape planning decisions in the Study Region.

Decision making under any cloud of uncertainty, as imposed by Standard AHP approaches, can be complex and attaining any significant conclusions will be based on any number of caveats [2]. In the identification of suitable agricultural land that compliments the continuous nature of the environment, for both a current and future timeframes, there will be greater protection of valuable agricultural land

in planning decisions. This can be particularly poignant in regional growth areas, where urban and rural expansion interfaces with productive agricultural land. The development of a suitability model that more aptly reflects natural systems will potentially provide a more accurate output that has a greater predictive value for agricultural land suitability.

**Acknowledgments:** All sources of funding of the study should be disclosed. Please clearly indicate grants that you have received in support of your research work. Clearly state if you received funds for covering the costs to publish in open access.

**Author Contributions:** Harmen Romeijn, Robert Faggian and Vasco Diogo conceived the paper and research; Harmen Romeijn designed the computer simulation models and experiments; Harmen Romeijn ran the computer simulations and models; Harmen Romeijn analysed the outputs and data; Harmen Romeijn, Robert Faggian, Vasco Diogo and Victor Sposito wrote the paper.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

- Olesen, J.E.; Bindi, M. Consequences of climate change for European agricultural productivity, land use and policy. *Eur. J. Agron.* **2002**, *16*, 239–262. [[CrossRef](#)]
- Keshavarzi, A.; Sarmadian, F.; Heidari, A.; Omid, M. Land suitability evaluation using fuzzy continuous classification (A case study: Ziaran region). *Mod. Appl. Sci.* **2010**, *4*, 72. [[CrossRef](#)]
- FAO. *A Framework for Land Evaluation*; FAO Soils Bulletin; Food and Agriculture Organisation of the United Nations: Rome, Italy, 1976.
- Wang, F.; Brent Hall, G.; Subaryono. Fuzzy information representation and processing in conventional GIS software: Database design and application. *Int. J. Geogr. Inf. Syst.* **1990**, *4*, 261–283. [[CrossRef](#)]
- Nisar Ahamed, T.R.; Gopal Rao, K.; Murthy, J.S.R. GIS-based fuzzy membership model for crop-land suitability analysis. *Agric. Syst.* **2000**, *63*, 75–95. [[CrossRef](#)]
- Carver, S.J. Integrating multi-criteria evaluation with geographical information systems. *Int. J. Geogr. Inf. Syst.* **1991**, *5*, 321–339. [[CrossRef](#)]
- Jankowski, P.; Richard, L. Integration of GIS-based suitability analysis and multicriteria evaluation in a spatial decision support system for route selection. *Environ. Plan. B Plan. Des.* **1994**, *21*, 323–340. [[CrossRef](#)]
- Hossain, H.; Sposito, V.; Evans, C. Sustainable land resource assessment in regional and urban systems. *Appl. GIS* **2006**, *2*, 24.1–24.21. [[CrossRef](#)]
- Dujmovic, J.J.; de Tré, G.; Dragicevic, S. Comparison of multicriteria methods for land-use suitability assessment. In Proceedings of the Joint 2009 International Fuzzy Systems Association World Congress and 2009 European Society of Fuzzy Logic and Technology Conference IFSA/EUSFLAT, Lisbon, Portugal, 20–24 July 2009.
- McHarg, I.L. *Design with Nature*; Published for the American Museum of Natural History; Natural History Press: Garden City, NY, USA, 1969.
- Saaty, T.L. *The analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation*; McGraw-Hill International Book Co.: New York, NY, USA; London, UK, 1980.
- Saaty, T.L. *Fundamentals of Decision Making, and Priority Theory: With the Analytic Hierarchy Process*, 1st ed.; Analytic Hierarchy Process Series; RWS Publications: Pittsburgh, PA, USA, 1994.
- Saaty, T.L. *Decision Making for Leaders: The Analytical Hierarchy Process for Decisions in a Complex World*, 3rd ed.; RWS Publications: Pittsburgh, PA, USA, 1995.
- Mikhailov, L. Deriving priorities from fuzzy pairwise comparison judgements. *Fuzzy Sets Syst.* **2003**, *134*, 365–385. [[CrossRef](#)]
- Elaalem, M. A Comparison of Parametric and Fuzzy Multi-Criteria Methods for Evaluating Land Suitability for Olive in Jeffara Plain of Libya. *APCBEE Procedia* **2013**, *5*, 405–409. [[CrossRef](#)]
- Zadeh, L.A. Fuzzy sets. *Inf. Control* **1965**, *8*, 338–353. [[CrossRef](#)]
- Zadeh, L.A. *Fuzzy Sets and Their Applications to Cognitive and Decision Processes*; Academic Press: New York, NY, USA, 1975.
- Burrough, P.; MacMillan, R.; Deursen, W.V. Fuzzy classification methods for determining land suitability from soil profile observations and topography. *J. Soil Sci.* **1992**, *43*, 193–210. [[CrossRef](#)]

