Wageningen UR, Centre for Geo-Information

Minor thesis report

GIRS-2012-26

Opinion Dynamics in Agent Based Land Use Decision Making

Name student: Brehanu H. Meka

Registration No: 810516555030

Supervisor: dr. ir. Arend Ligtenberg

22 October 2012

Opinion Dynamics in Agent Based Land Use Decision Making

Brehanu H. Meka

Registration number: 810516555030

Supervisor

dr.ir. Arend Ligtenberg

Minor thesis submitted in partial fulfilment of the degree of Master of Science in Geo-Information Science at Wageningen University and Research Centre, The Netherlands.

22 October 2012

Wageningen, The Netherlands

Thesis code number: GRS80424
Thesis Report: GIRS-2012-26
Wageningen University and Research Centre
Laboratory of Geo-Information Science and Remote Sensing

Acknowledgment

I would like to thank my supervisor dr. ir. Arend Ligtenberg for providing me the idea of working on this topic and his support in shaping the whole research direction. Many thanks to my study advisor Ing. Willy Ten Haaf for all his encouragement, guidance and support throughout my study period. My gratitude also goes to all MGI family at WUR for the good time I had with them and all the skill and knowledge I acquire there from.

Table of Contents

List of figures

List of tables

Abstract

Models of opinion dynamics have been widely used in different fields. However, the application of opinion dynamics in agent based land use decision making has not been well investigated. The objective of this study was to investigate how exchange of opinion in agent based land use decision making influences the process of land use choice and how best choice can be made. Literature review was conducted to study typical models of opinion dynamics and model parameters. A hypothetical 50 parcels by 50 parcels unit of land was created. Ten hypothetical agents (decision makers) and ten initial set of suitability weight layers corresponding to the ten agents opinion about the suitability of each parcel in the input land unit for an intended land use were created. These were used as input in simulating the process of opinion exchange among agents in selecting the most suitable cluster of 10 by 10 parcels for the intended land use purpose. REPAST Simphony was used for model construction and simulation. Three different models of opinion dynamics were selected: model 1; where an agent interacts with all other agents at a time but depend only partially on other agents' opinion, model 2; where agents interact with all other agents at a time and depends solely on the opinion of other agents to form its own opinion, model 3 'pair wise' where an agent interact and exchange opinion with only one other agent at a time. The models were run for different combination of confidence bound and rigidity coefficient parameters and results were compared. Comparisons were also made with the baseline scenario where opinion dynamics was not applied. Comparisons were done based on the mean suitability weight of the most suitable cluster of parcels, the number of competing clusters, the spatial stability of the most suitable cluster and the number of meeting among agents to make the choice. Large mean suitability value means most agents agreed on the suitability of the cluster for the intended purpose. Smaller number of competing cluster reduces alternatives and help to easily locate the best cluster. Smaller number of meetings mean fast consensus. Results show that application of opinion dynamics (exchange of opinion among decision makers) significantly affects the process of land use choice and how best the choice can be made. The best result in terms of mean suitability weight of the most suitable cluster, the number of competing clusters (the smallest) and spatial stability of the most suitable cluster was achieved for model 1 combined with the largest confidence bound. Rigidity coefficient appeared to influence the number of meetings required to make decision. As rigidity coefficient increases the number of meetings required to choose the most suitable cluster appeared to increase. This was further supported by the fact that model 2, where rigidity coefficient is zero, required the smallest number of meeting (2) to reach stable mean suitability weight of the most suitable cluster. However, variations of model 2 appeared to result in large number of competing clusters and relatively smaller mean suitability weight at confidence bound value 0.5 and above. This led to the conclusion that model 1 combined with larger value of confidence bound and smaller rigidity coefficient yields the best cluster of parcels with few number of opinion exchange (meeting). Model 3 appeared to exhibit the largest mean suitability weight and smallest number of competing clusters for larger confidence bound (0.5). But model 3 led to unstable (continuously increasing) mean suitability weight and unstable (continuously decreasing) number of competing clusters. This means that very large number of meetings is required to make an optimal choice, which is practically unfeasible. While model 1 and model 2 yield better results than the baseline scenario at higher value of confidence bound, model 3 appeared to be worse than the baseline scenario taking the mean suitability weight of the most suitable cluster, the number of competing clusters and the required number of meetings as criteria. For the best scenario (model 1 with confidence bound 0.5 and rigidity coefficient 0.25) the spatial location of the most suitable cluster appeared to stay about the same as for the baseline scenario. This may indicate that the actual location of the most suitable cluster is determined more by the initial opinion of agents than by the exchange of opinion among agents. But the baseline scenario yielded very large number competing clusters. Thus, exchange of opinion appeared to reduce alternatives and streamline choice.

Key words: Opinion dynamics, land use decision, agent based modelling, confidence bound, rigidity coefficient

1. Introduction

1.1 Background

Agent based modelling has been widely used in land use study. Major areas of application include policy analysis, planning, participatory planning and land use change pattern analysis (Robin et al., 2007, Federico et al., 2011). A number of agent based land use models has been developed over the past two decades (Robin et al., 2007, Bousquet and Le, 2004, Dawn et al., 2003). These models cover areas of application ranging from agricultural land use change study (e.g. Federico et al., 2011) to modelling evolution of urban land (e.g. Nicholas et al., 2011, Mahamadou et al., 2011).

An agent-based model consists of autonomous decision-making entities, an environment through which these entities interact, rules that define the relationship between entities and their environment, and rules that determine sequencing of actions in the model(Dawn et al., 2001). Such entities are called agents. Agents encapsulate the behaviours of the various individuals that make up a system (Dyke et al., 1998). Agents encapsulate rules that translate both internal and external information into internal states, decisions, or actions (Dawn et al., 2001). For example, land owners can be considered as an agent in land use modelling. The decision that each owner makes about how to use his/her land determines how land use pattern changes in certain area over time. The land owner combines his/her knowledge and values, information about the biophysical environment, and the spatial social environment to decide on land use. Agents have particular behaviours through which they influence other agents and their environment. Agents interact with each other and with their environment based on defined rules. Over time, the interaction of agents among themselves and with their environment leads to change in the whole system.

Agent based models follow bottom-up approach (John Wainwright and James Millington, 2010): behaviour of autonomous individual entities and their interaction are studied in order to understand system scale patterns. While agent interactions may lead to recognizably change in land use pattern, a set of global equilibrium conditions is not employed in these models, in contrast to modelling techniques such as conventional physical equation based models (Dawn et al., 2001). This leads to a high degree of flexibility that allows researchers to account for heterogeneity and interdependencies among agents and their environment.

As compared to equation based models, agent based models are known for their ability to incorporate individual level variables to the modelling process as opposed to system level variables. Consequently, agent-based modelling is a powerful technique to simulate the actions and interactions of individual agents to assess emerging system level patterns (Federico et al., 2011).

Agent based modelling allows to capture the complex nature of both spatial interaction and explicit human decision making on land use showing land use land cover change patterns and associated population dynamics as self-organising process emerging from local interactions (Quang et.al, 2008). Agent based modelling allows for the representation of a heterogeneous population (Crooks, 2012).

Agent bases modelling gives great flexibility to handle system complexity such as adding more agents, tuning the behaviour of agents and their interaction among agents(Dawn et.al, 2003). Due to this capability and the realization of the fact that decisions do not always work in top-down manner (Pickles, 1995) agent based modelling is being widely used in land use study.

The basic idea of agent based modelling is to study interaction among individual agents towards understanding of large scale patterns such as change in land use. An agent is an autonomous entity in a system that has its own behaviour and interacts with other agents and its environment (Federico E. et al, 2011). Agent based modelling is superior to other land use models in that it enables incorporation of individuals decision making, social processes and non-monetary influences in decision making and dynamically link social and environmental processes (Robin et al., 2007, Nicholas Magliocca et al., 2011 , Federico E. Bert et al., 2011).

There are also limitations to agent based modelling. The limitations of agent based modelling come from the complex nature of human and natural. Based on review of relevant studies Quang et.al, 2008 mentioned three limitations with most agent based land use models. One limitation is related with the way real human communities are represented (Brown and Robinson, 2006 as cited in Quang et al 2008). Most agent based land use models forget heterogeneity among human agents and apply the same decision making model for all human agents (Quang et.al, 2008). The other limitation related with the fact that the dynamic self-sustained nature of land (environment in general) are not represented and considered as static in most agent based models (Quang et.al, 2008). This means that the land is assumed to remain unchanged except by the action of human agents. The third challenge is to formulate decision making mechanism. Some models use goal-driven approach which does not always work especially in developing countries where assumptions of optimizing behaviour are unrealistic (Jager et al., 2000). We suppose that changing opinion of human agents due to interaction and exchange of opinion with other agents is one aspect of the complexity in representing human agent in agent based modelling.

