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Adaptation to Climate Change in Regional Australia: A Decision-Making Framework for Modelling Policy for Rural Production

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Abstract

A decision-making framework was developed and applied in regional Australia to identify adaptation issues arising in agricultural systems and rural production as a consequence of climate change. Australian agriculture is very susceptible to the adverse impacts of climate change, with major shifts in temperature and rainfall projected. An advantage of the framework is that it provides a suite of tools to aid in the formulation of strategies for sustainable regional development and adaptation. The decision-making framework uses a participatory approach that integrates land suitability analysis with uncertainty analysis and spatial optimisation to determine optimal agricultural land use (at a regional scale) for current and possible future climatic conditions. It thus provides a robust analytic approach to (i) recognise regions under threat of productivity declines, (ii) identify alternative cropping systems better adapted to likely future climatic conditions and (iii) investigate policy actions to improve the sub-optimal situations created by climate change. The decision-making framework and its methods were applied in a case study of the South West Region of Victoria.

The Challenges of Climate Change

BACKGROUND

The climate of the Earth is regulated in part by atmospheric gases, referred to as greenhouse gases (GHGs), because they trap radiation in a manner analogous to the glass of a greenhouse, resulting in a general warming effect. The GHGs include water vapour, carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O) and halocarbons (a group of gases containing fluoride, chlorine and bromide). Since the Industrial Revolution (around 1750), global atmospheric concentrations of CO_2, CH_4 and N_2O have increased markedly as a result of human activities, and now far exceed pre-industrial values. Their sources include fossil fuel combustion from industry and transport, agricultural activities and land-use changes. The consensus in the scientific literature is that the rapid global warming identified in the last few decades is because of human-induced climate change in conjunction with some natural variations (Intergovernmental Panel on Climate Change – IPCC 2007a,d, Millennium Ecosystem Assessment (MEA) 2005; Pittock 2005; Ruth et al. 2006).

Climate scientists have explored various global scenarios of future GHG and aerosols emissions (IPCC Special Report on Emissions Scenarios – SRES) based on assumptions about future demographic, economic, scientific and technological changes (Nakicenovic and Swart 2000). Complex models of the climate system, driven by the SRES scenarios, are then used to formulate climate change projections. All existing models simulate further global warming. The magnitude of warming depends on the emission scenario examined and the response of each climate change model. According to the IPCC (2007d), the best estimate and likely ranges for global average surface air warming at the end of the 21st century in the low global warming scenario (B1) is 1.8°C (the likely range is 1.1–2.9°C) and the best estimate for the high global warming scenario (A1FI) is 4.0°C the (likely range is 2.4–6.4°C).

The United Nations Framework Convention on Climate Change is the key platform for international policy responses to climate change (United Nations General Assembly 1992). Two broad categories of responses are identified: 'mitigation' and 'adaptation'. Mitigation aims to reduce the causes of climate change by slowing and eventually halting the increase in GHG emissions (e.g. through emissions abatement and sequestration), whereas adaptation attempts to lessen the impact of climate stress on natural and human systems. Mitigation and adaptation are complementary processes, but the benefits will accumulate over different spatial and temporal scales and, in many cases, they can be formulated and implemented separately. Mitigation activities have global benefits; adaptation, on the other hand, works on the local or regional scale of an impacted system. Adaptation is a selective strategy taking advantage of positive impacts whilst reducing negative ones (Goklany 2005; IPCC 2007b; Klein et al. 2007).

Despite the current lack of understanding on the synergies and trade-offs between adaptation and mitigation, both activities are recognised as essential to achieving an appropriate mix of actions to maximise the benefits and minimise the costs of responding to climate change. Most industrialised nations have already committed themselves to adopt policies and corresponding measures on mitigation. Nonetheless, the first impacts of climate change are already being observed and research indicates that mitigation efforts will not prevent the Earth's climate from changing within the next few decades (Christensen et al. 2007; IPCC 2007c; Meehl et al. 2007). For this reason, reducing the vulnerability of the economic sectors and communities to the impacts of climate change by means of adaptation is unavoidable. This article primarily focuses on adaptation responses.

THE THREAT TO AUSTRALIAN AGRICULTURE

Agriculture is an important component of the Australian economy, accounting for over 18% of total Australian exports. Australia is one of the world's largest exporters of wool, beef, mutton and lamb, wheat and sugar. Related manufacturing of food, beverages and tobacco contributes a further 3% to Australia's GDP (ABARE 2007). Australia is likely to be one of the most adversely affected countries with respect to reductions in agricultural production as a result of climate change (Crimp et al. 2002; Heyhoe et al. 2007; Preston and Jones 2007). Decreases of between 17% (Cline 2007) and 22% (Gunasekera et al. 2007) are predicted in Australian agricultural productivity by 2050 assuming that climate changes follow the SRES A2 (medium range) emissions scenario pathway. Regional declines in agriculture productivity resulting from changes in climate would have important implications for international trade patterns in agricultural commodities (Gunasekera et al. 2008; Webb et al. 2007). The studies cited above do not assume any planned adaptation or mitigation measures. It can be argued, therefore, that if planned mitigation and adaptation measures are implemented, the magnitude of the adverse impacts could be reduced, possibly significantly. For instance, it may well be that other unknown crop production opportunities could emerge from a different climate pattern and it would be advisable to have strategies in place for addressing such eventualities.

THE NEED FOR ROBUST DECISION-MAKING

Climate change is a pressing and highly complex policy issue involving multiple factors and significant levels of disagreement about the nature of the problem and the best way to address it. It is thus an example of a so-called 'wicked' policy problem (Rittel and Webber 1973, Australian Government, Australian Public Service Commission (APSC) 2007). It is generally implied that more accurate (i.e. reduced uncertainty) and more precise (i.e. higher resolution at regional and local levels) climate change projections will assist in solving the challenge of adaptation by providing a more faithful description of the future (e.g. MOHC. 2007, World Meteorological Organization – WMO 2008). Bankes (1993) has observed that such actions and efforts may fall prey to false reductionism, and he states that 'The belief is that the more details a model contains the more accurate it will be. This reductionism is false in that no amount of detail can provide validation, only the illusion of reality'. This mindset is observable in many climate change studies. There are nevertheless important limitations on our ability to accurately and precisely predict future climate conditions (or, more generally, future behaviour of any complex system). These include widening uncertainties (a 'cascade' or 'explosion' of uncertainty), lack of objective constraints (with which to reduce the uncertainty of predictions) and the problem of equifinality (Pittock 2005). Moreover, climate change is only one of many uncertain processes that influence society and its activities. Climate change projections and impact and adaptation modelling have therefore to be placed within broader decision-making frameworks.

This is not dissimilar to the situation faced in daily life by organisations that make decisions without reasonable predictions of the future to support them. Several authors have proposed that society should seek to identify strategies that are 'robust' against a broad range of plausible futures (e.g. Lempert and Schlesinger 2000; Lempert et al. 2006; Regan et al. 2005). For these authors, robust strategies perform well compared with the alternatives over a wide range of reasonable assumptions about the future. In this context, the research reported in this article aims at contributing to the adaptation of agricultural (including forestry) systems to climate change. Its purpose is to formulate a decision-making framework capable of identifying issues (problems and opportunities) arising in agricultural systems and rural production as a consequence of climate change. In particular, the framework should answer key policy questions related to climate change impacts on agriculture at a regional scale. These are questions such as: (i) which rural regions are more vulnerable to climate change, considering different GHG emissions scenarios? (ii) what regions/areas require further investigation given the deep uncertainties related to climate change impacts? (iii) are there alternative agriculture commodities that farmers could cultivate to take advantage of the changing climate and therefore produce improved agricultural outputs (i.e. finding new opportunities)?

