Environmental Modelling & Software xxx (2012) 1–11

Contents lists available at SciVerse ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

# Spatial model steering, an exploratory approach to uncertainty awareness in land use allocation

Marcos Nino-Ruiz [a,*], Ian Bishop [a], Christopher Pettit [b]

[a] *CRC for Spatial Information, The University of Melbourne, Parkville, VIC 3010, Australia*
[b] *Faculty of Architecture, Building and Planning, The University of Melbourne, VIC 3010, Australia*

A R T I C L E I N F O

*Article history:*
Received 1 May 2011
Received in revised form
18 May 2012
Accepted 14 June 2012
Available online xxx

*Keywords:*
Spatial model steering
Land use allocation
Spatial decision support system
Service oriented architecture
Uncertainty awareness

A B S T R A C T

One evidenced based approach for exploring future agricultural land use change scenarios is Land Use Allocation (LUA). This approach can be used to support medium to long term strategic planning. Specifically, land managers can consider a number of diverse environmental social, economic and physical factors, and explore land use allocation scenarios before choosing to produce one or more commodities in a given region. One of the most successful ways to implement a LUA approach is through the integration of geoprocessing with Multi-Criteria Decision Making methods (MCDM). Leveraging this spatial MCDM modeling approach with the Service Oriented Architecture (SOA) paradigm, we have developed a Spatial Model Steering (SMS) framework that enables users to explore the decision space and thus increase their awareness of the influence of key variables. In this framework a user can visually steer the LUA model key factors, explore and compare "what if" future land use scenarios by changing these factors and visualizing a range of potential LUA outcomes. In doing so, we believe that users can develop increased confidence in their understanding of the key factors governing the underlying models and ultimately obtain greater awareness of the uncertainty in the outcomes.



## Software availability

Name of software: CCVIZ spatial model steering framework
Developers: Cooperative Research Centre for Spatial Information
Contact address: Room 308, Level 3, Doug McDonell Bldg., The University of Melbourne, VIC 3010, Australia
Hardware required: None
Software required: Internet browser. Some capabilities available only if Google Earth free plug-in is installed
Program language: Java (server) and client script technologies (JavaScript, XML, XHTML, etc.)
Availability and cost: This framework is accessible at: http://geotest.eresearch.unimelb.edu.au/. Nonetheless, it remains accessible only to project partners although user accounts can be made available to researchers upon request to the authors and subject to a licensing agreement.

## 1. Introduction

Today's global environmental issues of complex and interrelated phenomena such as population growth, water shortage and climate change, demand our serious attention. The impacts of such changes on global food security and agriculture are likely to be substantial (Brown and Funk, 2008). Furthermore, agricultural adaptation to such challenges will likely include a re-allocation of land use, food production changes, re-engineering of agricultural infrastructure, such as irrigation, and crop type adjustment (Lobell et al., 2008). Only by exploring the implications of integrating global agricultural systems, energy systems and carbon price schemes, can a comprehensive understanding of the profound implications of climate change for agriculture and global food security be achieved. This is particularly relevant to Australia, since it is projected to be one the countries most affected, especially in the agricultural sector, by these global changes (Cline, 2007; Gunasekera et al., 2008). One evidenced based approach for exploring future agricultural land use change scenarios is Land Use Allocation (LUA) (Chen et al., 2010; Santé-Riveira, 2008). LUA can be broadly defined as the medium to long-term strategic planning process by which land managers consider diverse environmental, social, economic and physical factors, before choosing to produce one or more commodities in a given region. This process is often one of the first

* Corresponding author. Tel.: +61 3 93573700; fax: +61 3 93495185.
*E-mail address:* marcosnr@unimelb.edu.au (M. Nino-Ruiz).

1364-8152/$ – see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.envsoft.2012.06.009

steps taken by these stakeholders to understand and assess both their land's current and medium term suitability and its cumulative long-term effects. These processes thus may contribute to an overall assessment of the regional impact on biodiversity, land productivity due to soil quality, as well as land and water management. In addition to regional planners and policy makers themselves, industry groups, land managers and community leaders are also keenly interested in land allocation decisions and their long-term implications. Hence these stakeholders may wish to model and understand the allocation options and likely outcomes (Chen et al., 2010), thus facilitating their response to specific parameters such as climate projections (Sposito, 2010) market prices (Benke et al., 2011) and carbon emission pricing schemes (Wise, 2009). Among the technologies to assist in such landscape analysis for understanding and assisting land use allocation, geographical information systems (GIS) have been particularly valuable for undertaking spatial analysis, including geoprocessing of multiple spatial data layers (Fiorese and Guariso, 2010; McNeill, 2006; Ménard, 2007; Uy, 2008).

However, LUA solutions are often based on applications built upon frameworks (such as GIS) and are tailor-made for a particular purpose (delimited area, crop type, etc.). They provide limited scope for supporting collaboration through linkage of expert models and a wider sharing of modeling results (Kassahun et al., 2010; Li, 2007; Sànchez-Marrè et al., 2008). To address this issue, current scientific research is actively developing "e-science" frameworks (De Roure et al., 2003; Riedel, 2009; Simmhan, 2005). These frameworks share resources and enhance distributed simulation, analysis and visualization. Many of these e-science infrastructures use one or more distributed software paradigm in order to support collaborative research (Hutanu, 2006). In particular, many organizations leverage distributed computer technologies based on the Service Oriented Architecture (SOA) paradigm (Alameh, 2003; Granell et al., 2010; Riedel, 2008). SOA is based on loosely coupled modules that offer services through standard communication protocols, while maintaining a layered architecture that organizes and orchestrates functionality among the modules. This approach supports a natural evolution of modular components, which in turn supports distributed governance and responsibilities, of utmost importance in a collaborative framework (Riedel, 2008; Salter, 2009).

Nonetheless, in order to benefit from SOA in supporting environmental assessments like LUA, we need to establish their adaptability through Environmental Integrated Modeling Frameworks, (EIMFs) (Denzer, 2005; Kassahun et al., 2010; Rizzoli et al., 2008). An essential aspect of these EIMFs is the need to take into account that there are inherent limitations to our ability to predict future environmental conditions. This is due to the fact that all complex models are imperfect and maintain a degree of uncertainty, especially when projecting a future outcome. As we look further into the future the degree of uncertainty increases (Granell et al., 2010). One useful taxonomy for analyzing this uncertainty is the following (Refsgaard et al., 2007):

- *Bounded uncertainty*: an uncertain event is composed of individual outcomes that are "known" or its range and possible values can be assessed quantitatively.
- *Unbounded uncertainty*: some components of uncertain events cannot be quantified in any undisputed way, but they still can be qualified in terms of plausibility or convincingness of the evidence.

The bounded uncertainty is often referred as "statistical uncertainty" (Walker, 2003) and is the type of uncertainty traditionally addressed when assessing complex environmental models (Pahl-Wostl, 2007; Refsgaard et al., 2007). This research focuses on a subset of unbounded, implicit uncertainty understood as an awareness of uncertainty generated by exposure to the full range of plausible outcomes, namely stakeholders' awareness of key factors, involvement and self-perceived confidence when taking decisions under an EIMF. Moreover, when a loose-coupling architecture based on frameworks like EIMF is enabled, it allows for better comprehension of the roles of input variables at different levels and hence the many sources of uncertainty (Brugnach et al., 2008; Mysiak et al., 2005). On the one hand, this is deemed relevant because statistical uncertainty was the main focus of uncertainty assessment in the case study of Pelizaro et al. (2010), thus this research will complement and build upon that study. On the other hand, and even more important, because this implicit, unbounded uncertainty assessment is often left out or not properly taken into account when assessing the overall performance of EIMF's (Pahl-Wostl, 2007; Refsgaard et al., 2007). Equally important, this also encourages the evolution of EIMFs by facilitating the integration, reuse and sharing of model resources (Rizzoli et al., 2008). By understanding land allocation as a complex process, by accounting the uncertainty of factors in the model, and framing the allocation criteria within the constraints presented by the climate change forecasts, a good quality outcome can be obtained.