Opinion dynamics refer to change in people's opinion over time owing to the influence of other people opinion. Interest in the study of opinion dynamics seems to emanate from this idea of non-static opinion and the interest to model this dynamism. Opinions may be binary; example like or dislike certain product, or continuous where we have a continuum of opinion called opinion space represented using real numbers. In the continuous models each agent under consideration has an opinion with value somewhere in the opinion space, for example [0,1]. In the latter case, agents change their opinion from one value to another within the opinion space due to exchange of idea with each other. Therefore, the opinion of an agent at a given time t is a function of other agents' opinion at a previous time (t-1) and time itself. In this study the interest was to understand how opinion exchange affects decision making process among agents in agent based modelling for land use choice.

1.2 Definitions

A number of terms and phrases are used in this study. Understanding the meaning of these terms and phrases is important to capture the essence of this study.

- The terms Time step, simulation step, meeting, opinion exchange and negotiation are used interchangeably.
- ***Agent***: agents are land use decision makers. In making a decision, for example, about where to locate defined size of land unit for constructing a new building, each agent's idea is taken into account.
- ***Parcel***: individual unit of land within the whole land area under consideration.
- ***Opinion***: the opinion of an agent regarding the suitability of a given parcel of land for an intended land use purpose. It represents whether the agent thinks the parcel is relatively more suitable or less suitable for the intended land use.
- ***Suitability weight***: the weight between 0 and 1 that an agent assigns to a given parcel of land to represent his opinion about the suitability of the parcel for intended land use purpose. For example, if an agent assigns value 0 to the parcel, it means that the agent has an opinion that the parcel is totally unsuitable for the intended land use.
- ***Suitability weight layer***: a layer containing the suitability weight value for each and every parcel within the whole area of land under consideration. Suitability weight layer can correspond to an agent, in which case it represents the suitability weight that the agents assign to each and every parcel. Suitability weight layer can also represent the average suitability weight for each parcels calculated by taking all the agents in to account.
- ***Cluster***: a set of parcels of defined dimensions.
- ***Most suitable cluster***: a cluster with the largest value of mean suitability weight as compared to other clusters in the whole land area under consideration. The mean suitability weight is calculated as the average suitability weight of all parcels in the cluster.

- ***Competing cluster***: clusters with mean suitability weight close to the most suitable cluster (in this study within the range [w-0.1, w] where w represents the mean suitability weight of the most suitable cluster of parcels. Also such cluster overlap by less than 50 percent with the most suitable cluster or do not overlap at all
- ***Confidence bound***: the maximum difference in opinion among agents beyond which they do not exchange opinion (do not negotiate) regarding the suitability of a parcel of land for the intended land use.
- ***Rigidity coefficient***: the degree to which an agent adheres to its own opinion during opinion exchange.
- ***Baseline scenario***: the scenario that does not involve opinion dynamics model (land choice is made without negotiation among agents and just based on their initial opinion).

1.3 Problem statement

It may be required for land use decision makers to reach a decision about where to locate, for example, 100 hectare of new housing area for urban expansion. In agent based modelling agents calculate suitability weight of a given parcel of land for the required purpose based on some rule. The suitability weight from each agent is taken into account to determine where a land unit has to be allocated for the required land use purpose. An agent's behaviour, for example the weight it assigns to a parcel of land, can be influenced by the exchange of opinion with other agents. However, the effect of such opinion dynamics has on the process of land use decision making is not been well considered in currently available agent based models. Understanding the effect of opinion dynamics to agent based model outputs is of interest.

1.4 Objective

- ✓ The general objective this study is to investigate how exchange of opinion in agent based land use decision making influences the process of land use choice by decision makers and how best choice can be made.

1.5 Research questions

1. What are the different models of opinion dynamics (opinion exchange) and their parameters?
2. How fast is consensus reached regarding land use choice for different models of opinion dynamics?
3. How stable is the land use choice under different models of opinion dynamics?
4. How sensitive is decision making process to the parameters of opinion dynamics models?

Note: To serve as a foundation for this study we address the first research question through literature review before we present the methodological approaches for the other research questions.

1.6 Scope

This study investigated how repeated opinion exchange influences the process of land use choice among decision makers and how fast consensus is reached by taking initial suitability weight layers as an input. The initial suitability weight layers represent the opinion of each agent regarding the suitability of each parcel of land within a layer.

The rules based on which agents form their initial opinion about the suitability of a given parcel of land for an intended land use is not within the scope of this study. This study assumed that each decision maker (agent) has an initial set of suitability weights assigned to each parcel of land within the whole area of land from which to select defined size of land for the intended purpose. That means each agent has initial opinion about the suitability of each parcel of land for the intended land use in a form of suitability weight layer. In this study, these layers were generated using few random suitability weight seeds and then applying inverse distance interpolation. The detail is given in chapter 3 (methodology).

1.7 Outline

Chapter 1: this chapter presents introductory background, problem statement, research objective, research questions and the scope of the study.

Chapter 2: in this chapter models of opinion dynamics were reviewed based on literature. The details of some selected models and the typical model parameter were presented.

Chapter 3: based on the literature review in chapter two on models of opinion dynamics and in relation to the research objectives and questions, detailed methodological approach was presented. The method to generate suitability weight layers corresponding to the initial opinion of each agent was presented. Also the approach to introduce opinion dynamics was presented.

Chapter 4: Simulations were run for combinations of opinion dynamics models and model parameters. In this chapter results from these runs were presented and compared.

Chapter 5: In this chapter discussion was made based on findings and conclusions presented.

2. Models of opinion dynamics

2.1 Variations of opinion dynamics models

A number of opinion dynamics models has been developed and discussed by previous studies (Lorenz, 2007). Opinion dynamics models can be classified based on the nature of opinion as categorical or continuous. We refer to categorical models as those models where opinions are classified into nominal classes On the other hand models of continuous opinion dynamics refer to models that represent opinion as real numbers over a specified range called opinion space.

There are two major variations of continuous opinion dynamics model based on how agents communicate. The first one is where the opinion of an agent is shaped by the opinion of all the other agents, under the restriction that may be imposed on the allowed difference in opinion. This kind of models is thoroughly presented by Hegselmann and Krause (2002). The second one is where agents interact pairwise in a random fashion at each time step and exchange opinion if the difference in their opinion is below a given confidence bound. Hence the opinion of an agent is influenced by an opinion of only one agent at a time. But at each step an agent interacts with different agents. Such models are presented by (Deffuant et al., 2000). There are opinion dynamics models where agents interact if the difference in their opinion is below a threshold called confidence. Such models are called bounded confidence continuous opinion dynamics models.

Assume that the opinion of an agent 'i' at time 't' is given by $x_i(t)$. For n number of agents the opinion of all the agents at time 't' can be represented as a vector in an n-dimensional space:

$$X(t) = x_1(t), x_2(t), \dots, x_n(t)$$

If the opinion of agent 'i' is influenced by the opinion of all the other agents according to some weight for each agent, then the opinion of 'i' at time t+1 can be represented as:

$$x_i(t+1) = a_{i1}x_1(t) + a_{i2}x_2(t) + \cdots + a_{in}x_n(t)$$

where a_{ij} represents the influence weight of agent 'j' on agent 'i', for j an element of [1,n]

Agent 'i' adjusts his opinion at period t+1 by taking a weighted average for the opinion of other agents at time t. If the weight for agent j is zero, it means that agent 'i' totally disregards j's opinion. If it is one, it disregards all other agents' opinion and totally follows j's opinion. Putting the weights into a matrix, $A(t, x(t)) = (a_{ij}(t, x(t)))$, with *n* rows and *n* columns, yields the general form of continuous opinion dynamics model given by Hegselmann and Krause: $x(t+1) = A(t, x(t))\, x(t)$ for $t \in T$. (GM)

The model by Hegselmann and Krause has many versions: the classical model (CM), the time variant model (TV), the Friedkin and Johnsen model (FJ) and models with bounded confidence (BC). The classical model (CM) assumes fixed weight. A version of the CM that assumes an agent adheres to its initial opinion partly and depends on the opinion of other agents to some extent was given by (Friedkin and Johnsen 1990, 1999). In this version the opinion of agent 'i' at time t+1 is given as:

$$x_i(t+1) = g_i\, x_i(0) + (1 - g_i)(a_{i1}x_1(t) + \cdots + a_{in}x_n(t))$$

where g_i represents the weight by which the agent adhere to its initial opinion. The value g_j is referred to as rigidity coefficient (RC) in this study.