19. Liu, Y.; Jiao, L.; Liu, Y.; He, J. A self-adapting fuzzy inference system for the evaluation of agricultural land. *Environ. Model. Softw.* **2013**, *40*, 226–234. [[CrossRef](#)]
20. Burrough, P.A.; McDonnell, R.A.; Lloyd, C.D. *Principles of Geographical Information Systems*, 3rd ed.; Oxford University Press: Oxford, UK, 2015.
21. Sicat, R.S.; Carranza, E.J.M.; Nidumolu, U.B. Fuzzy modeling of farmers' knowledge for land suitability classification. *Agric. Syst.* **2005**, *83*, 49–75. [[CrossRef](#)]
22. Reshmidevi, T.V.; Eldho, T.I.; Jana, R. A GIS-integrated fuzzy rule-based inference system for land suitability evaluation in agricultural watersheds. *Agric. Syst.* **2009**, *101*, 101–109. [[CrossRef](#)]
23. Ceballos-Silva, A.; Lopez-Blanco, J. Delineation of suitable areas for crops using a Multi-Criteria Evaluation approach and land use/cover mapping: A case study in Central Mexico. *Agric. Syst.* **2003**, *77*, 117–136. [[CrossRef](#)]
24. Voogd, H. *Multicriteria Evaluation for Urban and Regional Planning*; Pion.: London, UK, 1983; Volume 14, p. 367.
25. Malczewski, J. GIS-based land-use suitability analysis: A critical overview. *Prog. Plan.* **2004**, *62*, 3–65. [[CrossRef](#)]
26. Chen, Y.; Yu, J.; Khan, S. The spatial framework for weight sensitivity analysis in AHP-based multi-criteria decision making. *Environ. Model. Softw.* **2013**, *48*, 129–140. [[CrossRef](#)]
27. Zhang, J.; Su, Y.; Wu, J.; Liang, H. GIS based land suitability assessment for tobacco production using AHP and fuzzy set in Shandong province of China. *Comput. Electron. Agric.* **2015**, *114*, 202–211. [[CrossRef](#)]
28. Sposito, V.A.; Benke, K.; Pelizaro, C.; Wyatt, R. Adaptation to climate change in regional australia: A decision-making framework for modelling policy for rural production. *Geogr. Compass* **2010**, *4*, 335–354. [[CrossRef](#)]
29. Houshyar, E.; SheikhDavoodi, M.J.; Almassi, M.; Bahrami, H.; Azadi, H.; Omid, M.; Sayyad, G.; Witlox, F. Silage corn production in conventional and conservation tillage systems. Part I: Sustainability analysis using combination of GIS/AHP and multi-fuzzy modeling. *Ecol. Ind.* **2014**, *39*, 102–114. [[CrossRef](#)]
30. Zimmermann, H.J.; Zadeh, L.A.; Gaines, B.R. *Fuzzy Sets and Decision Analysis*; TIMS studies in the Management Sciences; North-Holland Distributors; Elsevier Science: Amsterdam, The Netherlands; New York, NY, USA, 1984; p. 522.
31. Gordon, H.B.; Collier, M.; Dix, M.; Rotstayn, L.; Kowalczyk, E.; Hirst, T.; Watterson, I. *The CSIRO Mk3. 5 Climate Model*; CAWCR: Melbourne, Australia, 2010.
32. Nakicenovic, N.; Alcamo, J.; Davis, G.; de Vries, B.; Fenhann, J.; Gaffin, S.; Gregory, K.; Grubler, A.; Jung, T.A.; Kram, T. *Special Report on Emissions Scenarios: A Special Report of Working Group III of the Intergovernmental Panel on Climate Change*; Pacific Northwest National Laboratory, Environmental Molecular Sciences Laboratory (US): Richland, WA, USA, 2000.



© 2016 by the authors; licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC-BY) license (<http://creativecommons.org/licenses/by/4.0/>).