Furthermore, to consider the impacts of all alternatives derived within this multidimensional decision space, and especially to obtain expert driven, alternative scenarios, a Multi-Criteria Decision Making method (MCDM) combined with a GIS framework provides a useful strategy to cope with this challenge (Chen et al., 2010; Jankowski, 1995; Wang et al., 2010). One of the most used methodologies for combining MCDM with land use process is the Analytic Hierarchy Process (AHP) (Saaty and Vargas, 2001). AHP combines biophysical data using expert opinion in order to arrive at a single land suitability index. This initially involves development of a hierarchy of factors affected the suitability of land for different purposes. Experts are then asked to assess the relative importance to suitability of different factors at the same level of the hierarchy. The relative importance assessments are combined mathematically to produce a weight, which is applied to each normalised factor rating to generate an overall suitability index. A LUA process can then use these suitability assessments, in a variety of MCDM ways, to propose land allocations.

With all of these elements in mind, our objective was to gain insight into a complex environmental assessment process by implementing a Spatial Model Steering (SMS) approach. With SMS a user can visually steer key factors in the LUA model, then explore and compare "what if" scenarios by changing these factors and visualizing the corresponding outcomes. The SOA based spatial MCDM/AHP approach to LUA provided an ideal test environment and we sought to create a framework, which supported SMS and gave users flexibility in exploration of the decision space and confidence in their assessments. We suggest that this provides greater awareness of both factor influence and uncertainty than is possible through conventional approaches in which a process must be re-run in order to explore different assumptions, test plausible ranges of coefficients or find outcomes which meet objectives. This paper focuses on the framework development. A comparison between an SMS approach and a more conventional map based communication of LUA results in the context of climate change will be the subject of another paper.

However, the testing process was built into the framework and that is also reported here. At key moments in the steering process the users were presented with an online mini survey to assess their level of confidence in the scenarios and the uncertainties which emerged from the analysis. At all times, user interactions are logged for further analysis, of both the overall session performance and the

Please cite this article in press as: Nino-Ruiz, M., et al., Spatial model steering, an exploratory approach to uncertainty awareness in land use allocation, Environmental Modelling & Software (2012), http://dx.doi.org/10.1016/j.envsoft.2012.06.009

factor and uncertainty awareness of the user. This data can be used to assess the overall performance of the tool.

## 2. Background

Approaches based on complex adaptive systems have made substantial contributions to the analysis of climate change impact, and have been widely used in the exploration of predicted change in land and natural resource management (Hossain, 2006; Kumar et al., 2006; Lee, 2008; Ménard, 2007).

Frameworks that used web services as the communication protocol to control environmental simulations have been implemented successfully (Goodall et al., 2008; Pullen, 2005; Wainer, 2008). These frameworks provided simulations with real-time capabilities, as well as flexibility and extensibility. The same services technology has been widely applied in designing distributed virtual environments for geospatial data (Huang, 2003). The Commonwealth Scientific and Industrial Organization's (CSIRO) Solid Earth and Environment Grid also aims to address the issue of resources availability through the Open Geospatial Consortium (OGC) Web Services architecture (OGC 2006), thus facilitating the management of Australia's natural and mineral resources. The Earth system grid (Williams, 2009), not only enables grid sharing of analysis and climate modeling, but also real time distributed visualization of simulation output (Yang et al., 2008).

In addition, the scientific community has identified a need to address the lack of accessibility and interoperability of environmental models (Filippi and Bisgambiglia, 2004; Granell et al., 2010; Papajorgji et al., 2004). This challenge requires frameworks that emphasize reusability and modularity in their components, enhancing integration and connectivity. A reusable framework of this kind to integrate distributed services for collaboration has been proposed by (Tiejian et al., 2007). In this framework a web services "bus protocol" integrated self-made and third party collaborative tools, following a mash-up approach to meet specific framework needs, including security and management. Further examples of this trend, in the area of geospatial SOA, include environmental applications that address the challenges of data accessibility, service interoperability and reusability in varied contexts (Friis-Christensen et al., 2007; Granell et al., 2010; Kassahun et al., 2010; Michaelis and Ames, 2009). Similar approaches have been successful in implementing simulation or model steering for constant feedback throughout the process (Griffon et al., 2010; Li, 2007; Riedel, 2008; Stevens et al., 2007).

In regard to MCDM methods, successful GIS approaches have been used extensively in the past (Chen et al., 2010; Wang et al., 2010). A similar LUA/MCDM/AHP approach has been applied successfully in many instances where conflicting interests and demands must be met, like purchase of development rights programs (Duke and Aull-Hyde, 2002), Australian stakeholder preferences in regional forest agreements (Ananda and Herath, 2003) and wetland management by community leaders (Herath, 2004). In this research's region of interest (regional Victoria, Australia) a framework that combines this MCDM modeling, biophysical data and expert knowledge was implemented in McNeill (2006). In that research a land use impact model was used to analyze soil erosion impact, taking into account the relationships between landscape biophysical attributes and land management practices. The work included a sensitivity analysis that explored the relationships between model results and stakeholders understanding of uncertainty (Chen et al., 2010). Particularly relevant to this research is the Spatial Decision Support System (SDSS) presented in (Chen et al., 2010). In this SDSS a geo-referenced visualization of uncertainty is available to stakeholders. By representing uncertainties in a spatial dimension, they provided a deeper understanding of the model variability, at the same time making it an integral part of the decision making process. Even more important, they analysed the risk inherent to decision making by ranking and comparing multiple scenarios, thus quantifying how robust a certain decision was against other possible outcomes. This Steering Framework builds upon that line of research.

In summary, it is important for stakeholders in land management, particularly those persons involved in broad scale regional planning activities, to anticipate and plan for environmental changes. Anticipating likely future conditions depends on integration of future projections of global warming, market constraints and land allocation models. Such interlinking models, and the uncertainty associated with them, lead into a complex and cognitively demanding decision making process of land use management. This is due not only to the many input variables being assessed, but also to the inherent uncertainty associated with being able to model future scenarios and the complexities in the decision making process in itself. For all these reasons, the following research question arises: can we help stakeholders (people who have a vested interest in the outcome of land use management in the future, e.g. regional planners, farmers, policy makers, etc.) to better understand the underlying models and their dependence upon key factors? It is essential that these stakeholders can assess the significance of relevant key factors and how they impact the model outcomes, as well as the range and distribution of uncertainty in these outcomes. The contribution this research makes is in the development of an SMS exploratory framework by developing a SOA enabled steering framework that controls a LUA model and presents the outcomes in real time. This framework architecture enables stakeholders to change model inputs interactively in order to reassess specific, on-the-spot interests and scenarios. At the same time, our framework tracks the behavior of users and includes tests of their responses to support a detailed evaluation of the success of the framework. The results of this testing are the subject of a future paper.

## 3. LUA model case study

### 3.1. Environmental model summary description

As a source of variable inputs we took as a starting point the model described by Pelizaro et al. (2010), where the best combination of cropping systems for the South West region of Victoria was analysed. This particular model was chosen for the following reasons:

- It shared the same approach of combining biophysical data on a regional level, the future climate projection by Special Report on Emissions Scenarios (SRES) and a comprehensive analysis of uncertainty.
- The LUA model algorithm was implemented as a stand-alone application (Visual Basic programming language), but its main algorithm could be broken down into subcomponents, ready to be exported into a web-based framework.
- The published data was complete and readily available from the partner organization, Department of Primary Industries, Victoria.

The main components of the Pelizaro et al. (2010) model that were migrated to this software were:

- A multi-criteria evaluation process, where biophysical data was combined with experts' judgment that has been quantified using the Analytical Hierarchy Process (AHP). The AHP generated factor weights are applied to the spatial biophysical data

Please cite this article in press as: Nino-Ruiz, M., et al., Spatial model steering, an exploratory approach to uncertainty awareness in land use allocation, Environmental Modelling & Software (2012), http://dx.doi.org/10.1016/j.envsoft.2012.06.009

to produce maps which reflect a particular location's productivity under the given climate change scenario. Fig. 1 shows an example of the output of Land Suitability for Ryegrass/sub-clover land suitability in 2050, Intergovernmental Panel on Climate Change (IPCC) Special Emission scenarios (SRES) scenario A2 (an heterogeneous world, with economical development focused on diverse regions, this scenario is associated with medium level global warming) (Pelizaro et al., 2010).