In the time variant (TV) model the weight is not fixed and depends on time.

The most commonly used version of Hegselmann and Krause model is the continuous opinion dynamics under bounded confidence (BC). Bounded confidence restricts an agent to consider another agent's opinion if and only if the difference in their opinion is below certain threshold called confidence. Agents share opinion only if they have opinions that are somewhat close to each other. If the difference between the opinion of agent 'i' and agent 'j' is greater than the confidence values agent 'i' disregards the opinion of agent 'j'(i.e., give a weight of zero to j). BC models can be symmetric where the confidence difference threshold for the first agent to consider the opinion of the second agent is equal to the confidence difference threshold for the second agent to consider the opinion of the first agent or asymmetric.

When agents interact the opinion of an agent will be some form of average of other agents which may include itself. Models of opinion dynamics can also be classified based on the method of opinion averaging employed when agents interact. Opinions can be averaged using arithmetic mean, geometric mean, and etc. (Hegselmann and Krause, 2005). The output of the model differs for different type of averaging.

2.2 Model parameters

In section 2.1 we discussed some of the most common models of opinion dynamics. These models differ in the way they formalize exchange of opinion among agents. For example, some models assume that all participating agents influence each other and hence the opinion of an agent is shaped by the opinion of all other agents. Other models assume agents interact and exchange opinion in a random pair wise fashion at a time. Within each variation model behaviour may vary based on the value of parameters passed to the models. Here we discuss two typical opinion dynamics parameters that we use in this study: confidence bound and rigidity coefficient. These parameters are in essence the reflection of the level of agents' openness to others opinion and agents rigidity in terms of maintaining their own opinion.

i. Confidence bound

Confidence bound refers to the maximum difference in opinion between two agents beyond which they no more negotiate and exchange opinion. The larger the confidence bound value for a given opinion dynamics the higher the probability that model agents exchange opinion. The value of confidence bound determines whether or not consensus is reached among interacting agents. For example, in the bounded confidence continuous opinion dynamics (Hegselmann and Krause 2002), high value of confidence bound leads to convergence of opinion. Convergence of opinion means reaching consensus among multiple agents. Lower value of confidence leads to fragmentation of opinion and formation of multiple opinion clusters. If multiple opinion clusters are formed, members of cluster agree with each other but agreement across clusters will not be achieved anymore (Deffuant et al., 2000)].

ii. Rigidity coefficient

Rigidity coefficient refers to the level of agents' adherence to its own initial opinion. It is the measure of the probability that people are completely rigid and never change their opinion (Soham Biswas and Parongama Sen, 2009). Large value of rigidity coefficient represents conservative agents. For example, in the version of the classical model (CM) presented by (Friedkin and Johnsen 1990, 1999) an agent adheres to its initial opinion by a factor equal to the rigidity coefficient and depend on the opinion of other agents by a factor of one minus the rigidity coefficient. The larger the value of the rigidity coefficient, the more conservative agents are and hence the less probable agents reach consensus given that they widely vary in their initial opinion.

3. Methodology

In order to study how inclusion of opinion dynamics model influence the process of land use choice among decision makers we introduced ten different hypothetical decision makers (agents) and a 50 by 50 parcel of hypothetical land unit from which to select a continues land unit of 10 by 10 parcel for an intended hypothetical land use (e.g., residential house building) purpose. Ten different suitability weight layers were generated for the whole area of the land. Suitability weight refers to the suitability of a given land parcel for the intended purpose (e.g., residential house building) as perceived by a given decision maker (agent). In other words, suitability weight represents the opinion of an agent regarding how suitable a given land parcel is for the intended purpose. Each one of the ten suitability weight layer corresponds to the weight assigned by each one of the ten agents to the parcels within the whole land unit. The rules that agents use to form their initial about a land parcel is not within the scope of this study. We generate suitability weight layer corresponding to each agent initial opinion using initial set of random weight seeds and inverse distance interpolation.

The agents, the land unit, the intended land use (residential house building), and the suitability weights are all hypothetical. This approach corresponds to the designed agent-designed environment approach to agent based modelling (Dawn et al., 2001). Designed agents are not directly inferred from empirical data as opposed to analyzed agents, which are directly grounded in empirical data. Designed environment is one without empirical parameterization whereas an analyzed environment relies directly on empirical data (Dawn et al., 2001). Where there are no empirical data and the idea is just to simulate relationship between set of factors, the designed agent-designed environment could be the best way to go. Since the purpose of this study is to experiment how opinion dynamics models could influence land-use choice, we formulated hypothetical agents and hypothetical environment (land).

3.1 Agents and suitability weight layers generation

Ten different suitability weight layers were constructed that represents the initial weight of the ten agents for the whole land area.

For each agent, a suitability weight layer is constructed according to the following procedure:

1. Random suitability weight values between 0 and 1 were assigned to 200 randomly chosen land parcels within the whole land unit (50 by 50 parcels) to serve as seeds. The weights represent the suitability of the parcels for our hypothetical land use (residential house building) as perceived by the agent.

2. We assumed that an agent gives relatively similar weights for neighbouring land parcels than parcels that are far apart. Therefore, for land parcels other than the initial randomly assigned seeds, weight value was interpolated using inverse distance weighting. The interpolation considers only 48 (3 by 3 window) land parcels around the cell for which weight is calculated. Among these only cells which are already assigned with weight are considered. Shepard's simple inverse distance weight function (Shipard D., 1968) with power parameter p=2 was used:

$$u(x) = \sum_{i=0}^{N} \frac{w_i(X) u_i}{\sum_{j=0}^{N} w_j(X)}$$

where

$$w_i(X) = \frac{1}{d(x, x_i)^p}$$

x is an interpolated point,

x_j is an interpolating point,

d is distance between points,

N is total number of interpolating points,

p is power parameter

Figure 3.1 shows example of suitability weight layer for an agent generated by the above procedure.

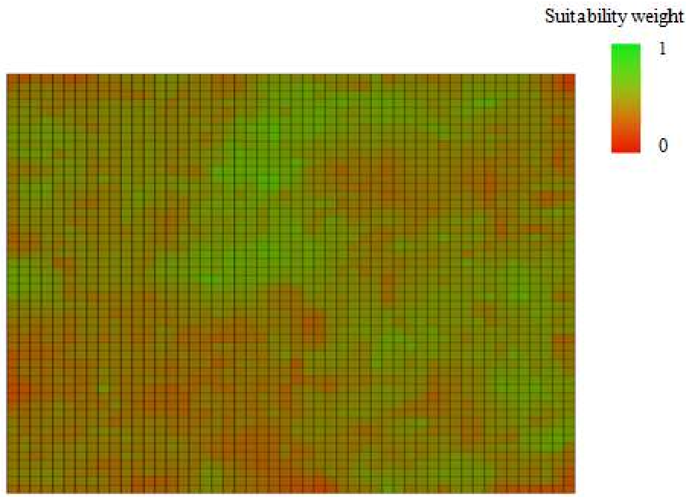

Figure 3. 1: Example of suitability weight layer corresponding to an agent's initial opinion (suitability weight)

Table 3. 1: Summary of model setup values

Parameters	Values
Input land (hypothetical) size	50 by 50 which is equal to 2500 equally sized land parcels
Size of land to be selected	10 by 10 which is equal to 100 parcels
Number of decision makers	10
Number of input suitability weight layers	10 corresponding to each agent
Number of seeds for interpolation	200
Minimum suitability weight of a pracel	0
Maximum suitability weight of a parcel	1
Interpolation neighbourhood size	3 which means 48 neighbouring parcels
Interpolation p-factor	2
Interpolation algorithm	Shipard’s simple inverse distance weight function

3.2 Simulation tool

Recursive Porous Agent Simulation Toolkit (Repast) version 2.0 was used for model simulation. Specifically we used Repast Simphony (where modelling makes use of Java API). Repast is a framework for agent based modelling with built-in rich graphical user interface components for simulation visualization. The graphical user interface also allows such things as model and agent parameters definition and initialization, graphing, data set definition and data export. In this study, data were exported as a text file then imported to Microsoft excel for analysis.

3.3 Opinion dynamics models

Some models of opinion dynamics were discussed in chapter 2. These models can be classified based on different aspects. One classification is based on how agents interact; all agent interaction and random pairwise interaction. The other is based on condition for interaction; with confidence/trust level, where agents interact only if the difference in their opinion is below a given threshold value called confidence, and without confidence. Models of opinion dynamics are also classified based on how they treat opinion; binary and continuous opinion. Method of averaging is another basis for the classification of opinion dynamics.