Framework for Climate Change Adaptation Policy Assessments in Agricultural Systems

The decision-making framework combines three loosely coupled models (Figure 1). Its departing module is the climate change projections which are derived from the SRES scenarios (Nakicenovic and Swart 2000) scaled down to the regional level. The first model integrates multi-criteria decision-making and GIS to map the degree of land suitability for the growth of those agriculture commodities relevant to the region of interest, given current and future climate conditions. Modifications in agriculture land suitability caused by climate change can then be assessed by comparing future suitability maps with

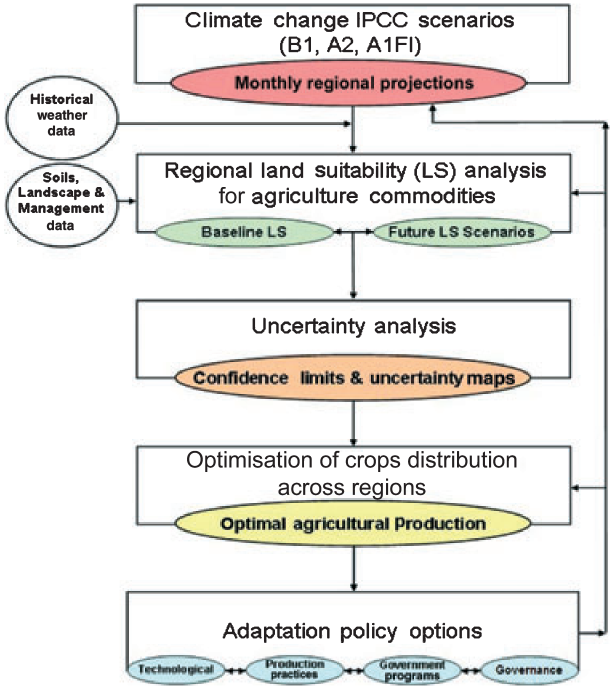

Fig. 1. Framework for the assessment of policy adaptation options.

current suitability maps. The second model estimates the uncertainties related to the first model. The third model uses optimisation algorithms to identify (sub-)optimal spatial distributions of cropping systems for the entire region based on one factor, or any combination of several factors, including land suitability, crop productivity (yields), market demand/price, revenue, environmental damage or transport costs. Outputs of the chain of models can then be fed into the analysis of adaptation policy options. The feedback loops in Figure 1 depict the iterative nature of the decision-making process. The framework allows the investigation of 'what if' policy questions by, for example, modelling crops that may be suitable in a wide range of plausible futures and examining the consequences of cultivating them.

The framework was initially applied in the South West Region of Victoria, Australia. Located in the south-eastern corner of the country, Victoria is the smallest yet most densely populated mainland state. The Victorian economy is the second largest in the country, accounting for a quarter of the nation's GDP. It is also responsible for about a quarter of national agricultural production total gross value with agriculture covering approximately 60% of the state's total land surface. South West Victoria was chosen because agriculture is vital to the region's and state's economy representing approximately 20% of Victoria's agricultural production total gross value in 2006–2007. The region is experiencing rapid agricultural land-use transformations as a result of climate change and modifications in the production trade patterns. Land previously devoted to beef and sheep production is now being used for a variety of grains (e.g. barley, winter wheat and oats), dairy, horticulture and forestry (Sposito et al. 2008). For analytic purposes, the region was defined spatially as the territory covered by two adjoining Catchment Management Authorities, namely Glenelg Hopkins and Corangamite (Figure 2).

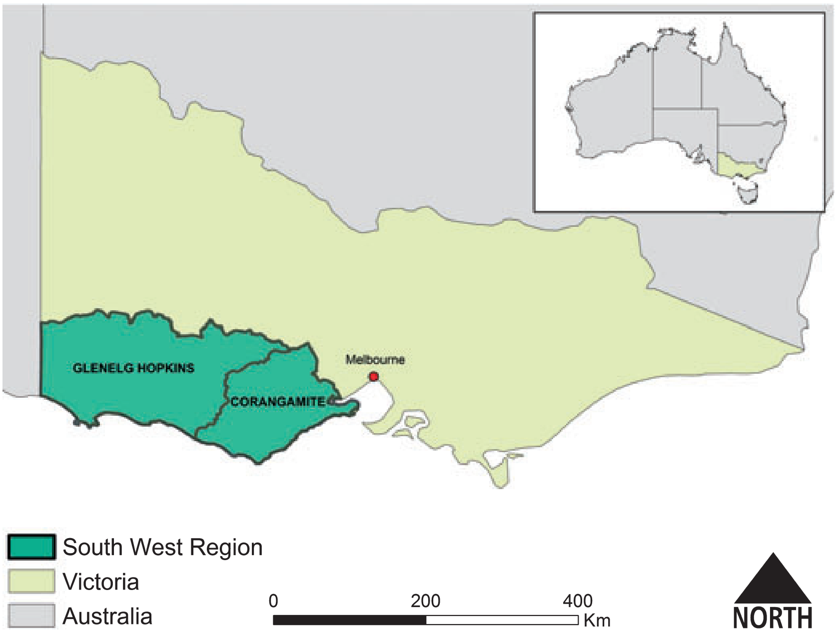

Fig. 2. The South West Region of Victoria, Australia.

In the case study, the year 2000 is taken as the base line year, whilst future climate projections for the year 2050 are those related to the SRES marker scenarios B1, A2 and A1FI (Hennessy et al. 2006; CSIRO and Bureau of Meteorology (BoM) 2007). The following sections describe the main components of the decision-making framework.

Land Suitability Analysis

MATCHING LAND USE TO REGIONAL BIOPHYSICAL CHARACTERISTICS

Land suitability can be defined as a measure of how well the qualities of a parcel of land match the requirements of a particular type of land use (FAO 1976; see also Steiner 2008). Identifying the suitable land for the growth of any agricultural commodity is a complex process. Each agricultural commodity has specific growth requirements characterised by a combination of biophysical characteristics, or factors; however, there is usually not a single combination of those factors that will produce optimal plant growth. The presence of certain factors can nevertheless compensate for the absence of others.

A semi-quantitative approach was developed by the authors to map/assess regional agricultural land suitability using a Multi-criteria Evaluation (MCE) method embedded in a Geographic Information System (GIS). MCE, also referred to as Multi-criteria Analysis (MCA), is a well-known methodology for dealing with complex decision problems where several aspects are considered simultaneously (Keeney and Raiffa 1993; Voogd 1983). Among the extensive array of MCA techniques that apply a systematic analysis, the Analytic Hierarchy Process (AHP), developed by Saaty (1994/2000, 1995), is one of the most widely used for land suitability analysis (LSA) (e.g. Collins et al. 2001; Duc Uy and Nakagoshi 2008; Hossain et al. 2006; Jankowski 1995; Thapa and Murayama 2008). In our case, the primary concern was how to combine biophysical data with expert judgement to arrive at a single land suitability index of evaluation. Biophysical data (soil, landscape and climate characteristics) are usually represented as criteria, which constitute the basis for a decision that can be measured and evaluated. Weights indicate the relative importance of the criteria in terms of their contribution to the overall evaluation index.

Expert judgement is incorporated into the process of selecting the criteria/factors to be included in the model and in assigning weights and ratings to each particular criterion. The criteria/factors are weighted by using a pair-wise comparison at each level of the hierarchy. Pair-wise comparison is a technique for capturing preferences, in which the participants compare all factors against each other but only two factors at a time. This participatory approach is a strong characteristic of the modelling adopted because expert knowledge can fill the gap of incomplete crop growth inventory and poor data quality issues. Participation of concerned stakeholders in workshops also serves to discuss likely climate change impacts on, and possible adaptation options in, their regions and economic activities.

LSA MODEL APPLICATION

The AHP method was applied to assess land suitability for eight agricultural commodities relevant to South West Victoria, given current and future climate conditions. The crops belong to three groups – grains (barley, oats and winter wheat), pasture (lucerne, phalaris and perennial ryegrass/sub-clover) and forestry (blue gum and radiata pine). An LSA model was developed for each of the eight crops using inputs from regional workshops. The conditions for plant growth of each crop and for each biophysical factor (soil, landscape and climate) were developed according to the highest productivity levels achieved in the region with common management practices. Workshop participants included growers, regional/local resource planners, and experts in agronomy, soil science, climate science and geography. The biophysical data sets (GIS layers with attached tables of attributes and ranges) utilised in the construction of the models include:

1. Soil: topsoil and subsoil textures, internal drainage, useable soil depth, depth to bedrock, depth to subsoil (B horizon), coarse fragments, pH (topsoil and subsoil), sodicity (topsoil and subsoil), Electrical Conductivity – EC (topsoil and subsoil), and concentration of organic matter categorised according to the Australian Soil Classification Order (Isbell 2002).
2. Landscape: elevation (Digital Elevation Model) and slope – direction (or aspect) and steepness.
3. Climate: temperature, rainfall, solar radiation, frost, chilling, light intensity and wind (force and direction).