- An ESRI™ ArcGIS stand-alone component that maps relative suitabilities for different crops (color coded from −1 restricted to 100% suitable). In the Pelizaro et al. study, results were validated by a panel of experts. When inconsistencies were found in this validation, the AHP was reweighted iteratively until every panel member was satisfied. With this fined-tuned AHP, land use suitability was estimated for every crop under future climate conditions according to the IPCC SRES. The model of choice was CSIRO MK 3.5 (Gordon, 2002).
- An uncertainty analysis related to the AHP used, which indicates quantitatively a level of confidence in the predictions obtained. Although an exact definition and taxonomy of uncertainty is subject to intense debate (Refsgaard et al., 2007), the Pelizaro et al. model has used the stochastic and epistemic taxonomy on uncertainty (Walker, 2003). Since epistemic uncertainty is associated with incomplete knowledge (found in the input data of soil, climate and landscape readings), that study focused on stochastic uncertainty by analyzing the aleatory uncertainty arising from the AHP weight-assignments captured in regional workshops. This analysis was performed by combining Monte Carlo simulations with a PERT probability distribution, a variant of the Beta distribution (Benke, 2008; Hahn, 2003; Jablonsky, 2007).

The final uncertainty assessment was presented as grey scale maps that linked land allocation and suitability estimates with corresponding probability distributions, but only for one crop (Ryegrass). Fig. 2 shows the corresponding uncertainty analysis for the land suitability outcome shown in Fig. 1 (Pelizaro et al., 2010).

### 3.2. Case study modifications from the original

The LUA algorithm used in this case study is the same linear weighted suitability model derived using AHP. In regard to the AHP creation, calibration and derivation, a detailed AHP hierarchy and suitability weighting for each crop has been published in (Pelizaro et al., 2010). It was however necessary to modify these weights in order to introduce two other factors, Crop Market price and a Carbon Tax applied to production. It was a requirement that when the importance of these new factors was set to zero, the LUA outcomes yielded the same results as the original study. These factors were not taken into account in the original study, which was entirely concerned with biophysical variables, but have been included here. While the biophysical data is unchanging through time, we wanted to include suitability factors which would be subject to substantial uncertainty (by virtue of their being applied to LUA well into the future) in order to test the ability of users to judge the relative significance of these factors and also to gain a sense of the overall implicit unbounded uncertainty contained in the suitability assessments.

To implement these factors in the modified algorithm, the weights for each biophysical factor were adjusted proportionately to take into consideration another factor, net market price, which was determined by the crop market price together with the carbon tax applied to production. Note that no attempt was made to

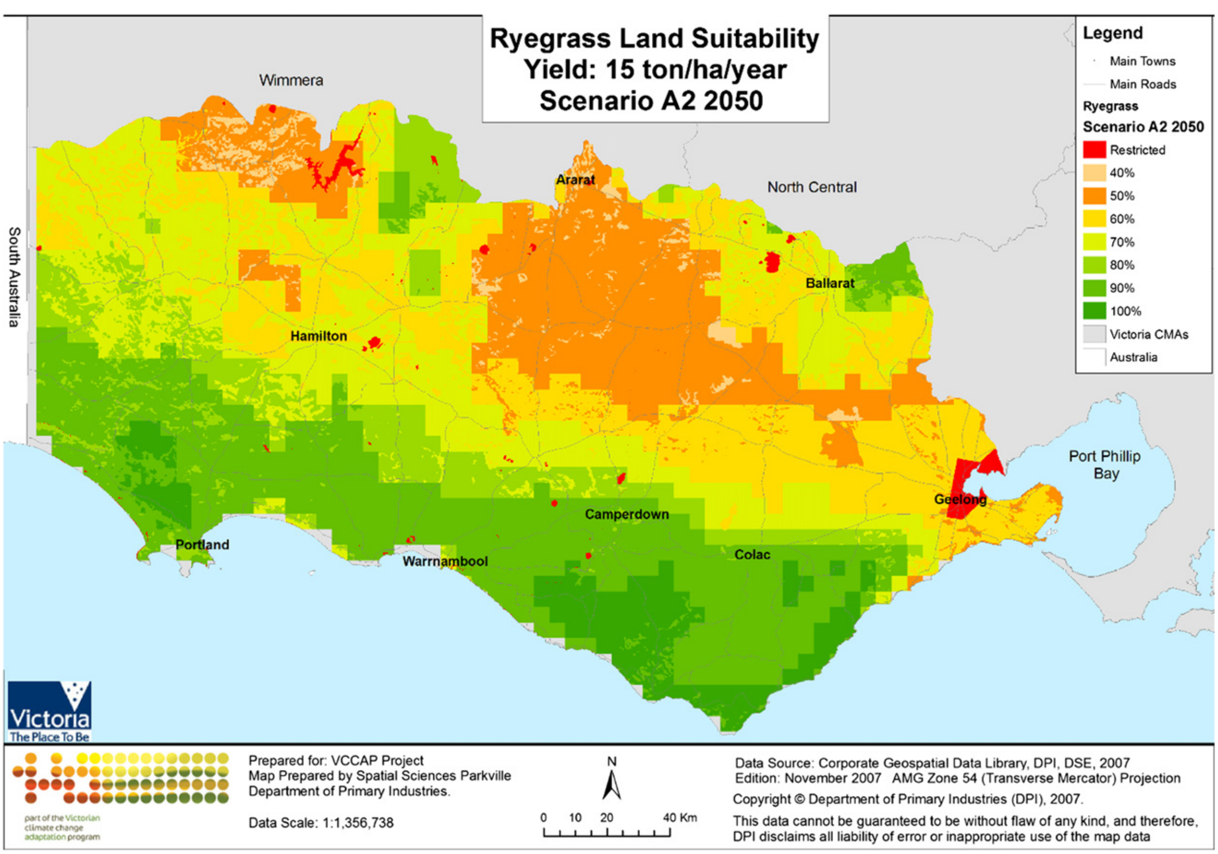


**Fig. 1.** Example of the output of land suitability for ryegrass/sub-clover land suitability in 2050, scenario A2 in (Pelizaro et al., 2010).

Please cite this article in press as: Nino-Ruiz, M., et al., Spatial model steering, an exploratory approach to uncertainty awareness in land use allocation, Environmental Modelling & Software (2012), http://dx.doi.org/10.1016/j.envsoft.2012.06.009