Though there are a number of classes of opinion dynamics models and different flavours within each class, this study considered only continuous dynamics models with bounded confidence. Two forms of continues opinion dynamics models with bounded confidence were considered: with partial dependence on initial self opinion (rigidity coefficient different from zero), and without dependence on initial self opinion (rigidity coefficient zero). Both all-agent and random pairwise interaction version of continuous dynamics model with bounded confidence were considered. Arithmetic mean was used for calculating weighted averages. For the sake of simplicity the weight that an agent put on another agent, i.e., the degree to which one agent's opinion influences another agent's opinion, stays constant with time. Therefore, we considered constant weight matrix. Also only symmetric confidence was considered. Table 3.1 shows the features of models we considered in this study.

Table 3. 2: Features of opinion dynamic models considered in this study (marked X)

Criteria	**Values**		
Opinion	☒ Continuous	☐ Binary	
Weight time dependant	☐ Yes	☒ No	
Confidence	☒ Bounded	☐ Unbounded	
Confidence symmetry	☒ Symmetric	☐ Asymmetric	
Agent interaction	☒ All agent	☒ Pairwise	
Dependence on initial opinion	☒ Partial	☒ None	
Averaging scheme	☒Arithmetic mean	☐Geometric mean	etc

We chose continuous models because it is highly likely that an agent assigns some value between 0 and 1 rather than weight of 0 or 1 for suitability of a given land parcel for residential house building. This means it is less likely to say a parcel of land is 100% suitable or 100% unsuitable. Therefore, using continuous opinion dynamics model reflects what would happen in real world than binary opinion models. Again we chose models with bounded confidence because in the real world people (agents) interact with each other and exchange their opinion only if they have somewhat similar opinions. An agent may share opinion with every other agent or only with one agent at a time. Therefore, both all agents and random pairwise interactions were considered. We considered agent's dependence on its initial opinion to see how agents rigidity affects model output.

As can be seen from table 3.1, all the case models we considered are continuous, bounded, symmetric and are based on arithmetic mean for calculation of average suitability for a given land parcel. These aspects being the same we have three models that differ on the basis of number of agents that interact to exchange opinion and agents dependence on their initial opinion (rigidity). These are:

- All agents interaction with initial self-opinion dependence
- All gents interaction with initial self-opinion independence
- Pair wise interaction with initial self-opinion dependence

3.4 Parameters for sensitivity analysis

Models sensitivity to the following parameters was investigated:

- Confidence bound (simulation run for values 0.1, 0.25, 0.5)
- Rigidity coefficient (simulation run for values 0, 0.25, 0.5, 0.75)

We assumed that very low suitability may converge to zero and large suitability weight may converge to one. In other words, if an agent gives very low suitability weight for a given parcel it is less likely that the agent is convinced to select that parcel and if it gives very high value it is unlikely that the agent yields its opinion about the suitability of the parcel for the intended purpose. Suitability values of 0.25 and 075 were used in our simulation as limits of convergence.

3.5 Simulation aspects monitored

Vis-à-vis the research questions of this study the following simulation aspects were monitored and compared for the combinations of opinion dynamics models and values of confidence bound and rigidity coefficient. The values were captured for each simulation step (also called meeting or opinion exchange) and outputs were exported for analysis.

- Mean suitability weight for the most suitable cluster of parcels. 'Most suitable cluster' refers to a set of 10 by 10 continues land parcels with the maximum mean suitability weight at each simulation step (meeting).
- Spatial stability of the most suitable cluster of parcels as measured by the stability of the centre coordinates of the cluster.
- Number of meetings (opinion exchange) to reach stable mean suitability weight

- The number of competing clusters. 'Competing clusters' are clusters of 10 by 10 parcels with mean suitability weight within the range of 0.1 below the means suitability weight of the most suitable cluster and that overlap by less than 50 percent with the most suitable cluster or do not overlap at all. The assumption is that the larger then number of computing clusters the more difficult it is to decide which cluster to choose for the intended land use purpose.

We consider the first two aspects as a measure of how best agents (decision makers) select suitable set of land parcels for the intended purpose through repeated negotiation (opinion exchange). If all agents have reached an opinion that the parcels within a given cluster are highly suitable for the intended purpose, the cluster will have high mean suitability weight. If the spatial location of the most suitable clusters of parcels chosen at each meeting does not change (spatially stable), it is considered that decision has been made as two where to locate the intended land use. Thus, higher value of mean suitability weight for a cluster and spatial stability of the most suitable cluster implies that agents has reached consensus with respect to the suitability of the cluster and its location for the intended land use purpose.

The number of meetings to reach a stable mean suitability weight of most suitable cluster is considered as a measure of how fast consensus can be reached.

The number of competing clusters is considered as the reflection of the final state of the negotiation process. Large number of competing clusters means, it is difficult to reach decision regarding the specific location to choose. This is because within small range of mean suitability weight we would have large number of alternative and equivalent clusters to choose. Thus, in order to choose one cluster from the set of alternative clusters may need further negotiations.

All aspect were investigated for each sensitivity analysis parameter values and compared. Comparisons were made with the baseline scenario as well.

3.6 Conceptual design and simulations

Baseline scenario

The baseline scenario refers to a scenario where opinion dynamics is not considered. The 10 suitability weight layers corresponding to each agents weight map for the land under consideration were saved for use in the simulations. The baseline scenario involves calculating a suitability weight layer representing the average weight of all the agents. Then a cluster of 10 by 10 land parcels with the highest mean suitability weight and the clusters centre coordinate were determined. This cluster represents the most suitable cluster for the baseline scenario. Also the number of competing clusters was calculated.

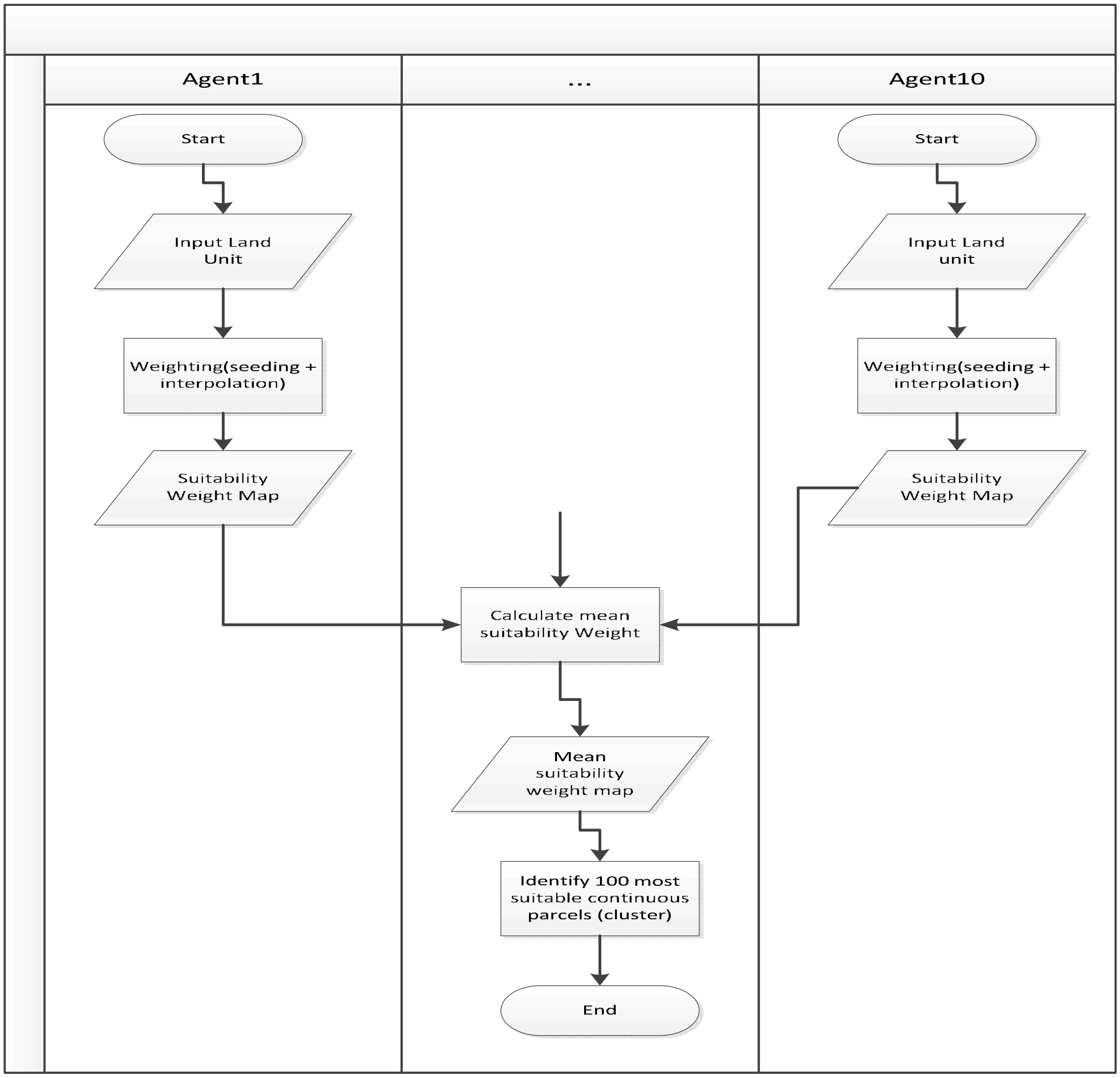

Figure 3. 2:Conceptual model for scenario without opinion dynamics (baseline)

The mean suitability weight the most suitable cluster, its spatial location and the number of competing clusters for the baseline scenario were compared with the corresponding mean suitability weight of most suitable clusters and the number of competing clusters for each modelling scenarios. The intension was to see how application of opinion dynamics model (agent negotiation) affects decision process and output. For example, whether a better agreement (better mean suitability weight) can be achieved, whether the decision about the exact spatial location of the most suitable cluster changes and whether specific cluster can be chosen or more number of competing clusters, that makes decision difficult, emerge.