As an example, Figure 3 shows the LSA model derived for perennial ryegrass/sub-clover (hereafter 'ryegrass'). At the pinnacle of the hierarchy (i.e. decision-tree) is the overall goal, which in our example is to obtain a production of 15 t/ha/year of ryegrass' dry matter (production currently being achieved in the study region). At each of the first two levels of the hierarchy, the biophysical factors considered add to 100% (or 1.00). For instance, at the first level, soil has a weight of 25% (0.25), landscape 5% (0.05) and climate 70% (0.7) reflecting the significance of climate for the growth of ryegrass. At the second level, within climate, rainfall is the most important factor with a weight of 75% (0.75). Further down the tree, for instance in the case of pH top soil (with a weight of 0.23), the various possible pH values are given ratings from the best

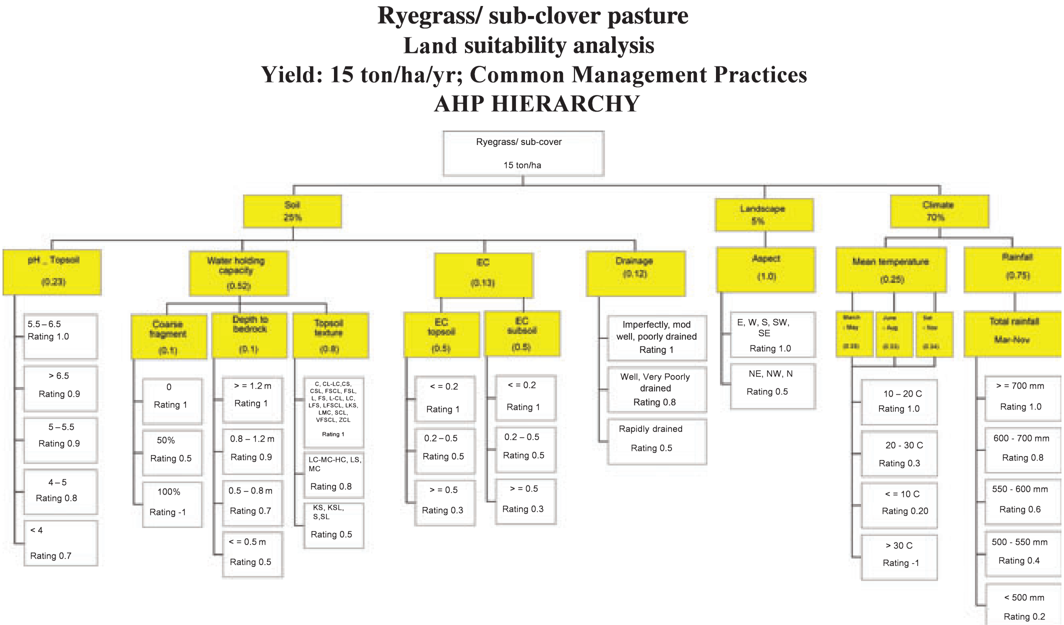

Fig. 3. The land suitability analysis model for perennial ryegrass pasture.

to the worst or limiting; thus a soil with a pH in the range of 5.5–6.5 is given the top rating of 1.00.

The LSA models were implemented using Model Builder in *ArcView* GIS (©ESRI). The input for each model is a set of maps or spatial representations of the criteria. Each map (representing a criterion) is reclassified according to the AHP rating and multiplied by the AHP weights. Then, maps are overlaid and finally summed-up according to the hierarchy level to produce a composite index map. This map ranks areas in terms of suitability for the growth of the commodity under consideration and has an index range of −1 to 10, where −1 means a site which is restricted for the plant growth and 10 represents a perfect site for the plant growth (i.e. 100% suitable). The crop productivity in a particular area can be estimated by multiplying the maximum yield defined at the pinnacle of the AHP hierarchy by the suitability index. For instance, if an area shows a suitability index equal to 8 for ryegrass, a yield of ($0.8 \times 15 =$)12 t/ha/year of dry matter is expected to be achieved in that area.

Each suitability composite map was sent for validation to the same panel of experts that developed the LSA model. If inconsistencies are perceived by any of the experts, weights and ratings in the model are adjusted and a new suitability map is generated. This validation process is repeated until every expert from the panel is satisfied with the output map. Maps were also validated by comparing the estimated yields resulting from the model application with the yields actually achieved in the region. The yields' values were obtained from agricultural censuses carried out by the Australian Bureau of Statistics. In most cases, a close correlation was found between yields estimated from the LSA maps and actual yields. It should be noted, however, that existing land uses are the result of many factors including past and current market conditions and tradition; whilst the LSA maps primary reflect biophysical conditions.

After the model is validated, land suitability under future climatic conditions can be estimated using widely diverging climate change scenarios to cover a broad range of plausible futures. The set of resultant maps illustrate where and how much land suitability is likely to alter if future climate changes occur as predicted by the SRES scenarios considered. The metrics of the models are assumed to remain constant. If a new variety of a particular crop is better adapted to the likely future climatic conditions; a new model can be developed and parameterised with new weights (based on the new data) to investigate whether the improved performance would actually occur.

LSA RESULTS AND DISCUSSION

For each agricultural commodity analysed in the study region, four land suitability index maps were prepared wherein one map is related to current suitability and three maps are related to future suitability (year 2050 for SRES scenarios B1, A2 and A1FI). As an example, Figures 4 and 5 show the ryegrass' current (year 2000) and future (year 2050 for the A1FI scenario) land suitability maps. Differences between current and future land suitability can be depicted as in Figure 6. Changes in suitability were aggregated into seven categories ranging from very high/high decrease (areas that would have a decrease in productivity varying from 60 to 100%) to very high/high increase (areas that would have an increase in productivity varying from 60 to 100%).

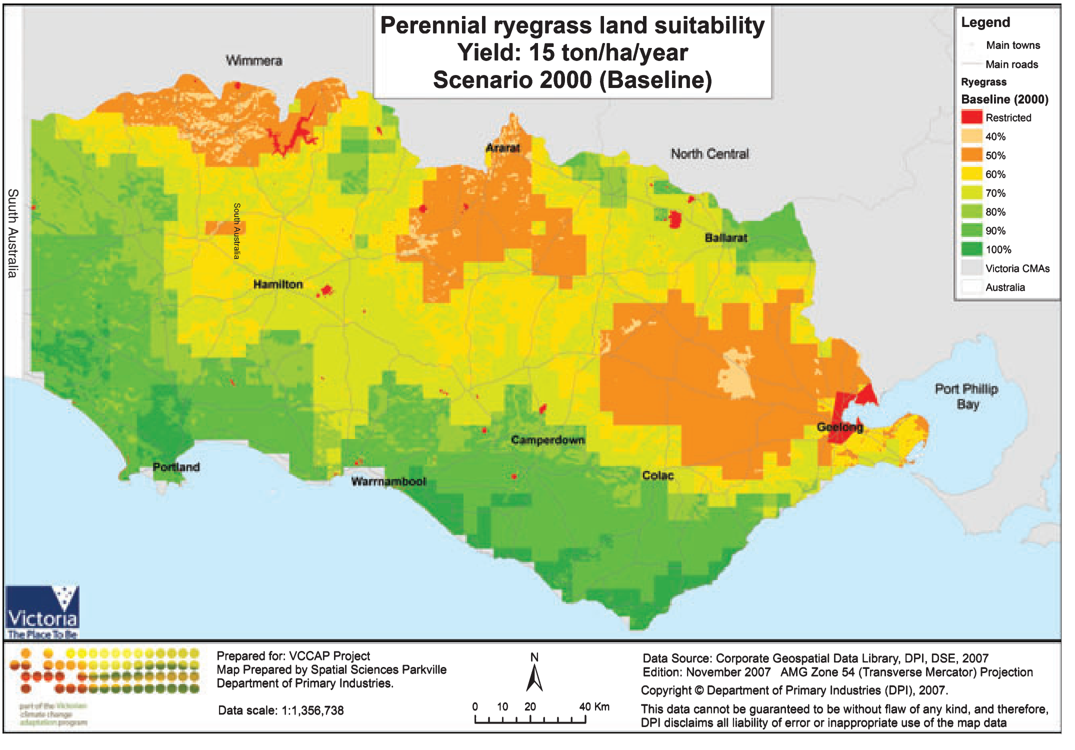

Fig. 4. Suitability of land for perennial ryegrass production, year 2000.