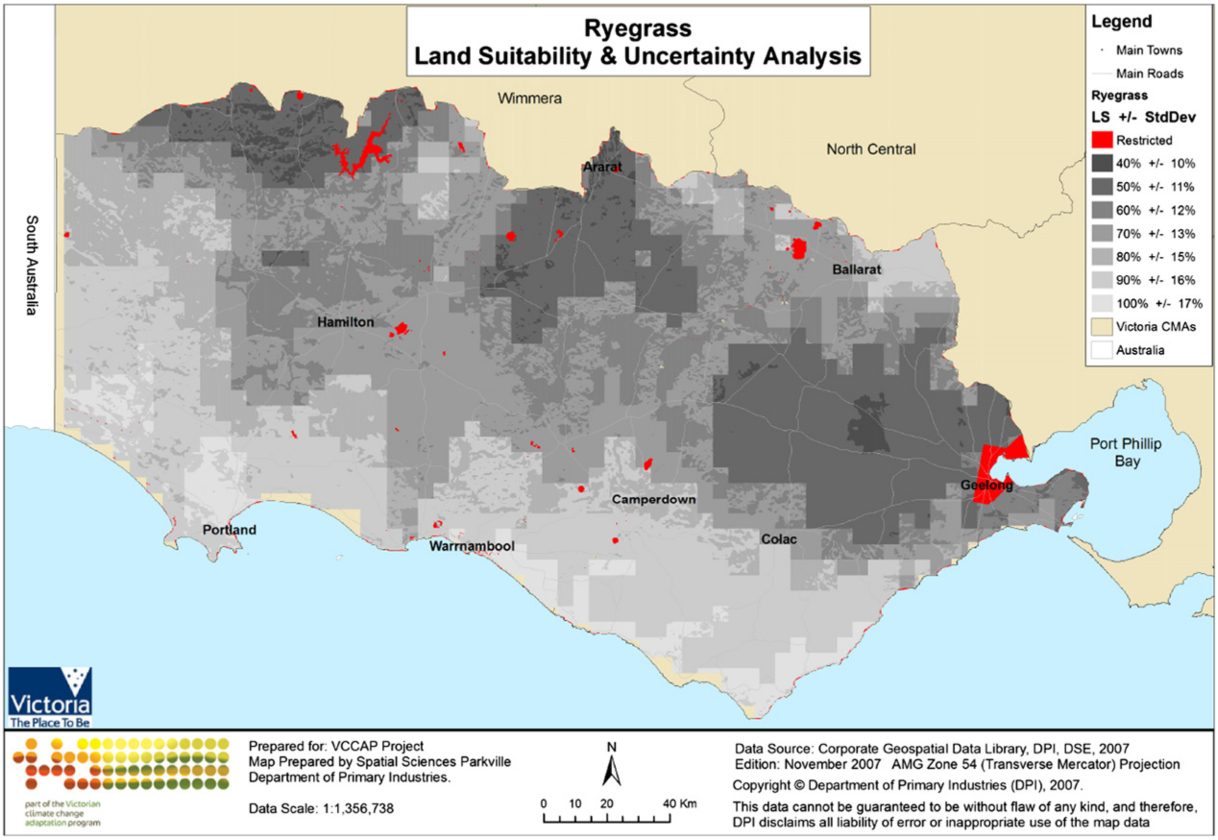


**Fig. 2.** Example of the corresponding uncertainty map for Fig. 1. Land suitability for ryegrass (Pelizaro et al., 2010).

undertake the necessary economic analysis to determine the relative significance of the net market price. Our main objective was to develop and test the framework, not to build a fully accurate model. We therefore chose a modest level of influence (a maximum weight of 0.06 or 6%) on overall suitability.

The algorithm, with the extra factors included, assigned a land suitability score to each grid cell in the study area using the following formula:

$$\text{Crop LS}_{(x,y)} = I_{\text{Soil}_{(x,y)}} + I_{\text{Terrain Slope}_{(x,y)}} + I_{\text{Rain}_{(x,y)}} + I_{\text{Compound Price}}$$

where $(I)$ represents each crop influence, and:

$$I_{\text{Soil}_{(x,y)}} = \left(\text{AHP weighted}_{\text{Topsoil and Subsoil Texture, Usable Soil Depth, Subsoil pH }(x,y)}\right) \times (W_{\text{Soil}})$$

$$I_{\text{Terrain Slope}_{(x,y)}} = \left(\text{Slope}_{(x,y)}\right) \times \left(W_{\text{slope}}\right)$$

$$I_{\text{Rain}_{(x,y)}} = \text{Rain}_{(x,y)} \times \left(\frac{S_{\text{Rain}}}{\mu_{\text{Rain SRES}}}\right) \times (W_{\text{Rain}})$$

$$I_{\text{Compound Price}} = \left(\frac{S_{\text{Ctax}}}{\mu_{\text{Ctax}}}\right) \times (W_{\text{CTax}}) \times \left(\frac{S_{\text{Market Price}}}{\mu_{\text{Market Price}}}\right) \times (W_{\text{Price}})$$

Here,

- $S_{[\text{parameter}]}$ represents the new global parameter value submitted through steering by the user.
- $\mu_{\text{Ctax}}$ equals the projected Carbon Tax (initially AUD23.00/tonne of $CO_2$) for Australia which came in effect on July 1, 2012
- $\mu_{\text{Rain SRES}}$ represents the mean SRES projected rainfall for this region, and
- $\mu_{\text{Market Price}}$ is the reference value for that crop current market price.

Also note that some values, for instance $I_{\text{Compound Price}}$, are constant throughout the coverage, and others $(I_{\text{Soil}_{(x,y)}} + I_{\text{Terrain Slope}_{(x,y)}})$, are not steerable and thus can be pre-computed for each $(x,y)$ before the steering phase.

Three parameters were implemented to be steerable in real time:

1. Rainfall, taking as a base point the same values as the original case study (SRES 2050 MK 3.5)
2. Commodities' prices, taking as a base point for each commodity its approximate average current market value in AUD.
3. Carbon emission pricing, in the form of a Carbon Tax as described in Wise (2009), with a base point of AUD23.

In regard to climate change projections of Rainfall, three SRES projections, which encompass the spectrum of possible scenarios, were chosen. In this study these are referred to as "Low level global warming" (B1), "mid level global warming" (A2) and "high level global warming" (A1FI). Data sets for south west Victoria were obtained from CSIRO MK 3.5 Climate change model (Gordon et al., 2010) for the year 2050.

Please cite this article in press as: Nino-Ruiz, M., et al., Spatial model steering, an exploratory approach to uncertainty awareness in land use allocation, Environmental Modelling & Software (2012), http://dx.doi.org/10.1016/j.envsoft.2012.06.009

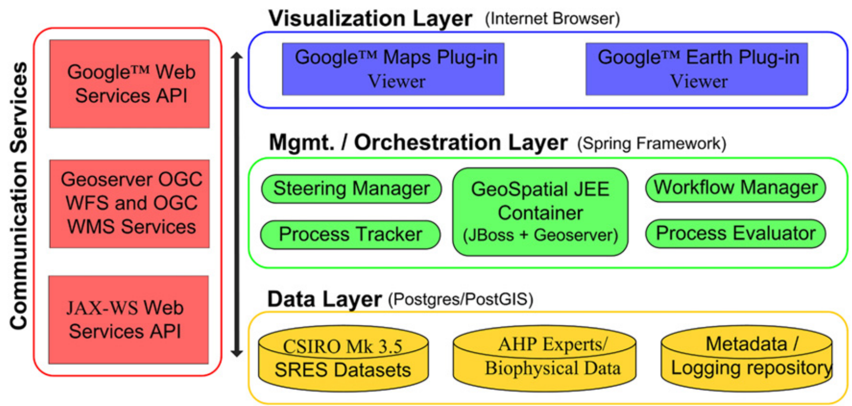


**Fig. 3.** Architecture implementation for Land Use Allocation and SOA enabled Spatial Model Steering.

In regard to the crop types included, the rationale was to have a representative of the three common types of land use in this region that was also present in the original study of (Pelizaro et al., 2010): one type of pasture (Ryegrass – *Lolium spp*), one type of cereal crop (Oats – *Avena sativa*) and one type of timber crop (Blue Gum – *Eucalyptus globulus*).

Finally, the Carbon Tax is applied to the commodities' prices to create a final compound price.

## 4. Steering framework architecture

### 4.1. Introduction

This framework provides an infrastructure to explore land use suitability and allocation and evaluate the type of uncertainty discussed in the previous section. Dynamic steering of a model's outcomes, as opposed to the traditional model paradigm (setup → run → analyze results → repeat process), brings many advantages for supporting expert based modeling paradigms such as MCDM. Instead of analyzing results in a separate post-processing step, stakeholders can modify and react quickly to unexpected deviations of the model, or changes in the environment, thus providing a deeper understanding of the model behavior (Huang, 2003; Kresimir, 2008). Even more importantly, visualization steering allows real (or near-real) time iteration towards the outcome that the stakeholders want to achieve, in the process finding out which parameter values are the most suitable for a particular purpose (Riedel, 2008). One of the advantages of this steering approach is a more transparent model – outcome relationship. In the alternative approach of "black box" development, a handful of scientists may configure a given model in a certain way to present a given outcome, which might reflect strongly what they consider an accurate outcome. With SMS, a stakeholder with different, or even conflicting interests, can see which changes to the parameters will yield an outcome that is closer to his interests, thus fostering collaborative work and discussions of how different and even conflicting interests can be resolved and included in the modeling process.