Scenarios with opinion dynamics

The initial 10 suitability weight layers were used as input. In this case at each time step of simulation (each meeting among agents) agents interacts with each other and adjust the weight they assign to each land parcel based on opinion of other agents according to a specific opinion dynamics model. Therefore, at each time step in the simulation the 10 suitability weight layers were updated. At each time step again an average suitability weight layer of the 10 suitability weight layers was calculated. From the average suitability value layer, the mean suitability weight of most suitable cluster of 10 by 10 neighbouring land parcels was calculated at each time step. The simulation continues until we get a stable spatial pattern. Stability is measured by the stability of mean suitability weight value of the most suitable cluster of 100 land parcels and the spatial stability of the cluster. The stability of mean suitability weight was monitored by drawing a graph during the simulation. Repast Simphony 2.0, was used for simulation in this study and it supports dynamic graphing of any parameter verses the simulation time stamp.

How to introduce opinion exchange

A hypothetical 10 by 9 weight matrix was created. The weight in this case refers to the extent to which an agent's opinion is influenced by opinion of another agent. $W_{ij,}$ represents the weight of agent j's opinion to agent i's opinion. The higher the value of W_{ij} the stronger the magnitude by which agent i is influenced by agent j. The sum of all weight W_{ij} for agent i where j ε [1, 9] should be 1. Note the value 9 for the second dimension of the weight matrix; an agent depends on the opinion of the remaining 9 agents. The case with dependence on initial self opinion was handled by the rigidity coefficient.

At each time step t, the weight assigned by agent i to a particular land parcel is given by the weighted average of other agents' weight for that parcel at time step t-1. The agents to be considered in the calculation and the level of dependence on others opinion were determined by a particular opinion dynamics model under consideration. This calculation was repeated for each land parcel. This way, the suitability weight map (value layer) for the whole land area for agent i at time step t was created.

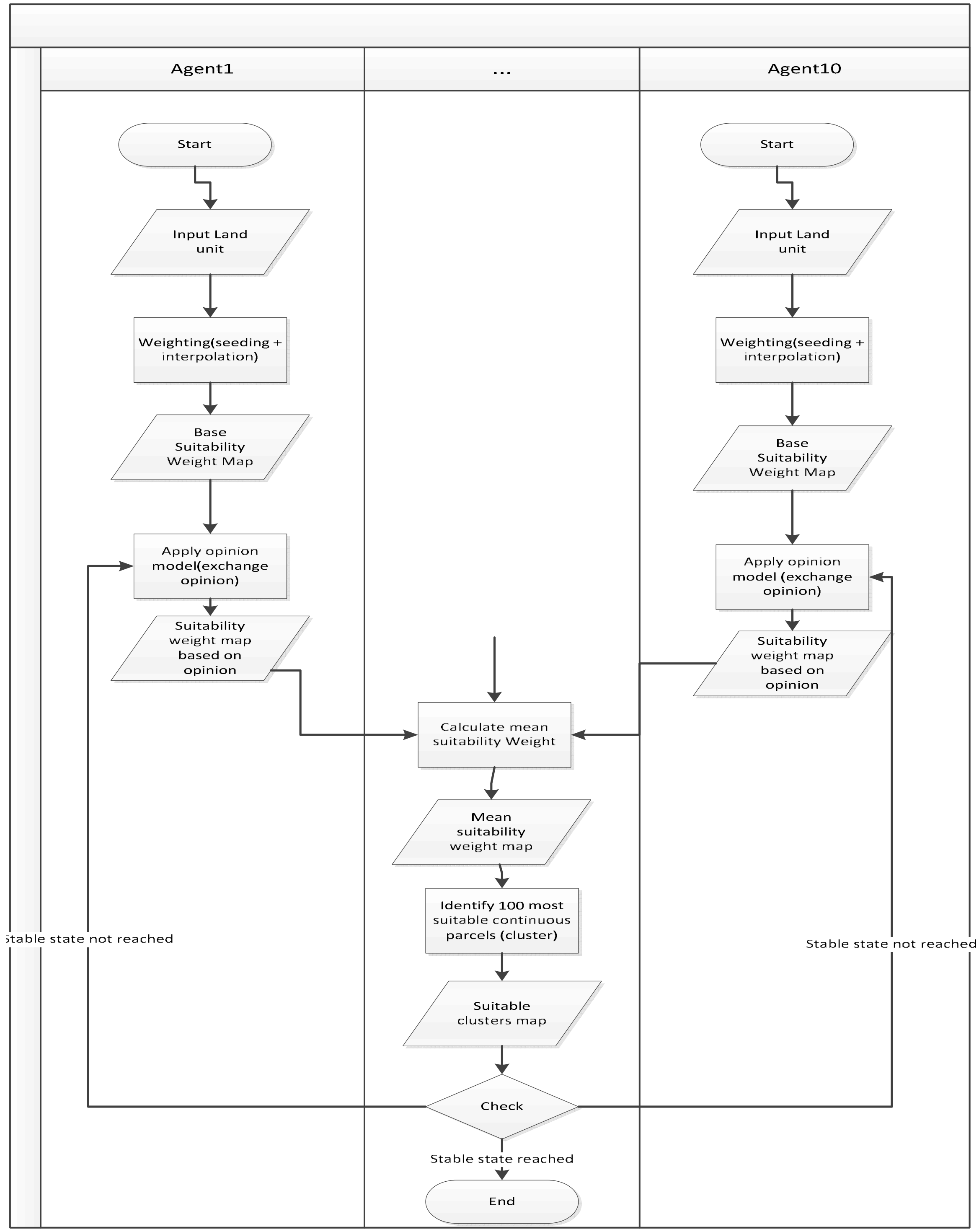

Figure 3. 3: Conceptual model for scenario with opinion dynamics model

4. Results and analysis

4.1 Baseline scenario

To serve as a baseline scenario the ten suitability weight layers corresponding to the ten decision makers (agents) were used as input to simulation. The baseline scenario refers to a scenario where opinion dynamics models were not applied. An average suitability weight layer was calculated by taking the average value of the suitability weight of each land parcel from the ten suitability weight layers. Since there is not opinion exchange for the baseline scenario, the result of the first simulation would not change with repeated simulation steps. Therefore, determination of the mean suitability weight of the most suitable cluster, the centre coordinate of the cluster and the number of competing clusters were determined from the average suitability weight layer generated by the first simulation step. Table 4.1 summarizes the value of these values for the baseline scenario. Figure 4.1 show the average suitability weight layer generated for the baseline scenario.

Note: the 'most suitable cluster' is the cluster to be chosen for the intended land use purpose once the dynamics reaches stable state. The 'number of competing clusters' refers the number other clusters of parcels with mean suitability weight within the range of 0.1 below the means suitability weight of the most suitable cluster and that overlap by less than 50 percent with the most suitable cluster or do not overlap at all.

Note: the origin coordinate (0,0) is at the left bottom of images (suitability weight layer maps) presented in this chapter. That is how REPAST does.