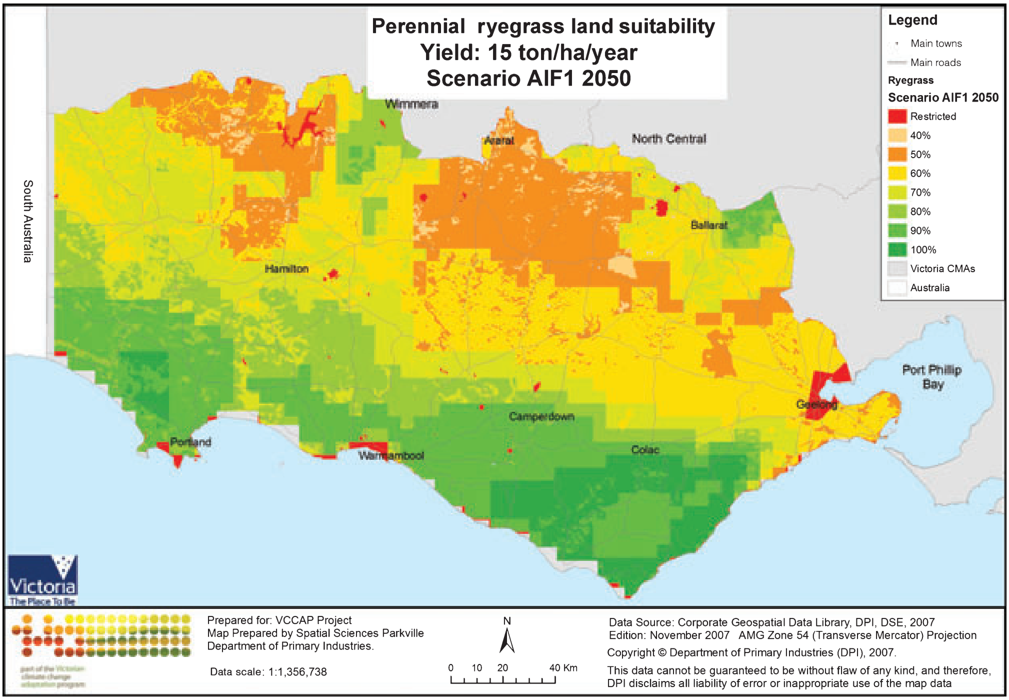

Fig. 5. Suitability of land for perennial ryegrass production, year 2050 SRES Scenario A1FI.

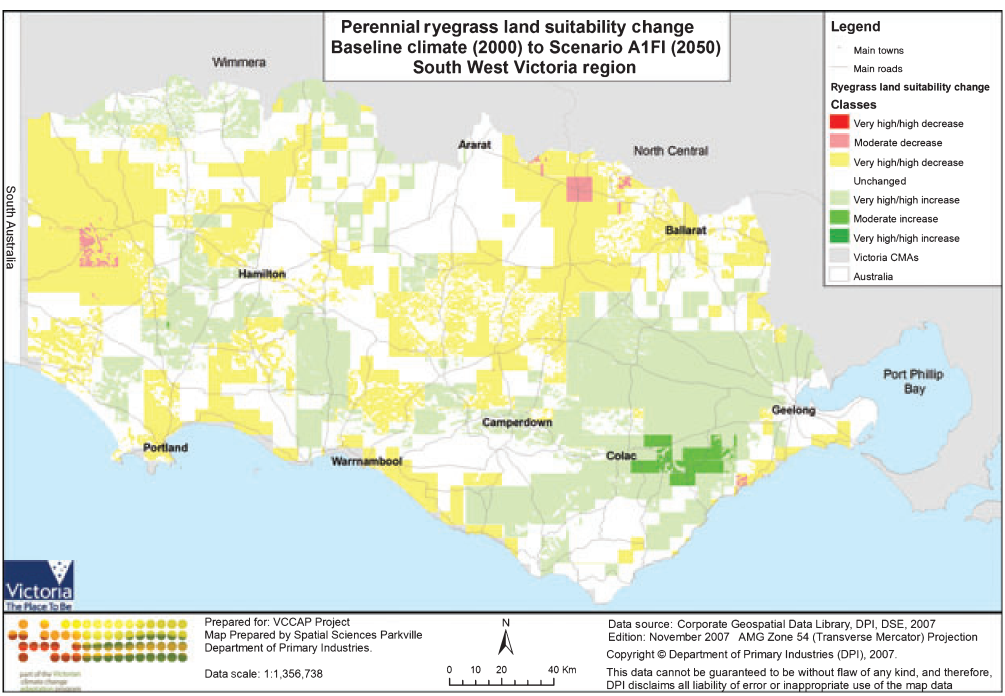

Fig. 6. Change in suitability of land for perennial ryegrass production, year 2000–2050 SRES Scenario A1FI.

Uncertainty Analysis

UNCERTAINTY IN PREDICTIONS

A problem with many deterministic models is that there is no indication of error in the predictions, which are provided as point estimates. The two primary types of uncertainty associated with modelling are referred to as 'aleatory' and 'epistemic' uncertainty (Helton and Burmaster 1996; Oberkampf et al. 2004). Aleatory uncertainty is inherent or irreducible uncertainty and is characterised by statistical variability. Epistemic uncertainty refers to reducible uncertainty and is associated with lack of knowledge (Beer 2006; Benke et al. 2007; Burgman 2005*)*. For LSA, the requirement is for some measure of uncertainty or confidence in predictions as a result of the weight assignments produced by the AHP method. The analysis of uncertainty in land suitability does not improve the allocation of crop types, either present or future, but it rather provides an indication of the error margin or confidence in the LSA prediction. This gives an indication of risk, which is necessary to balance the cost of action against the risk of prediction error. Also, uncertainty analysis reveals which model inputs have the most impact on the final prediction error. Although uncertainty is present in the LSA input data (including soil, landscape and climate data), we are particularly concerned with the effect of aleatory uncertainties arising from the weight assignments captured from the subject matter experts in regional workshops. At present, published research on uncertainty in hierarchical multi-criteria decision models is limited. Exploratory attempts have been made at analysing uncertainty in the AHP decision-making process, especially with respect to the criterion weights, but with significant computational overheads and consistency issues with the original AHP approach (e.g. Hahn 2003; Haines 1998; Jablonsky 2005). These studies provided insights into the problems faced by risk analysts in the interpretation of expert opinion from workshop sessions.

Aleatory uncertainty or variability is represented by probability distributions. As a specific method is under investigation (multi-criteria analysis using AHP), the uncertainty in this case is treated as aleatory in nature. Metrics for quantification of uncertainty from the output distribution include variance, the confidence interval and percentile data. The numerical simulation-based approach adapted for use in this study is based on recent research in uncertainty (Benke and Hamilton 2008; Benke et al. 2007, 2008). A feature of the approach taken is the serial application of Monte Carlo simulations to produce uncertainty metrics linked to predictions from a distributed spatial model. The sources of uncertainty associated with the LSA model are the weights, ratings and land suitability estimates (i.e. expert opinion, measurement data and predictions). The uncertainty characterisation is achieved by the use of Monte Carlo simulation to model variability in model output because of variability in the weights and ratings, followed by statistical representations of weight errors as a result of expert opinion. The computational aspects of Monte Carlo simulation for risk assessment and uncertainty have been documented in greater detail in specialised textbooks (e.g. Vose 2000). The method used to model uncertainty in predictions is detailed in Figure 7.