### 4.2. Description

Migration and reuse of legacy components found in the case study model were implemented in the Java Enterprise Edition platform (version 1.6). The JEE container of choice was RedHat™ Jboss 4.2. Each layer in the architecture was instantiated as follows (see Fig. 3):

#### 4.2.1. Communication services

Data is transferred from relevant layers through wrappers/interfaces that are implemented by standard contracts on each module (Standard Web Services protocols). To implement this we used the JAX-WS and Google™ API's for web development for our view layer web services needs. In the JEE container, we deployed a web archive version of Geoserver,[1] which implements OGC Web Feature Services (OGC 2005) and OGC Web Map Services to handle our mapping requests (OGC 2006). To implement web services with JAX-WS, we leverage the Java Spring Framework capabilities (version 3.0).[2] This framework only requires the use of *@WebService* and *@WebMethod* annotations to expose the functionality as a web service, thus abstracting the need of specifying the xml configuration of SOAP and WSLD, which the framework does automatically.

#### 4.2.2. View layer

This layer is composed of modules that offer the end visualization (mapping) outcome. These services are third party software that can range from the common Internet browser to more sophisticated readers of web 2.0 content. We implemented it using Google™ Maps v.2.0 and Earth 1.8 API, XHTML and JavaScript. We decided to switch from kml to png format as the WMS format of choice for performance in the refreshment rate on the screen.

#### 4.2.3. Data layer

Data sources can be composited to feed spatial and non-spatial information requirements that the orchestration layer needs to fulfill its cycle, thus abstracting the need for a particular data source. For instance, it retains biophysical, geospatial and climate change data required by the LUA process. Hibernate and PostGIS/PostgreSQL[3] were adopted for the data layer service to enable advanced logging capabilities.

#### 4.2.4. Management/orchestration layer

This architecture depends on workflows that link and sequence services according to modeling and visualization requirements. These automated services further delegate specialized functions such as modeling, management, security and similar features. This layer includes:

[1] http://geoserver.org.
[2] http://www.springsource.org/.
[3] http://postgis.refractions.net/.

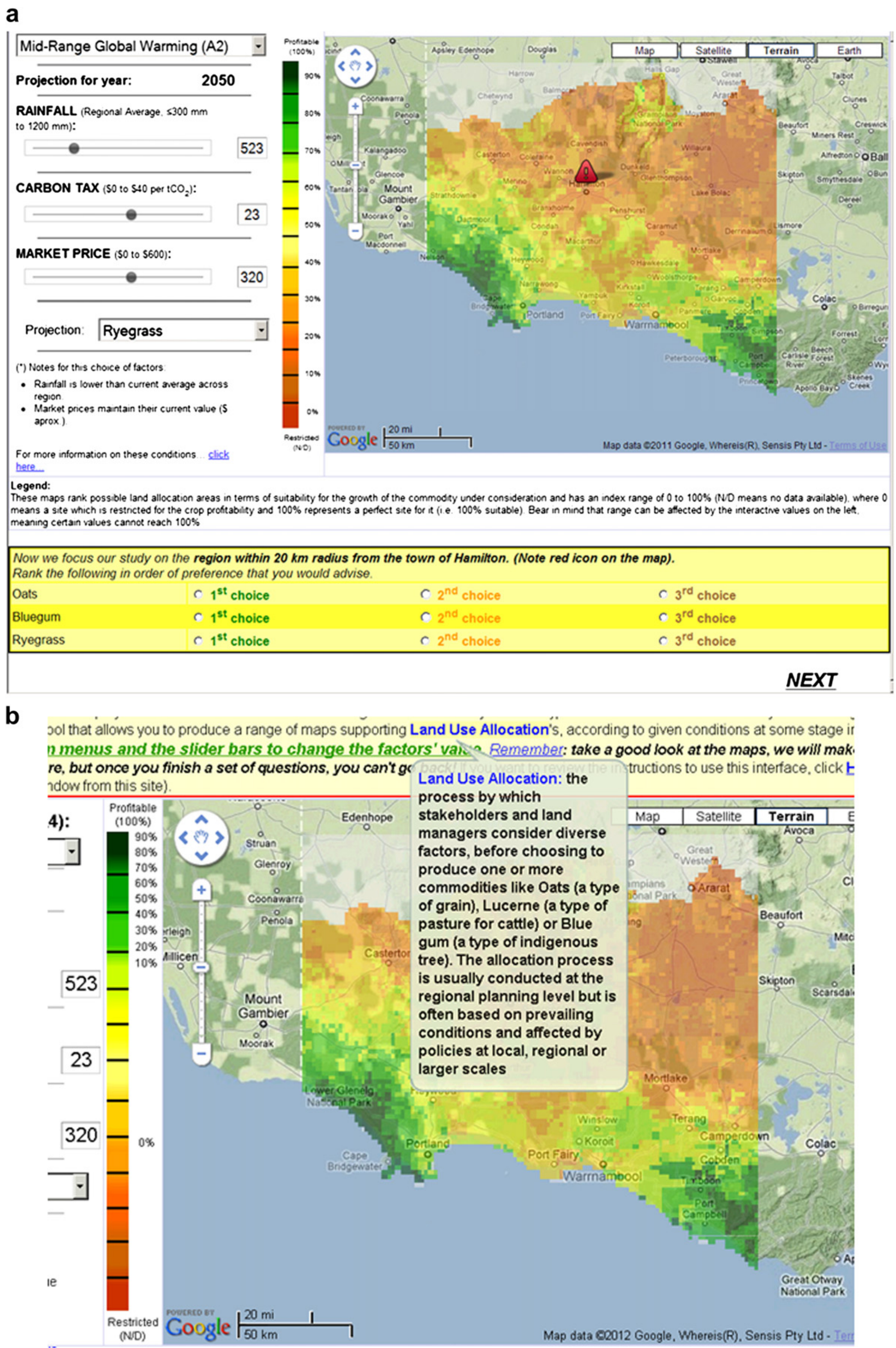


**Fig. 4.** Example of an online questionnaire, where the question will appear at the bottom of the screen, and the online glossary available, which will pop up an explanation of certain keywords.

- *Workflow manager*: responsible for managing a sequence of operations/processes to achieve a general framework goal (like redirecting new parameters to feed the steering manager, according to each user's session). It orchestrates the interaction of both human and machine actors that may intervene in a given process. Since most complex environmental models need to preserve state information, thus conflicting with web services guidelines of being stateless services, this manager also addresses model transaction integrity by using the Data layer for preserving state information. The strategy behind this controller was to have an entity in charge of handling multiple, concurrent access to the framework without affecting the special requests for the computing intensive steering process. In this manner, common tasks like authentication and web page flow would be addressed and configured separately from the steering process.
- *Steering manager*: responsible for coordinating between data feed/exchange and operations of the model instance running on the framework's execution platform, ensuring all asynchronous and time/resource intensive model requirements are met independent of the other services requests. This module also queues requests to it from the Workflow manager or other layers/services, thus avoiding incongruent or invalid data being delivered and/or analysed. It was deemed important to separate this manager from the previous one, because it takes care of the core functionality, steering, in order to have specialized modules to handle the demanding steering process. Equally important, envisioning a higher demand of computing resources for this processes, having this module divided from the common Workflow Controller allows a flexible scaling to other servers that can implement more Steering managers without having to change the whole architecture.
- *Process evaluator*: responsible for managing and processing online surveys results and requests for "scenario screenshots" to be taken and retained in the data layer. These snapshots can be useful later, not only to enable any user to restore previously complex sessions, but also for comparing and ranking possible outcomes from the parameter space determined by the model. This module is the one responsible for showing and capturing the survey information shown in Fig. 4a.
- *Process tracker*: implements advanced logging capabilities to record user interaction, gather direct user's feedback for any particular sub-process. Depending on the development life-cycle, some or all of this raw data is sent in a structured fashion to the data layer. Like an airplane's black box, later it can be useful to assess the overall tool's performance. We implemented this using slf4j and log4javascript with Ajax on the Spring 3.0 framework.

### 4.3. Workflow description

A description of a typical flow of information through this architecture would be as follows: a potential stakeholder is invited to perform an LUA analysis under certain conditions, for instance:

> "Your region of study is the region between Port Fairy, Koroit and Warnambool. Which crops would you recommend to farmers to maximize their net returns on land use?"