Table 4. 1: Aspect of the most suitable cluster for baseline scenario

Mean suitability weight	Cluster centre x-coor	Cluster centre y-coor	Number of competing cluster
0.569	23	41	17

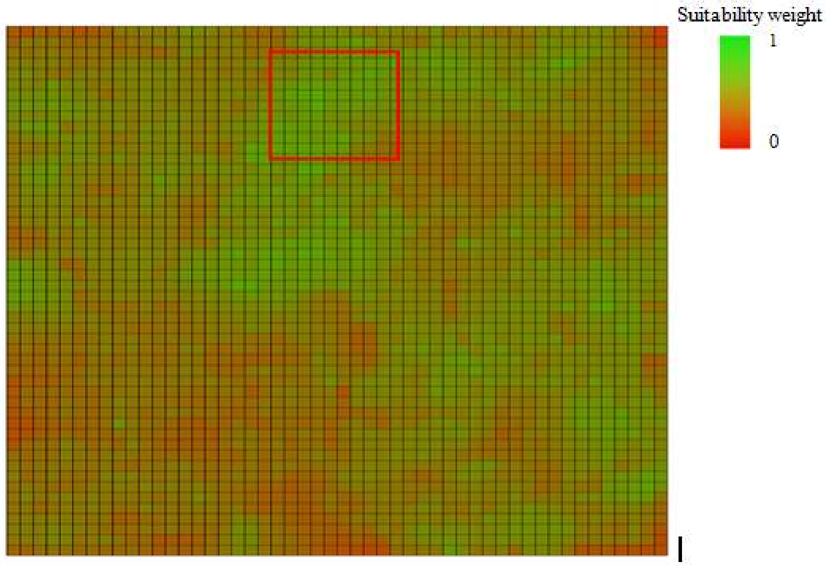

Figure 4. 1: Average suitability weight layer (baseline scenario)

The most suitable cluster for the baseline scenario has mean suitability weight of 0.569 and is centered at coordinate (23, 41) within the 50 parcel by 50 parcel area of land under consideration. There are 17 competing cluster with mean suitability weight within range of 0.1 below the mean suitability weight of the most suitable cluster. This indicates that, for the baseline scenario, it is difficult to come up with a single most suitable cluster within a given range of mean suitability weight difference among clusters.

4.2 Scenarios with opinion dynamics models

In this section results for simulations involving different combinations of opinion dynamics models and model parameters are presented. Three models of opinion dynamics were applied to the process of identifying the most suitable cluster of parcels for the intended land use. The models were configured and run with combination of three different values of confidence bound (CB) and rigidity coefficient (RC).

4.2.1 Model 1: All agents interaction with initial self-opinion dependence

This is the model where at each time step (meeting), an agent exchanges opinion with all other agents and form the next opinion regarding the suitability of each land parcels for the intended purpose. During repeated meeting an agent adheres to its current opinion by a factor equal to the rigidity coefficient (RC) and recalculates the rest of its next opinion based on the opinions of all other agents according to weight factors associated with the agents. Three cases were simulated for this model.

The first case of this model of opinion dynamics was run by varying the confidence bound value (0.1, 0.25, and 0.5) and keeping rigidity coefficient to a value of 0.25. Agents adhere to their initial opinion about the suitability of land parcels for the intended land use purpose by a factor of 0.25. At each time step of simulation (meeting), an agent exchange opinion about the suitability of a land parcel with all other agents to form its next opinion about the land parcel. The agent depends on the opinion of other agents by a factor of 0.75.

The second and the third cases were run for rigidity coefficient (RC) value 0.5 and 0.75 respectively and varying confidence bound values (0.1, 0.25 and 0.5) in both cases.

Table 4. 2: Model 1, case 1 (Varying CB and RC=0.25)

Confidence bound(CB)	**Rigidity Coefficient (RC)**
0.1	0.25
0.25	0.25
0.5	0.25

The result for case 1 shows that, keeping the rigidity coefficient at 0.25, the mean suitability weight of the most suitable cluster increases with increasing value of confidence bound. For our case the highest value of mean suitability weight of the most suitable cluster was achieved for confidence bound value of 0.5. Moreover, the number of competing clusters decreases with increasing value of confidence bound. The stable number of competing clusters for confidence bound 0.5 is 2; whereas the stable number of competing clusters for confidence bound 0.25 fluctuate between 5 and 6. For the confidence bound 0.1 the number increases to 13.

The time it took (number of meetings) to reach stable value of mean suitability weight is about 3 for all values of confidence bound (figure 4.2). However, the number of competing cluster achieved stable value on the first meeting for confidence bound 0.5 case while it is achieved during the third meeting for the case of 0.1 confidence bound (figure 4.3). Continues fluctuation of the number of competing clusters between 5 and 6 was observed for confidence bound 0.25. It can be seen that while the number of meeting to reach a stable state is about the same, various values of confidence bound result in different output in terms of choosing the best cluster of the intended land use and the level of fragmentation of opinion regarding where to locate the best cluster for the intended land use.

For confidence bound value of 0.5 the relatively higher value of mean suitability weight shows that most agents generally assign higher suitability values parcel inside the most suitable cluster. This means, relatively higher consensus is reached among the agents regarding the suitability of the selected cluster (most suitable cluster) for the intended land use. The higher level of consensus among agents with regard to the suitability of the most suitable cluster for the case of higher confidence bound is also evidenced by the fewer number of competing clusters. Fewer number of competing clusters means that ambiguity in selecting optimal location for the intended land use is reduced.

On the other hand, lower values of confidence bound led to smaller mean suitability weight value and large number of closer alternatives (competing clusters). By considering the mean suitability weight of the most suitable cluster and the number of competing clusters as a measure of consensus, confidence value of 0.5 yields the best level of consensus among agents and far better than the baseline scenario. In terms of the mean suitability weight of the most suitable cluster the cases with confidence bound 0.1 and 0.25 yielded values even smaller than the baseline scenario. However, still better results were achieved in terms of reducing the number of alternative clusters in the baseline scenario.

Table 4. 3: Model 1, case 1 result (aspects of most suitable cluster)

	Mean suitability weight	**Cluster centre x-coor**	**Cluster centre y-coor**	**# of competing cluster**
Baseline	0.569	23	41	17
CB=0.1	0.326	26,26	41,42	13
CB=0.25	0.425	23,23	30,33	5
CB=0.5	0.664	23,25	39,43	2

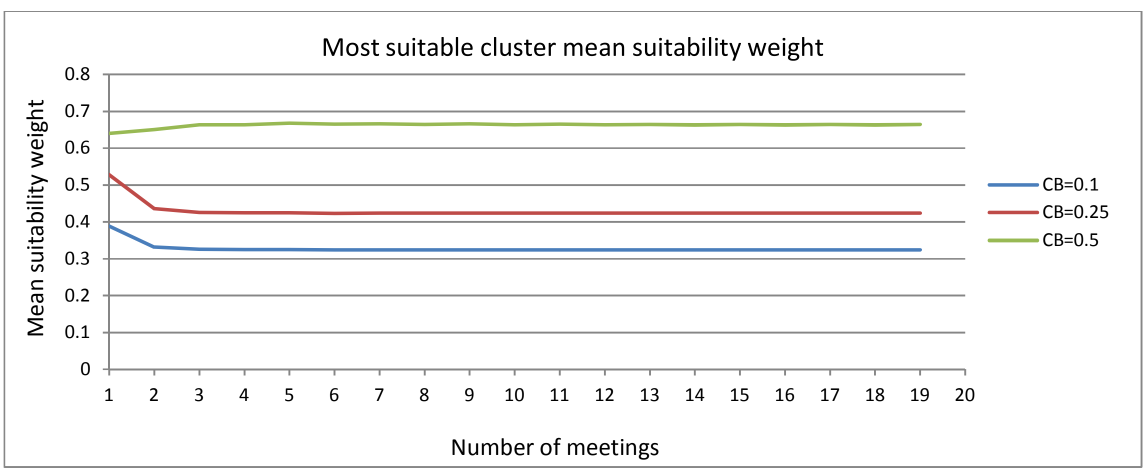

Figure 4. 2: Model 1, case 1 most suitable cluster mean suitability weight during repeated meetings

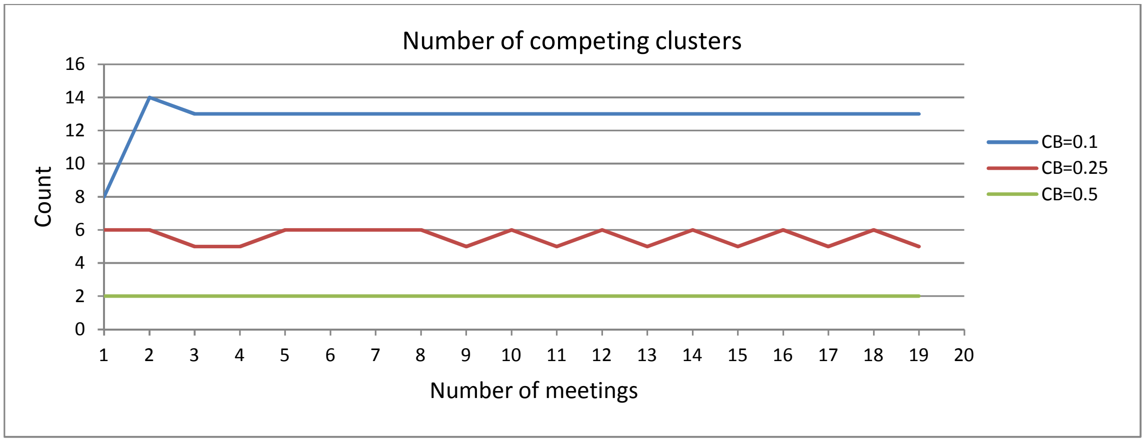

Figure 4. 3: Model 1, case 1 number of competing clusters during repeated meetings