Once the weights have been assigned by a given method, the uncertainties are combined and propagated through the model. The weight values are subject to various constraints on magnitudes, bounds and the unit-sum condition for a given level in the decision tree. These constraints are used in combination with probability density functions to represent the possible errors in the numerical values of the weights. The actual ratings at the base of the tree also have associated uncertainty and can be treated in

Algorithm for uncertainty analysis

Module 1:

1.1 Convert AHP decision tree to spreadsheet form (Transpose Matrix).

Module 2: Execute single Monte Carlo simulation (MCS):

For *x* = *1* to *n* trials
Begin
- 2.1 Assign PERT distribution to weights and ratings.
- 2.2 Select weights and ratings by Latin Hypercube sampling.
- 2.3 Check constraint satisfaction for each AHP layer.
- 2.4 Apply constraint transformations if necessary.
- 2.5 Execute AHP model.

End.

Module 3: Execute MCS Series

For *y* = *1* to *m* MCS experiments
Begin
- 3.1 Increment mean values of ratings vector.
- 3.2 Repeat module 2 for new ratings vector.
- 3.3 Plot percentiles against mean of MCS output.
- 3.4 Compute standard deviations and coefficients Of variation.
- 3.5 Compute 90% confidence intervals from percentile differences.

End.

Fig. 7. Method for the determination of uncertainty metrics.

the same manner (i.e. representation of variability by probability density functions). Different climatic conditions in the future would be associated with different ratings data, which are provided by climate model predictions (e.g. for rainfall or temperature), and which in turn would change the land suitability predictions in the LSA model. The uncertainty analysis can be repeated for the LSA model associated with the new data.

UNCERTAINTY RESULTS AND DISCUSSION

Using the software package @RISK (Palisade Corporation), a series of Monte Carlo simulations were carried out on the AHP model. Sampling from input probability distributions was subject to the Latin Hypercube method, which executes stratified random sampling without replacement across the full range of each parameter (Iman and Conover 1983; McKay et al. 1979). Variability in the weights as a result of expert opinion was represented using the PERT probability distribution. Constraint satisfaction requires defined lower and upper bounds on weights and ratings, as defined by the AHP model inputs, and the unit-sum condition on weights to hold for each layer in the AHP hierarchy. As the full range of the allowed weight values in AHP model was used in the simulation, the results represent an estimate of the upper bound on uncertainty in the model predictions.

A series of Monte Carlo simulation experiments was executed, with 10,000 iterations per experiment. In each successive experiment, the mean values of the ratings (at the base of the AHP) were incremented and a new LS value (and LS distribution) was produced (see procedure in Figure 7). A plot of mean LS against the distribution metric (e.g. standard deviation) provided a calibration plot. An example of one complete simulation in this series is shown by the histogram in Figure 8. Monte Carlo simulation output distributions are sometimes skewed, although this has no effect on the estimation of the confidence interval in this study as it is based on using percentile differences from the

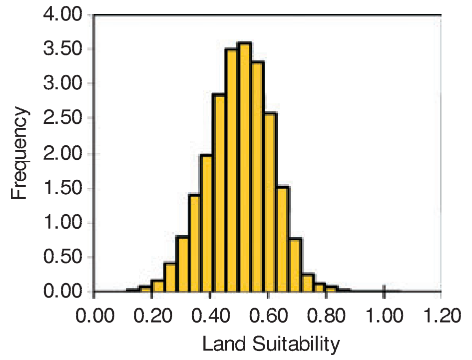

Fig. 8. Histogram of land suitability analysis model output for perennial ryegrass data, LS = 0.5.

cumulative probability distribution (Benke and Hamilton 2008). From the plot shown in Figure 8, the standard deviation and the confidence interval can be calculated for a single land suitability mean value, LS = 0.5.

Standard deviations were determined for a range of different land suitability values by executing Monte Carlo simulations, as described in the previous paragraph. Both the weightings and ratings were represented by PERT probability distributions. This process provided a set of model predictions for different levels of land suitability together with a corresponding set of probability distributions (from which the metrics of uncertainty are derived, such as the standard deviation and variance).

A graphical representation can then be used to provide a measure of the visualisation of uncertainty. Noting that the AHP is a linear weighted model with input from expert opinion, a sampling of points from a limited number of different LS levels provides sufficient information for construction of the plot of LS versus the chosen uncertainty metric. Monte Carlo simulations were used to produce separate LS distributions for plotting the percentiles, with all linear regression fits statistically significant with level of significance $\alpha = 0.01$, as confirmed by the *t*-test on all correlation coefficients ($r > 0.99$). The uncertainty metrics were then computed from the output distributions and assigned to the LS values, as shown in Figure 9. The uncertainty metrics consist of the 90% confidence interval (CI), the 20th and 80th percentiles from the cumulative distribution, the coefficient of variation (C.V.) and the standard deviation (Std. Dev.).

The uncertainty measures assigned to the various LSA model predictions can be allocated spatially by correspondence with the land-use suitability map, as shown in the example of Figure 10. In this case, uncertainty is measured as the standard deviation (Std. Dev.) in the land suitability map, where dark areas represent the highest levels of relative uncertainty (C.V.).

Optimisation of Crop Distribution

THE OPTIMISATION PROBLEM

The main objective of this module in the decision-making framework (see Figure 1) is to identify which crops should be grown at various locations across the region to optimise specified figures of merit, such as crop productivity (yield), market demand/price, revenue, environmental damage, transport costs or any combination of them. Solutions generated by any optimisation procedure should, in the real world, provide an additional

Ryegrass suitability

Legend	Prediction	90% CI	20th perc	80th perc	C.V.	Std. Dev.
	Restricted					
	0.70	± 0.22	0.59	0.81	0.18	0.13
	0.80	± 0.24	0.68	0.92	0.16	0.15
	0.90	± 0.26	0.77	1.00	0.13	0.16
	Victoria CMAs					

Uncertainty metrics

Fig. 9. Perennial ryegrass uncertainty metrics.

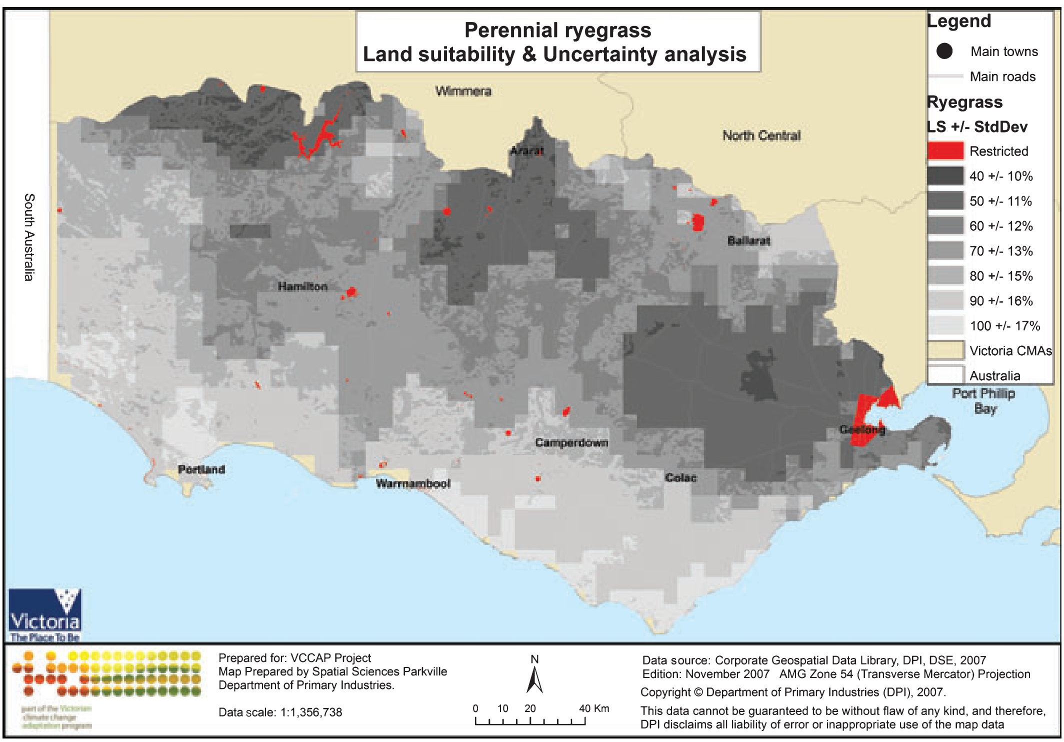

Fig. 10. Perennial ryegrass uncertainty map.

input, rather than the sole input, to the decision-making process. The generation of theoretically optimal regional patterns of crop systems adds additional capability to planning and decision-making. This can enhance the formulation of strategies for sustainable regional development and adaptation. Actions in response to an optimal spatial distribution should decrease the vulnerability of the regional/local economy to climate change due, in particular, to the inappropriate locations of particular crops.