The user can visually steer the LUA model variables (e.g. chose IPCC SRES A1FI: Emphasis on fossil fuels, for the year 2050), then explore "what if" options such as decreasing the rainfall or

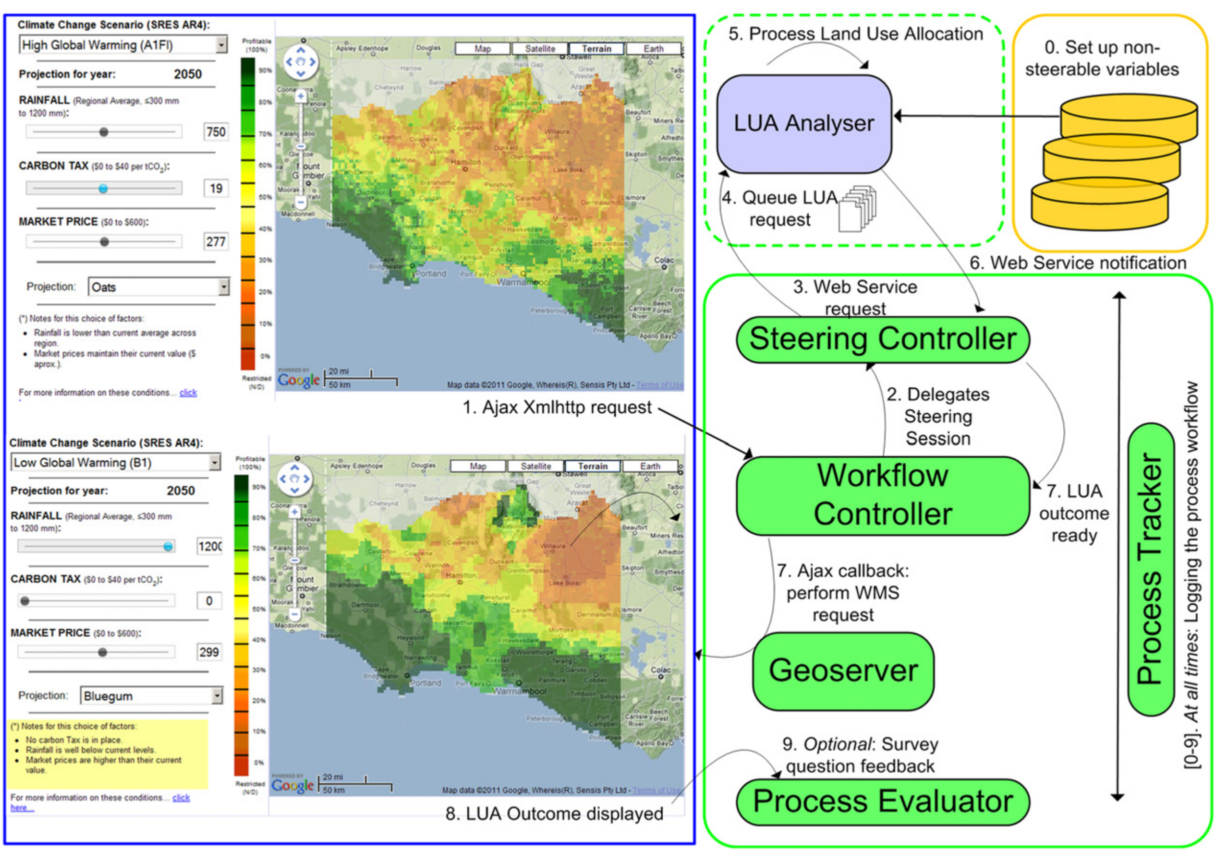


**Fig. 5.** Workflow diagram with key steps description.

thinking the carbon tax may be high at the time. During his/her whole session, the user will be visualizing the corresponding changes after a minimal delay, depending on technology constraints.[4]

At key moments in the steering process the user will be presented with online mini surveys to assess his level of confidence in the scenarios analysed and the outcome considered most relevant (see Fig. 4a). At all times, the user's interaction will be logged for future comparison and analysis, on both the overall session performance and uncertainty awareness of the user. This data can be analysed jointly between developers and stakeholders when assessing the overall performance of the tool, thus getting useful insight into the areas which the framework should address further. To support the process during the interaction with the framework, there is an online glossary available to users where most keywords have pop up explanation (see Fig. 4b).

### 4.4. Steering framework in action

As seen in Fig. 5, when the user logs in, the WorkFlow Controller creates its corresponding *sessionSandBox*, which is the "canvas" where the user can perform LUA processes. On creation the Workflow Controller populates this instance with the LUA global variables that are fixed during the steering session (e.g. Sub soil Ph, drainage, etc. see Pelizaro et al. (2010) for full description of the algorithm factors) [see step 0].

When the user requests a LUA [step 1], the browser performs an Ajax call (XmlHttpRequest) that is acknowledged by the Workflow Controller, which delegates the Steering session to the logic expert, the Steering Controller [2]. This one receives the steering parameters (Carbon Tax, SRES scenario, Market Price) sent by the user, and creates a Web Service call to the LUA Analysis service, which could be located physically in another server machine, where the algorithm resolution actually takes place [3]. Here a stateless LUA Analyser queues [4] and then processes all the LUA requests received (there might be other users requesting different LUA outcomes simultaneously) [5]. When the outcome is ready, this module notifies the Steering Controller when the corresponding outcome has been processed [6], along with its location on the Geoserver instance. The Steering Controller then informs the view layer that it can perform the asynchronous call on the Web Map Service end of Geoserver [7]. The Google Map or Earth API, depending of which layer the user is viewing, will refresh the map with the updated outcome [8]. When the user wants to end his interaction, the Workflow manager can also save its state, and during all this time it has coordinated with the process evaluator and process Tracker to gather all the relevant data from the interaction.

In this implementation the decoupling of the analysis component from the others modules allowed setting up a dedicated machine to perform this very resource intensive task. By the same token, if user traffic were to become intensive as well, the same physical decoupling could be achieved with almost no re-engineering cost, again because such SOA implementation is readily available and easily configurable in corporate level frameworks such as Spring 3.0.

## 5. Discussion

Any environmentally complex decision involves risk compounded by uncertainty in model inputs and model parameters. A comprehensive analysis of uncertainty can provide an indication of the error margin or confidence in any decision process, thus an insight into the risk associated with it. The main aim of this exploratory architecture is to provide users with an environment in which the roles of different elements in the decision environment can be understood and the range of uncertainty in long-term outcomes can be assimilated through perceptions of the variations in outcomes. This can be advanced through a participatory environment where different scenarios and extreme patterns can be analysed (Brugnach et al., 2008).

This implementation enables scientists, stakeholders and modelers alike to follow a comprehensive yet easy-to-use procedure to canvass the behavior of some sources of uncertainty, not only in the parameter space, but also in the geographic dimension. Uncertainty assessment is usually carried out using more analytical procedures only at the end of the modeling process, and even then the "statistical uncertainty" is the one that is given the highest priority (Refsgaard et al., 2007). By exploring model outcomes through the unbounded implicit and insightful combination of steering key input parameters, comparing them and answering carefully placed mini surveys, most stakeholders without substantial background in uncertainty theory, can nevertheless provide near immediate feedback on their confidence and uncertainty awareness to modelers and project managers. Consequently, each step in the development/learning lifecycle can be completed with greater confidence. This effect is complemented by the advanced logging framework that tracks user interaction, giving a behind the scenes insight as to this particular SMS implementation, or any DSS as a whole. Analysis of these logs by the modelers can enhance communication of the key factors that affect the users confidence in the model and their uncertainty awareness.

Furthermore, the embedded Process Evaluator provides a check point to avoid the risk of reading too much into the outputs and/or predictions of the models (Jakeman et al., 2006). With the tracking interaction stored and available for future data mining, it provides a stable ground for a longer-term view of the potential of a certain model, including how flexibly it can respond to changing management requirements, as well as increasing the transparency of the overall process to all stakeholders (Oxley, 2007).

On the other hand, spatial model steering brings forward many advantages. Instead of analyzing results in a separate post-processing step, stakeholders can modify and react quickly to unexpected deviations of the model and changes in the environment, thus providing a deeper understanding of the system behavior (Kresimir, 2008). Moreover, it provides a supporting framework for visual analytics in exploring the decision space in near-real time. It is also extensible, by adhering to service contracts that are defined collectively by regulatory organization such as OGC and IEEE, thus bringing web based simulation steering to a wider community (Huang, 2003).