With regard to the spatial stability of the most suitable cluster the various values of confidence bound seems to exhibit similar behaviour. Under all values of confidence bound, the most suitable cluster at each simulation step stayed at about the same spatial location. During repeated opinion exchange the centre coordinate of the most suitable cluster under each confidence bound value assumed only two points which are very close to each other. Figure 4.4 shows the location of the centre coordinate of the most suitable cluster during repeated opinion exchange. An interesting observation about the spatial location of the most suitable cluster is that for confidence bound values 0.1 and 0.5 the location has not shifted significantly from the location of the most suitable cluster for the baseline scenario (the scenario without opinion dynamics). See table 4.3 for the x and y coordinates values of the clusters.

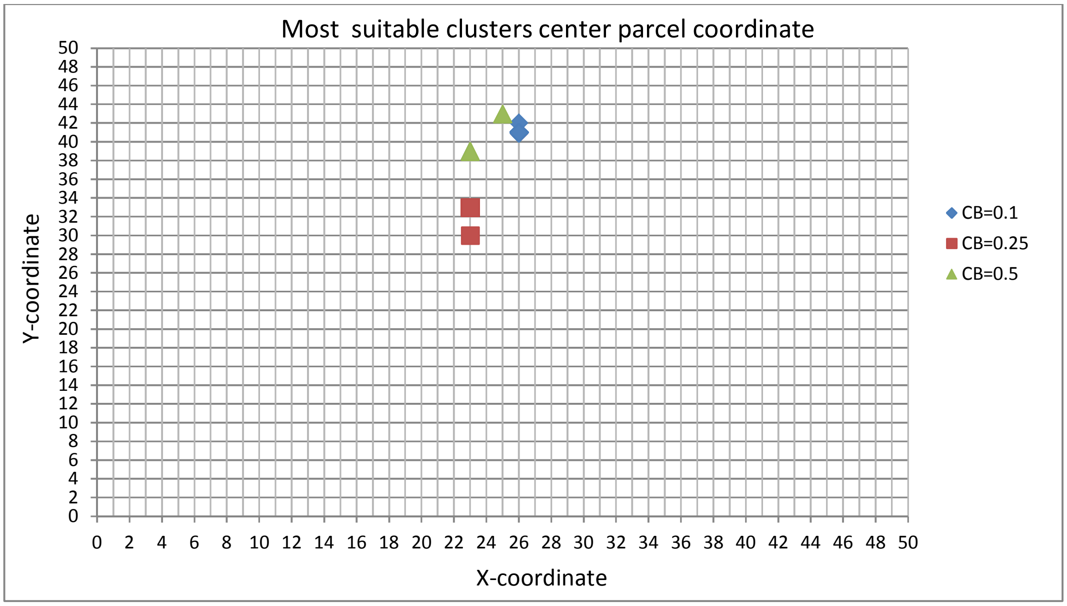

Figure 4. 4: Model 1, case 1 centre coordinates of most suitable cluster

In general best result was observed for the largest confidence bound value (0.5) when rigidity coefficient is kept at value 0.25. Agents were able to identify a cluster with the highest mean suitability weight than in the case of lower confidence bound values. The number of competing clusters is very small relative to the other confidence bound cases. Moreover, the most suitable cluster has stable spatial location and is identified just after few meetings (3 to reach stable mean suitability weight and 1 for number of competing cluster). Figure 4.5 shows the stable state average suitability weight layers for the three values of confidence bound.

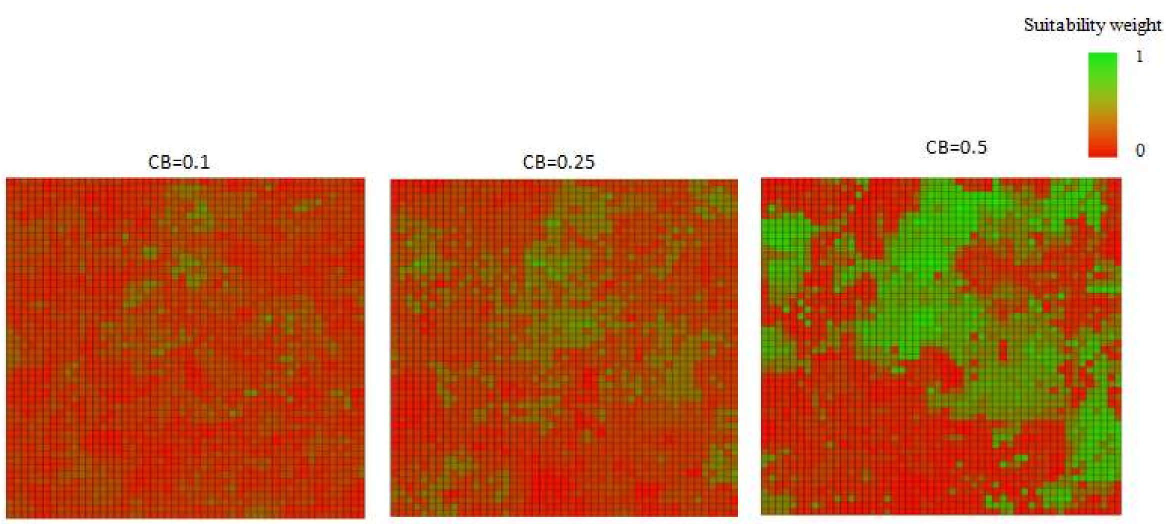

Figure 4. 5: Model 1, case 1 stable average suitability weight layers

In the second case of the first model we considered constant rigidity coeffient value of 0.5 and varying value of confidence bound.

Table 4. 4: Model 1, case 2 (Varying CB and RC=0.5)

Confidence bound (CB)	Rigidity Coefficient (RC)
0.1	0.5
0.25	0.5
0.5	0.5

Keeping the rigidity coefficient at 0.5, the mean suitability weight of the most suitable cluster increases with increasing value of confidence bound. The highest value of mean suitability weight of the most suitable cluster and the smallest number of competing clusters were achieved again for confidence bound value of 0.5 (table 4.5).

The time it takes (number of meetings) to reach stable value of mean suitability weight is a little bit prolonged as compared to the case where rigidity coefficient is 0.25 (figure 4.6). However, the number of meeting to achieve stable number of competing clusters stayed the same except for the case with confidence bound 0.1 (figure 4.7). Various values of confidence bound result in different output in terms of choosing the best cluster of the intended land use and the level of fragmentation of opinion regarding where to locate the best cluster for the intended land use.

Table 4. 5: Model 1, case 2 result (aspects of most suitable cluster)

	Mean suitability weight	Cluster centre x-coor	Cluster centre y-coor	# of competing cluster
Baseline	0.569	23	41	17
CB=0.1	0.318	25,26	40,41	15
CB=0.25	0.425	22,22,23	30,33,33	5
CB=0.5	0.659	21,23,23, 25	33,39,40,43	2

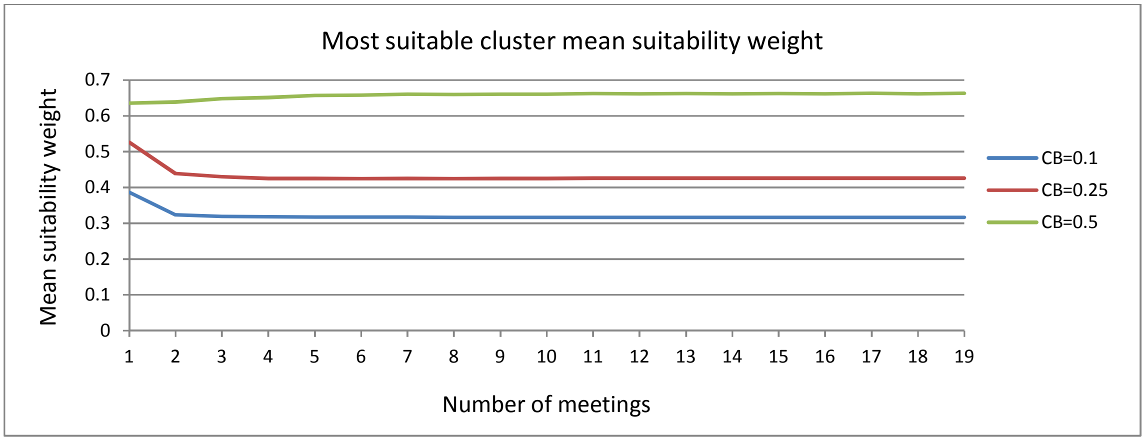

Figure 4. 6: Model 1, case 2 most suitable cluster mean suitability weight during repeated meetings