THE CROP OPTIMISER © SOFTWARE TOOL

The spatial optimisation of a small set of agricultural commodities according to one or two factors can be reduced to a relatively well-defined problem solved by exhaustive search. This method tests each crop possibility for each particular spatial unit and chooses the best solution in terms of the higher land suitability, yield produced and/or market value. As the optimisation problem increases in complexity, with multiple factors and the likely inclusion of non-linear objective functions and constraints, the number of possibilities is too vast to easily find an optimal solution. This has encouraged the authors of this article to experiment with various optimisation approaches to address this problem, including the use of a genetic algorithm and stochastic procedures, through the development of a *Crop Optimizer* © Program.

The *Crop Otimizer* © Program enables a user to input text files which show the size of the spatial unit (grid cell) in the regional analysis along with, for each cell, a number indicating the land suitability (0–9) for each crop in that cell. It then uses these numbers, combining them with values for crop prices, yields, transport costs, environmental damage, etc. and so eventually determines the optimal spatial spread of the crops across the grid cells. Such an optimal distribution can be compared with a cell-based map of the currently grown crops to obtain guidance on the changes that would be required to move the existing cropping system towards an optimal pattern. Users can also explore the effects of changing the market prices and/or the yields of different crops to see how this affects the optimal pattern.

A screen dump of the program for the optimisation of the selected eight crops in Victoria's South West Region is shown in Figure 11. The program records the user choices and dynamically shows how the crop-distribution pattern changes into an optimal pattern. Once the crops' pattern has achieved optimality, the screen shows a measure of the quality of the optimal solution along with the total number of hectares under each type of crop.

For example, the screen shows that the user has chosen to optimise on the basis of current land suitability values and revenue. The structure of the objective function utilised is displayed at the top of the graph in the bottom right corner {Quality = *F*(Land Suitability, Yield, Price)}. The user also chose to work at a medium-scale resolution (i.e. 5-km grid cells, which is the same resolution as the regionally downscaled climate projections), to consider all eight crop types (as indicated by the check circles in each crop type) and to use the probabilistic search method. Moreover, the user has chosen to allow more than one crop to be grown in each grid cell, and to let the program run for 79 iterations. This prompted a flurry of changing maps in the bottom left corner until the optimal one, as shown in Figure 10, emerged after about 50 iterations. The algorithm's increases, in terms of the quality of its successive best solutions, are shown in the graph on the bottom right; whilst the score for the optimal pattern is written in red totalling $1296 billion. The total number of hectares that would be cultivated under each crop to generate such revenue is depicted by the red numbers at the top of the screen.

It is also possible to optimise on the basis of a number of other variables and combinations of them. For instance, the user could have clicked only on land suitability at the top left of the screen. This would have generated a pattern which maximises the 'crop area times land suitability of the hectares used' products. That is, the crop(s) grown in any cell would be those whose land suitability is highest, and the solution's quality would be expressed in terms of 'area times suitability' units.

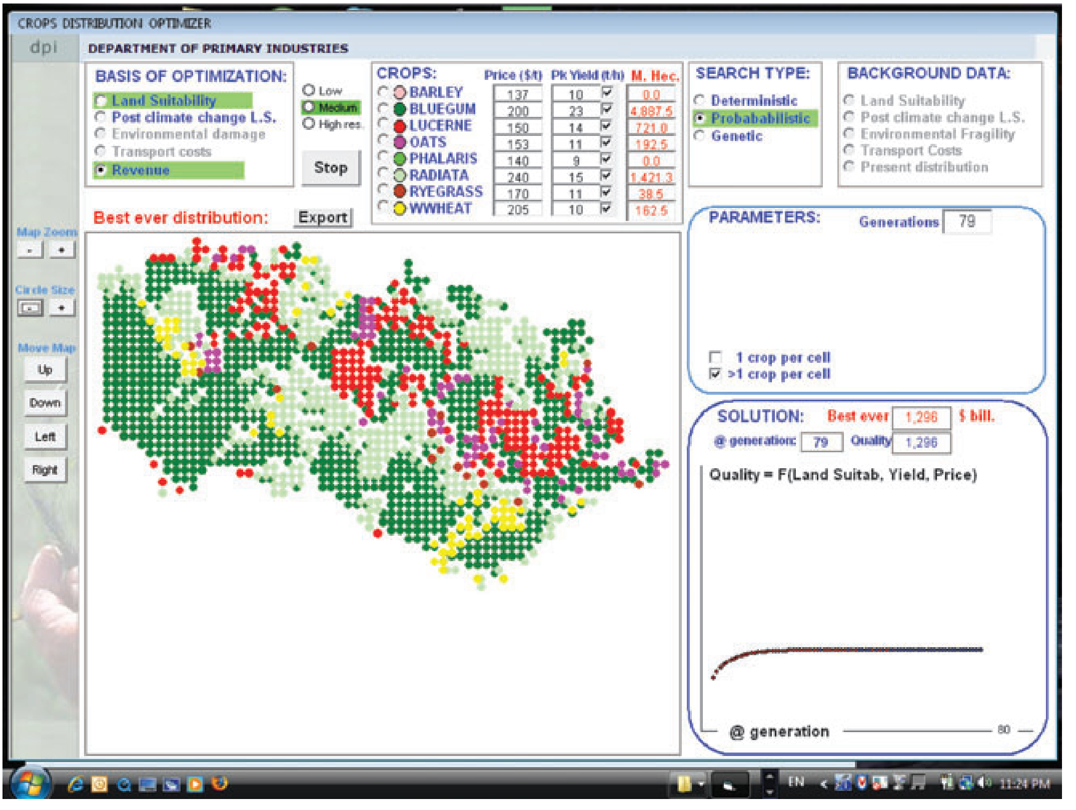

Fig. 11. Screen dump of the *Crop Optimizer* © Program.

Because solution patterns are very sensitive to small changes in prices, yields or other factors, an extensive exploration of the initial assumptions and their subsequent impact on what is eventually generated to be the optimal pattern can be fully explored.

DETERMINATION OF OPTIMAL ALLOCATIONS – SEARCH METHODS

The objective functions in the *Crop Optimizer* © Program enable three types of search methods. First, the optimum pattern can be found 'deterministically', i.e. each cell is simply populated with that crop(s) which scores the highest for the objective function. Second, the optimum can be found 'probabilistically'. In this case, a pattern is generated randomly; the second iteration generates alternative crops in the zone and, if the second iteration's crop in that cell is superior to the first iteration's crop, by improving the figure of merit, then that cell's crop(s) are updated – otherwise the first iteration's crop is retained. More iterations then repeat this process; in this way, the algorithm progressively moves towards the global optimum.

The third search method uses a 'genetic algorithm approach' (Wyatt 2008) and current work is focused on improving the performance of this mechanism. When this is achieved, a user-friendly, generic model will be available to optimise the distribution of any number of crops across any region. As such, it will become a valuable decision-aiding tool for assisting planners and policy makers. In particular, the software will enable users to toggle between the map of the optimal crop pattern and various other maps showing inputs, such as land suitability levels for the different crops in the zones and even a map of crop types that are being currently grown within the cells. Comparison of the optimal pattern with current practice is likely to be most instructive. Therefore, in addition to finding optimal patterns, the *Crop Optimizer* © Program is also a powerful exploratory tool for asking 'what-if' questions about possible future trends in commodity prices and other relevant factors. It would then provide an informative, decision-support instrument for boosting user insights into the opportunities in the region of interest in plausible future (climate change) conditions.