In regards to lessons learnt during this EIMF development, we found that full compliance with certain "de facto" practices in the SOA environment had a considerable impact on the performance of the framework when deployed on our available platforms, specifically, in the real time rendering of the model output. We came to these findings through the assimilation of common practices and standards of the software industry in regards to automated testing coverage of code produced. This practice enhances quality assurance of code, as well as it reusability and flexibility (Fiorese and Guariso, 2010,Buehler, 2003, p. 202; Stockwell, 1999, p. 203). To implement this testing coverage we used the following technologies:

[4] Loading times are dependent on the platform of deployment, Internet speed, CPU and GPU characteristics of the client, etc.

Please cite this article in press as: Nino-Ruiz, M., et al., Spatial model steering, an exploratory approach to uncertainty awareness in land use allocation, Environmental Modelling & Software (2012), http://dx.doi.org/10.1016/j.envsoft.2012.06.009

- Pylot 2.6 Open source web performance tool[5] (For system wide Testing).
- SeleniumHQ Web Application Testing System[6] (For View layer Testing).
- TestNG API[7] (For Unit and Integration testing of Java software components).

These tests suggested that, for our particular platform, the rendering of maps would be more responsive if they were requested from Geoserver with a png format (optimized media file for the Internet), rather than the standard kml format for geospatial features.

The focus here has been on the architecture for SMS and subsystems for evaluation rather than the evaluation itself. An extensive analysis with stakeholders of how this steering framework can enhance model understanding is being carried out, and its results will be published in a separate paper. Finally, the current state of this approach enables interaction with the first level of input variables such as rainfall, but not the underlying AHP decision tree as well as the Monte Carlo uncertainty analysis.

## 6. Concluding remarks

We share the vision with the modeling community of a distributed modeling approach in which geospatial enabled environmental modules can be reused and combined at will, where data and models can be shared as virtual resources among peers, employing web services and/or grid technology to achieve tangible environmental goals. We believe that this development makes a modest contribution to this vision. By integrating the variables as previously explained, the system enables users to gain a deeper understanding of the model and key variables being used and implicitly an insight into the range of plausible outcomes and hence uncertainty. For instance, which factors are more relevant than others, as well as the uncertainty inherent in the LUA model. In this light, this framework illustrates the technical implementation necessary for managing environmental resources with a broad perspective, one that takes into account all, and often conflicting, interests in different spatial and temporal scales. With this in mind, a planned line of work includes support for visual collaborative sessions inside the framework, where peers can exchange scenarios outcomes and their conclusions drawn from the increased factor and uncertainty awareness.

Additionally, this framework attempts to mirror the following perception: systems dealing with complex environmental concerns should not be dependant on a specific software or economic/scientific paradigm (Pahl-Wostl, 2007; Rivington, 2007; Warren, 2008). Moreover, when a loose-coupling architecture like the one proposed here is enabled, it permits a better uncertainty analysis, where a holistic notion of the system can be obtained (Warren, 2008). This perception also offers the possibility of looking at options arising from different decisions taken when the wider community is involved. Of course, it is a difficult task for a single product to support many tools, because many tools imply many data models. There is no magical all-pervasive platform that supports all use cases efficiently (Jakeman et al., 2006), but if the framework is flexible and cohesive enough, its modularity will support its necessary evolution in time.

If the power of Information Communication and Technology (ICT) is harnessed in conjunction with a proper understanding of the human context within which this approach must evolve, a useful EIMF can be implemented. These are the first steps to create highly relevant assessments of complex environmental impacts, providing communities and institutions with the flexibility to assemble new individual modules and modeling paradigms, further fostering the exploration of potential environmental solutions and leveraging the human decision making process to envision and achieve a sustainable future.

[5] http://www.pylot.org/.
[6] http://seleniumhq.org/.
[7] http://junit.sourceforge.net/.

## References

Alameh, N., 2003. Chaining geographic information web services. IEEE Internet Computing 7 (5), 22.
Ananda, J., Herath, G., 2003. The use of Analytic Hierarchy Process to incorporate stakeholder preferences into regional forest planning. Forest Policy and Economics 5 (1), 13–26.
Benke, K., Wyatt, R., Sposito, V., 2011. A discrete simulation approach to spatial allocation of commodity production for revenue optimisation over a local region. Journal of Spatial Science 56 (1), 89–101.
Benke, K.K., 2008. Parameter uncertainty, sensitivity analysis and prediction error in a water-balance hydrological model. Mathematical and Computer Modelling 47 (11, 12), 1134.
Brown, M.E., Funk, C.C., 2008. Food security under climate change. Science 319 (5863), 580–581.
Brugnach, M., Pahl-Wostl, C., Lindenschmidt, K.E., Janssen, J.A.E.B., Filatova, T., Mouton, A., Holtz, G., van der Keur, P., Gaber, N., 2008. Chapter four complexity and uncertainty: rethinking the modelling activity. In: Jakeman, A.J., Voinov, A.A., Rizzoli, A.E., Chen, S.H. (Eds.), Developments in Integrated Environmental Assessment. Elsevier, pp. 49–68.
Buehler, O., Wegener, J., 2003. Evolutionary functional testing of an automated parking system. Proceedings of the International Conference on Computer, Communication and Control Technologies (CCCT'03) and the Ninth International Conference on Information Systems Analysis and Synthesis (ISAS'03), Florida, USA.
Chen, Y., Yu, J., Khan, S., 2010. Spatial sensitivity analysis of multi-criteria weights in GIS-based land suitability evaluation. Environmental Modelling & Software 25 (12), 1582–1591.
Cline, W.R., 2007. Global Warming and Agriculture.
De Roure, D., Jennings, N.R., Shadbolt, N.R., 2003. The Semantic Grid: A Future e-Science Infrastructure. John Wiley & Sons, Ltd.
Denzer, R., 2005. Generic integration of environmental decision support systems – state-of-the-art. Environmental Modelling & Software 20 (10), 1217–1223.
Duke, J.M., Aull-Hyde, R., 2002. Identifying public preferences for land preservation using the analytic hierarchy process. Ecological Economics 42 (1, 2), 131–145.
Filippi, J.B., Bisgambiglia, P., 2004. JDEVS: an implementation of a DEVS based formal framework for environmental modelling. Environmental Modelling & Software 19 (3), 261–274.
Fiorese, G., Guariso, G., 2010. A GIS-based approach to evaluate biomass potential from energy crops at regional scale. Environmental Modelling & Software 25 (6), 702–711.
Friis-Christensen, A., Ostländer, N., Lutz, M., Bernard, L., 2007. Designing service architectures for distributed geoprocessing: challenges and future directions. Transactions in GIS 11 (6), 799–818.
Goodall, J.L., Horsburgh, J.S., Whiteaker, T.L., Maidment, D.R., Zaslavsky, I., 2008. A first approach to web services for the National Water Information System. Environmental Modelling & Software 23 (4), 404–411.
Gordon, H., O'Farrell, S., Collier, M., Dix, M., Rotstayn, L., Kowalczyk, E., Hirst, T., Watterson, I., 2010. The CSIRO Mk3.5 Climate Model. Centre for Australian Weather and Climate Research.
Gordon, H.B., 2002. The CSIRO Mk3 climate system model.
Granell, C., Díaz, L., Gould, M., 2010. Service-oriented applications for environmental models: reusable geospatial services. Environmental Modelling & Software 25 (2), 182–198.
Griffon, S., Auclair, D., Nespoulous, A., 2010. Visualising changes in agricultural landscapes. In: Brouwer, F., Ittersum, M. (Eds.), Environmental and Agricultural Modeling. Springer, Netherlands, pp. 133–157.
Gunasekera, D., Tulloh, C., Ford, M., Heyhoe, E., 2008. Climate Change: Opportunities and Challenges in Australian Agriculture. Citeseer.
Hahn, E.D., 2003. Decision making with uncertain judgments: a stochastic formulation of the analytic hierarchy process. Decision Sciences 34 (3), 443.
Herath, G., 2004. Incorporating community objectives in improved wetland management: the use of the analytic hierarchy process. Journal of Environmental Management 70 (3), 263–273.
Hossain, H., 2006. Sustainable land resource assessment in regional and urban systems. Applied GIS 2 (3), 24.
Huang, B., 2003. Web-based dynamic and interactive environmental visualization. Computers, Environment and Urban Systems 27 (6), 623.
Hutanu, A., 2006. Distributed and collaborative visualization of large data sets using high-speed networks. Future Generation Computer Systems 22 (8), 1004.