Preliminary comparison of the search methods has been made and is the subject of a forthcoming publication. Some noteworthy results are that (i) deterministic search, by exhaustive testing, is only feasible for small problems with low computational cost per function evaluation, (ii) genetic algorithms are suitable for future scaling-up and for more complex non-linear objective functions with higher computational cost, and (iii) probabilistic search is less affected by either of the two previous methods with scaling-up the size of the problem and is more likely to find a global optimum – but, most importantly, it allows for the future incorporation of uncertainty analysis because of its statistical nature.

Adaptation Policy Options

A variety of adaptation options are available and have been proposed as having the potential to increase the resilience of agricultural (including forestry) systems to climate change risks – see, for instance, the typology developed by Smit and Skinner (2002). Agricultural adaptation options can be grouped according to four broad categories not necessarily mutually exclusive: (i) technological developments (Easterling 1996; Smithers and Blay-Palmer 2001; Sposito et al. 2009), (ii) government programs (Turvey 2001), (iii), production practices (Easterling 1996; Webb et al. 2007) and (iv) governance arrangements (Australian Government, Australian Public Service Commission (APSC) 2007, Foote et al. 2007; Ison forthcoming). The framework can then be used to asses those that are reflected, particularly in changes in land uses. Given the iterative nature of the framework (see Figure 1), possible adaptation options can be fed into the construction of new (or modification of existing) suitability models to start the assessment anew.

Conclusion

The decision-making framework for climate change impacts and adaptation in agricultural systems and rural production has three salient features. First, it can be used to identify areas under threat of productivity decline or areas requiring further assessment (e.g. areas subject to considerable uncertainty in future land suitability). Second, it can be used to identify alternative agricultural commodities more suitable for production under future climate conditions. Third, it can be used to investigate adaptation options to improve complex or 'wicked' situations created by climate change, both current and in the future. This information can subsequently be used in the formulation of a regional adaptation strategy capitalising on potential opportunities, whilst reducing the negative effects of a changing climate.

Future research work is aimed at evolving the framework into a Spatial Decision Support System (SDSS) for enhancing sustainable regional development, of which an adaptation strategy would be a major component. The SDSS would assist in bridging the gap between scientific knowledge and pragmatic policy formulation. A SDSS can potentially accomplish this by adding an analytic process and providing consistency and transparency in the policy and decision-making process. The proposed SDSS would provide practitioners with a suite of tools to analyse the problem and associated issues, by systems modelling and 'what-if' analysis, and advance solutions for sustained improvements (Sposito et al. 2009).

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Short Biographies

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Kurt Benke was awarded a PhD in Mathematics and Computer Science from Deakin University, and MSc and BSc degrees in Physics from the University of Melbourne. Australia. He also received a postgraduate Diploma in Applied Statistics from RMIT. Employed originally as a physicist at the Kodak Research Laboratory in Australia, he carried out theoretical and experimental research in image science and optical physics, X-ray physics and electromagnetic scattering. His subsequent research career covered the public and private sectors, mainly in the Defence Department and Aerospace industry, where he undertook research in human and computer vision, signal processing, artificial intelligence and mathematical optimisation. He is an assessor of grant applications for the Australian Research Council (ARC) and invited examiner for MSc and PhD degrees in Physics and Computer Science. He is currently with the Department of Primary Industries (DPI) engaged in research in systems modelling, risk assessment and uncertainty analysis of complex large-scale natural systems.

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Ray Wyatt holds degrees from three universities, including a PhD (Urban Planning) from Reading University, UK, and a BA (Honours. Geography) from Queensland University, Australia. He was formerly Associate Professor at Melbourne University, after working as a strategic planner in both public and private enterprises before becoming an academic. He has taught in five countries, consulted and published in the fields of decision aiding, applied artificial intelligence, urban planning, transportation, graphic communication and professional practice. He has authored or co-authored numerous refereed articles, presented conference papers, written many consultant reports, programmed major software packages and given invited addresses around the world. Wyatt was a joint founding editor of two refereed journals and has served on the editorial boards of various journals. He is the Chair, International Board of Directors, for the *CUPUM* series of conferences and has written three single-authored books: *Intelligent Planning* (1989, London, Unwin Hyman), *Computer-aided Policymaking* (1999, London, Routledge), and *Preference Prediction* (forthcoming).

Note

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References

ABARE (2007). Statistical tables. *Australian Commodities* 14 (3), pp. 541–577.

Australian Government, Australian Public Service Commission (APSC) (2007). *Tackling wicked problems – a public policy perspective*. Canberra: APSC.

Bankes, S. (1993). Exploratory modelling for policy analysis. *Operations Research* 41, pp. 435–449.

Beer, T. (2006). Ecological risk assessment and quantitative consequence analysis. *Human and Ecological Risk Assessment* 14, pp. 51–65.

Benke, K. K. and Hamilton, A. J. (2008). Quantitative microbial risk assessment: uncertainty and measures of central tendency for skewed distributions. *Stochastic Environmental Research and Risk Assessment* 22, pp. 533–539.

Benke, K. K., Hamilton, A. J. and Lowell, K. E. (2007). Uncertainty analysis and risk assessment in the management of environmental resources. *Australasian Journal of Environmental Management* 14, pp. 16–22.

Benke, K. K., Lowell, K. E. and Hamilton, A. J. (2008). Parameter uncertainty, sensitivity analysis and prediction error in a water-balance hydrological model. *Mathematical and Computer Modelling* 47, pp. 1134–1149.

Burgman, M. (2005). *Risk and decisions for conservation and environmental management*. Cambridge, UK: Cambridge University Press.

Christensen, J. H., et al. (2007). Regional climate projections. In: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M. and Miller, H. L., (eds) *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge: Cambridge University Press, pp. 847–940.

Cline, W. (2007). *Global warming and agriculture: impact estimates by country*. Washington, DC: Centre for Global Development and Peterson Institute for International Economics.

Collins, M. G., Steiner, F. R. and Rushman, M. J. (2001). Land-use suitability analysis in the United States: historical development and promising technological achievements. *Environmental Management* 28 (5), pp. 611–621.

Crimp, S. J., et al. (2002). *Evaluation of the potential impact of climate change on native pasture production – implications for livestock carrying capacity*. A report to the Australian Greenhouse Office (AGO), Canberra: AGO.

CSIRO and Bureau of Meteorology (BoM) (2007). *Climate change in Australia – technical report 2007*. Canberra: CSIRO and BoM. [Online]. http://www.climatechangeinaustralia.gov.au

Duc Uy, P. and Nakagoshi, N. (2008). Application of land suitability analysis and landscape ecology to urban greenspace planning in Hanoi, Vietnam. *Urban Forestry and Urban Greening* 7, pp. 25–40.

Easterling, W. E. (1996). Adapting North American agriculture to climate change in review. *Agriculture and Forestry Meteorology*, 80, pp. 1–54.

FAO (1976). *A framework for land evaluation*. Soils Bulletin 22. Rome: Food and Agricultural Organisation (FAO).

Foote, J. L., et al. (2007). Systemic problem structuring applied to community involvement in water conservation. *Journal of the Operational Research Society* 58, pp. 645–654.

Goklany, I. M. (2005). A climate policy for the short and medium term: stabilization or adaptation? *Energy Environment* 16, pp. 667–680.

Gunasekera, D., Kim, Y., Tulloh, C. and Ford, M. (2007). Climate change: impacts on Australia agriculture. *Australian Commodities* 14 (4), pp. 657–676.

Gunasekera, D., Tulloh, C., Ford, M. and Heyhoe, E. (2008). Climate change: opportunities and challenges in Australian agriculture. In: *Proceedings of the faculty of agriculture, food and natural resources annual symposium (FAFNR 08)*, University of Sydney, 13th June.

Hahn, E. D. (2003). Decision making with uncertain judgements: a stochastic formulation of the analytic hierarchy process. *Decision Sciences* 34, pp. 443–466.

Haines, L. M. (1998). A statistical approach to the analytic hierarchy process with interval judgements. Distributions on feasible regions. *European Journal of Operational Research* 110, pp. 112–125.