Jablonsky, J., 2007. Measuring the efficiency of production units by AHP models. Mathematical and Computer Modelling 46 (7, 8), 1091.

Jakeman, A.J., Letcher, R.A., Norton, J.P., 2006. Ten iterative steps in development and evaluation of environmental models. Environmental Modelling & Software 21 (5), 602–614.

Jankowski, P., 1995. Integrating geographical information systems and multiple criteria decision-making methods. International Journal of Geographical Information Science 9 (3), 251.

Kassahun, A.A., Athanasiadis I.N., Rizzoli, A.E., Krause, A., Scholten, H., Makowski, M., Beulens, A.J.M., 2010. Towards a service-oriented e-infrastructure for multidisciplinary environmental research. Firth Biennial Meeting: International Congress on Environmental Modelling and Software (iEMSs 2010).

Kresimir, M., 2008. Interactive visual steering – rapid visual prototyping of a common rail injection system. IEEE Transactions on Visualization and Computer Graphics 14, 1699–1706.

Kumar, S., Peters-Lidard, C., Tian, Y., Houser, P., Geiger, J., Olden, S., Lighty, L., Eastman, J., Doty, B., Dirmeyer, P., 2006. Land information system: an interoperable framework for high resolution land surface modeling. Environmental Modelling & Software 21 (10), 1402–1415.

Lee, C.L., 2008. Biophysical and system approaches for simulating land-use change. Landscape and Urban Planning 86 (2), 187.

Li, M., 2007. Real-time collaborative design with heterogeneous CAD systems based on neutral modeling commands. Journal of Computing and Information Science in Engineering 7, 113.

Lobell, D.B., Burke, M.B., Tebaldi, C., Mastrandrea, M.D., Falcon, W.P., Naylor, R.L., 2008. Prioritizing climate change adaptation needs for food security in 2030. Science 319 (5863), 607–610.

McNeill, J., 2006. Using GIS and a land use impact model to assess risk of soil erosion in West Gippsland. Applied GIS 2 (3), 19.

Ménard, A., 2007. Simulating the impact of forest management scenarios in an agricultural landscape of southern Quebec, Canada, using a geographic cellular automata. Landscape and Urban Planning 79 (3, 4), 253.

Michaelis, C., Ames, D., 2009. Evaluation and implementation of the OGC web processing service for use in client-side GIS. GeoInformatica 13 (1), 109–120.

Mysiak, J., Giupponi, C., Rosato, P., 2005. Towards the development of a decision support system for water resource management. Environmental Modelling & Software 20 (2), 203–214.

Oxley, T., 2007. Space, time and nesting integrated assessment models. Environmental Modelling & Software 22 (12), 1732.

Pahl-Wostl, C., 2007. The implications of complexity for integrated resources management. Environmental Modelling & Software 22 (5), 561–569.

Papajorgji, P., Beck, H.W., Braga, J.L., 2004. An architecture for developing service-oriented and component-based environmental models. Ecological Modelling 179 (1), 61–76.

Pelizaro, C., Benke, K., Sposito, V., 2010. A Modelling framework for optimisation of commodity production by minimising the impact of climate change. Applied Spatial Analysis and Policy, 1–22.

Pullen, J.M., 2005. Using Web services to integrate heterogeneous simulations in a grid environment. Future Generation Computer Systems 21 (1), 97.

Refsgaard, J.C., van der Sluijs, J.P., Højberg, A.L., Vanrolleghem, P.A., 2007. Uncertainty in the environmental modelling process – a framework and guidance. Environmental Modelling & Software 22 (11), 1543–1556.

Riedel, M., 2008. Extending the collaborative online visualization and steering framework for computational grids with attribute-based authorization. Proceedings of the IEEE 104.

Riedel, M., 2009. Research advances by using interoperable e-science infrastructures. Cluster Computing 12 (4), 357.

Rivington, M., 2007. An integrated assessment approach to conduct analyses of climate change impacts on whole-farm systems. Environmental Modelling & Software 22 (2), 202.

Rizzoli, A.E., Leavesley, G., Ascough Ii, J.C., Argent, R.M., Athanasiadis, I.N., Brilhante, V., Claeys, F.H.A., David, O., Donatelli, M., Gijsbers, P., Havlik, D., Kassahun, A., Krause, P., Quinn, N.W.T., Scholten, H., Sojda, R.S., Villa, F., 2008. Chapter seven integrated modelling frameworks for environmental assessment and decision support. In: Jakeman, A.J., Voinov, A.A., Rizzoli, A.E., Chen, S.H. (Eds.), Developments in Integrated Environmental Assessment. Elsevier, pp. 101–118.

Saaty, T.L., Vargas, L.G., 2001. The seven pillars of the analytic hierarchy process. Models, Methods, Concepts & Applications of the Analytic Hierarchy Process, 27–46.

Salter, J.D., 2009. The digital workshop: exploring the use of interactive and immersive visualisation tools in participatory planning. Journal of Environmental Management 90 (6), 2090.

Sànchez-Marrè, M., Gibert, K., Sojda, R.S., Steyer, J.P., Struss, P., Rodríguez-Roda, I., Comas, J., Brilhante, V., Roehl, E.A., 2008. Chapter eight intelligent environmental decision support systems. In: Jakeman, A.J., Voinov, A.A., Rizzoli, A.E., Chen, S.H. (Eds.), Developments in Integrated Environmental Assessment. Elsevier, pp. 119–144.

Santé-Riveira, I., 2008. GIS-based planning support system for rural land-use allocation. Computers and Electronics in Agriculture 63 (2), 257.

Simmhan, Y.L., 2005. A survey of data provenance in e-science. SIGMOD Record 34 (3), 31.

Sposito, V., 2010. Adaptation to climate change in regional Australia: a decision making framework for modelling policy for rural production. Geography Compass 4 (4), 335.

Stevens, D., Dragicevic, S., Rothley, K., 2007. iCity: a GIS-CA modelling tool for urban planning and decision making. Environmental Modelling & Software 22 (6), 761–773.

Stockwell, D., 1999. The GARP modelling system: problems and solutions to automated spatial prediction. International Journal of Geographical Information Science 13 (2), 143–158. 1365–8816, Taylor & Francis.

Tiejian, L., Jinliang, S., Su, C., Yuzhu, L., Yanxiang, X., Cheng, D., Wei, L., 2007. A services oriented framework for integrated and customizable collaborative environment. IEEE International Conference on Information Reuse and Integration. IRI 2007, pp. 385–393.

Uy, P.D., 2008. Application of land suitability analysis and landscape ecology to urban greenspace planning in Hanoi, Vietnam. Urban Forestry & Urban Greening 7 (1), 25.

Wainer, G.A., 2008. Distributed simulation of DEVS and Cell-DEVS models in CD++ using web-services. Simulation Modelling Practice and Theory 16 (9), 1266.

Walker, W.E., 2003. Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support. Integrated Assessment 4 (1), 5.

Wang, J., Chen, J., Ju, W., Li, M., 2010. IA-SDSS: A GIS-based land use decision support system with consideration of carbon sequestration. Environmental Modelling & Software 25 (4), 539–553.

Warren, R., 2008. Development and illustrative outputs of the Community Integrated Assessment System (CIAS), a multi-institutional modular integrated assessment approach for modelling climate change. Environmental Modelling & Software 23 (5), 592.

Williams, D.N., 2009. The earth system grid: enabling access to multimodel climate simulation data. Bulletin of the American Meteorological Society 90 (2), 195.

Wise, M., 2009. Implications of limiting $CO_2$ concentrations for land use and energy. Science 324 (5931), 1183.

Yang, C., Li, W., Xie, J., Zhou, B., 2008. Distributed geospatial information processing: sharing distributed geospatial resources to support Digital Earth. International Journal of Digital Earth 1 (3), 259–278.