Helton, J. C. and Burmaster, D. E. (1996). Guest editorial: treatment of aleatory and epistemic uncertainty in performance assessments for complex systems. *Reliability Engineering and System Safety* 54, pp. 91–94.

Hennessy, K., Page, C., Durack, P. and Bathols, J. (2006). *Climate change projections for Victoria*. Prepared for the Victorian Department of Primary Industries, Melbourne: CSIRO Marine and Atmospheric Research.

Heyhoe, E., et al. (2007). Adapting to climate change. *Australian Commodities* 14 (3), pp. 167–178.

Hossain, H., Sposito, V. and Evans, C. (2006). Sustainable land resource assessment in regional and urban systems. *Applied GIS* 2 (3), pp. 24.1–24.21.

Iman, R. L. and Conover, W. J. (1983). *A modern approach to statistics*. New York: Wiley.

IPCC (2007a). *Climate change 2007: synthesis report. An assessment of the intergovernmental panel on climate change based on a draft prepared by Bernstein, L., Bosch, P., Canziani, O. et al.*. Cambridge, UK: Cambridge University Press. [Online]. http://www.ipcc.ch

IPCC (2007b). In: Metz, B., Davidson, O. R., Bosch, P. R., Dave, R. and Meyer, L. A. (eds) *Climate change 2007: mitigation. contribution of working group III to the fourth assessment report of the intergovernmental panel on climate change*. Cambridge, UK: Cambridge University Press. [Online]. www.ipcc.ch

IPCC (2007c). In: Parry, M. L., Canziani, O. F., Palutikof, J. P., van der Linden, P. J. and Hanson, C. E. (eds) *Climate change 2007: impacts, adaptation and vulnerability. contribution of working group II to the fourth assessment report of the intergovernmental panel on climate change*. Cambridge, UK: Cambridge University Press. [Online]. www.ipcc.ch

IPPC (2007d). In: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M. and Miller, L. H. (eds) *Climate change 2007: the physical science basis. contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change*. Cambridge, UK: Cambridge University Press. [Online]. www.ipcc.ch

Isbell, R. F. (2002). *Australian soil classification*, 2nd edn. Melbourne: CSIRO Publishing.

Ison, R. (forthcoming). *System practice: how to act in a climate-change world*. Milton Keynes, UK: The Open University.

Jablonsky, J. (2005). *Measuring efficiency of production units by AHP models*. Honolulu: ISAHP.

Jankowski, P. (1995). Integrating geographical information systems and multiple criteria decision making methods. *International Journal of Geographic Information Systems* 3 (2), pp. 251–273.

Keeney, R. and Raiffa, H. (eds) (1993). *Decision with multiple objectives: preferences and value trade-offs*. Cambridge: Cambridge University Press.

Klein, R. J. T., et al. (2007). Inter-relationships between adaptation and mitigation. In: Parry, M. L., Canziani, O. F., Palutikof, J. P., van der Linden, P. J. and Hanson, C. E.(eds), *Climate change 2007: impacts, adaptation and vulnerability, contribution of working group II to the fourth assessment report of the intergovernmental panel on climate change*. Cambridge, UK: Cambridge University Press, pp. 745–777.

Lempert, R. J. and Schlesinger, M. E. (2000). Robust strategies for abating climate change. *Climatic Change* 45, pp. 387–401.

Lempert, R. J., Groves, D. G., Popper, S. W. and Bankes, S. C. (2006). A general analytic method for generating robust strategies and narrative scenarios. *Management Science* 52, pp. 514–528.

McKay, M. D., Conover, W. J. and Beckman, R. J. (1979). A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. *Technometrics* 21, pp. 239–245.

Meehl, G., et al. (2007). Global climate projections. In: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M. and Miller, H. L. (eds) *Climate change 2007: the physical science basis, contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change*. Cambridge, UK: Cambridge University Press, pp. 747–846.

Millennium Ecosystem Assessment (MEA) (2005). Reid, W. W., et al. (eds) *Ecosystems and human well-being – synthesis, a report to the MEA*. Washington, DC: Island Press.

MOHC. (2007). *Climate research at the Met Office Hadley Centre: informing Government policy into the future*. Exeter: Met Office Hadley Centre.

Nakicenovic, N. and Swart, R. (eds) (2000). *IPCC special report emissions scenarios*. A Special Report of the Intergovernmental Panel on Climate Change (IPCC). Cambridge, UK: Cambridge University Press.

Oberkampf, W. L., et al. (2004). Challenge problems: uncertainty in systems response given uncertain parameters. *Reliability Engineering and Safety* 83, pp. 11–19.

Pittock, A. B. (2005). *Climate change – turning up the heat*. Melbourne: Earthscan, CSIRO Publishing.

Preston, B. L. and Jones, R. N. (2007). *Climate change impacts on australia and the benefits of early action to reduce global greenhouse gas emissions. a consultancy report for the australian business roundtable on climate change*. Canberra: CSIRO. [Online].http://www.csiro.au/files/files/p6fy.pdf)y

Regan, H. M., et al. (2005). Robust decision-making under severe uncertainty for conservation management. *Ecological Applications* 15, pp. 1471–1477.

Rittel, H. W. and Webber, M. M. (1973). Dilemmas in a general theory of planning. *Policy Sciences* 4 (2), pp. 155–169.

Ruth, M., Donaghy, K. and Kirshen, P. (2006). *Regional climate change and variability: impacts and responses*. Edward Elgar: Cheltenham, UK.

Saaty, T. L. (1994/2000). *Fundamentals of decision making and priority theory with the analytic hierarchy process*. Pittsburgh: RWS Publications.

Saaty, T. L. (1995). *Decision making for leaders: the analytic hierarchy process for decisions in a complex world*. Pittsburgh: RWS Publications.

Smit, B. and Skinner, M. W. (2002). Adaptation options in agriculture to climate change: a typology. *Mitigation and Adaptation Strategies for Global Change* 7, pp. 85–114.

Smithers, J. A. and Blay-Palmer, A. (2001). Technology innovation as strategy for climate change adaptation in agriculture. *Applied Geography* 21 (2), pp. 175–197.

Sposito, V., et al. (2008). *Climate change impacts on agriculture and forestry systems in south west Victoria, Australia*. Melbourne: Department of Primary Industries.

Sposito, V., Aurambout, J.-P., Raybould, L. and Pettit, C. (2009). *Planning support system for natural resources management in the south west region of Victoria, Australia*. Melbourne: Department of Primary Industries.

Steiner, F. (2008). *The living landscape – an ecological approach to landscape planning*, 2nd edn. Washington, DC: Island Press.

Thapa, R. B. and Murayama, Y. (2008). Land evaluation for peri-urban agriculture using analytical hierarchical process and geographic information system techniques: a case study of Hanoi. *Land Use Policy* 25 (2), pp. 225–239.

Turvey, C. G. (2001). Weather derivatives for specific event risks in agriculture. *Review of Agriculture Economics* 23 (2), pp. 333–351.

United Nations General Assembly (1992). *United Nations framework convention on climate change*. New York: United Nations.

Voogd, H. (1983). *Multicriteria evaluation for urban and regional planning*. London: Pion.

Vose, D. (2000). *Risk analysis*. Chichester: John Wiley & Sons.

Webb, L., Hennessy, K. and Whetton, P. H. (2007). Horticulture. In: Stokes, C.J. and Howden, S.M. (eds.) *Climate change adaptation in australian primary industries*. Canberra: CSIRO Publishing, pp. 181–206.

World Meteorological Organization – WMO (2008). *Future climate research and observations: GCOS, WCRP and IGBP learning from the IPCC fourth assessment report*. GCOS-117, WCRP-127, IGBP Report No, 58, WMO/TD No. 1418, London: WMO.

Wyatt, R. (2008).Optimisation of the regional distribution of agricultural production – a genetic algorithm prototype. In: Sposito, V., Pelizaro, C., Benke, K., Anwar, M., Rees, D., Elsley, M., O'Leary, G., Wyatt, R. and Cullen, B.. *Climate change impacts on agriculture and forestry systems in south west Victoria, Australia*. Melbourne: Department of Primary Industries, pp. 156–171.