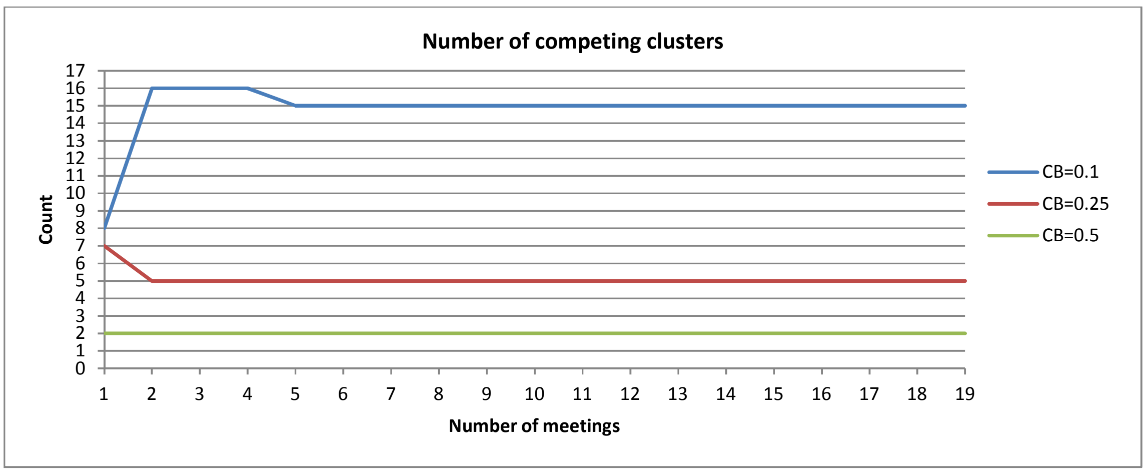

Figure 4. 7: Model 1, case 2 number of competing clusters during repeated meetings

The spatial location of the most suitable cluster showed shift from the baseline scenario for the case with confidence bound 0.25 and 0.5(figure 4.8). For confidence bound 0.1, the most suitable cluster at each simulation step stayed at about the same spatial location as the baseline scenario. During repeated opinion exchange the centre coordinate of the most suitable cluster for confidence bound value 0.5 assumed four different points. The cases with confidence bound 0.25 and 0.1 assumed three and two different points respectively. Figure 4.8 shows the location of the centre coordinate of the most suitable cluster during repeated opinion exchange. See table 4.5 for the x and y coordinates values of the clusters.

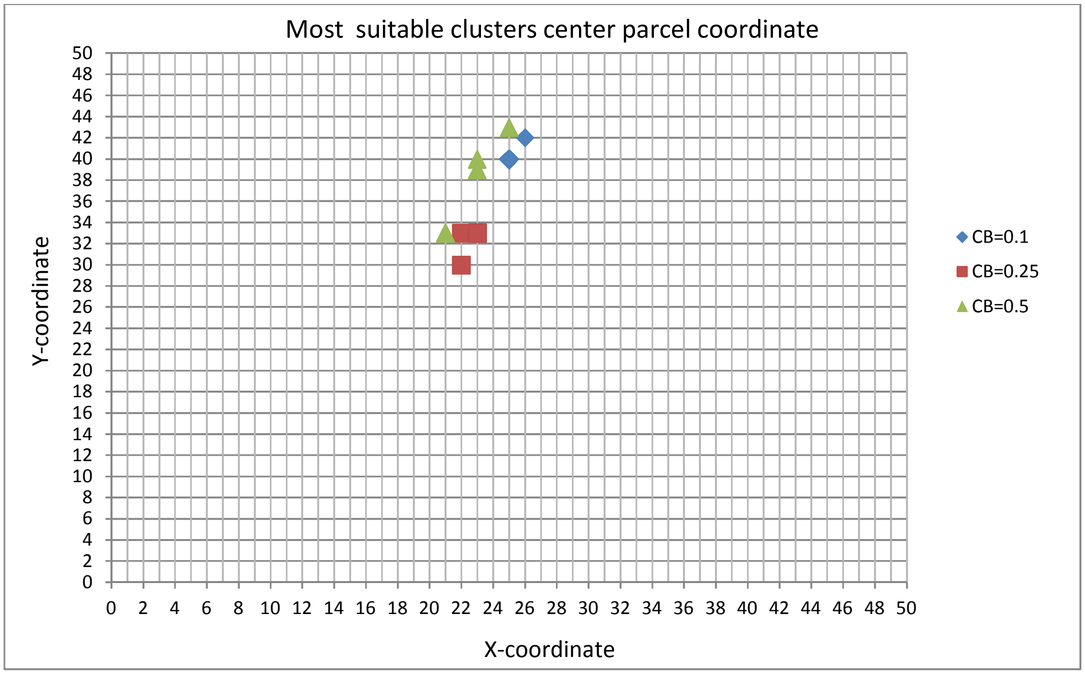

Figure 4. 8: Model 1, case 2 centre coordinates of most suitable cluster

The best result in terms of mean suitability weight of the most suitable cluster and the number of competing clusters was observed for the largest confidence bound value (0.5) when rigidity coefficient is kept at value 0.5. Agents were able to identify a cluster with the highest mean suitability weight and the smallest number of competing clusters than the case with lower confidence bound values. However, the most suitable cluster for confidence bound 0.5 is spatially less stable. This can hamper consensus among agent with regard to where to exactly locate most suitable cluster for the intended land use. Figure 4.9 shows the stable state average suitability weight layers for the three values of confidence bound.

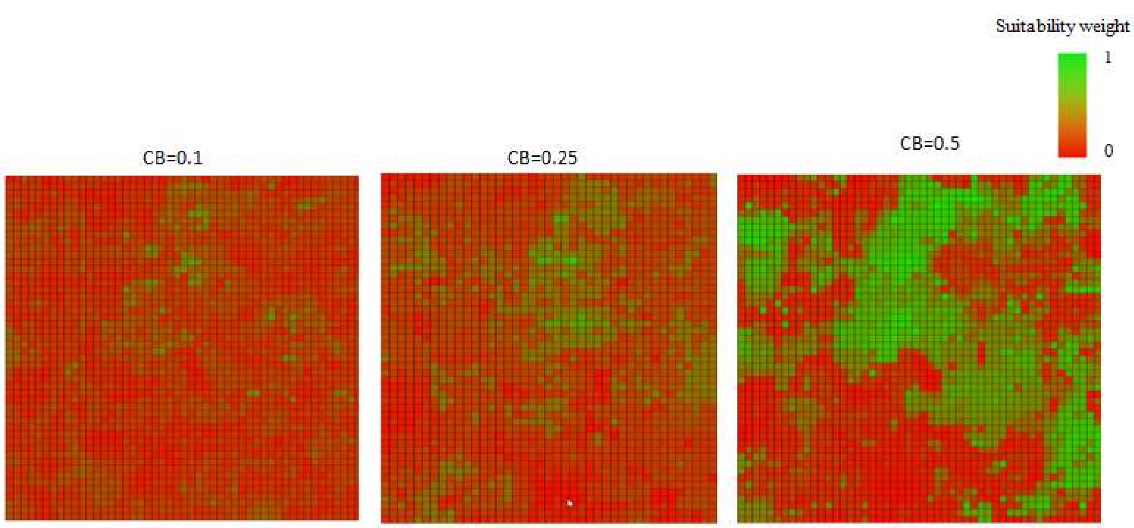

Figure 4. 9: Model 1, case 2 stable average suitability weight layers

Table 4. 6: Model 1, case 3 parameters (Varying CB and RC=0.75)

Confidence bound (CB)	Rigidity Coefficient (RC)
0.1	0.75
0.25	0.75
0.5	0.75

Relatively similar results were observed as in the second case. Keeping the rigidity coefficient at 0.75, the mean suitability weight of the most suitable cluster increases with increasing value of confidence bound. The highest value of mean suitability weight of the most suitable cluster and the smallest number of competing clusters were achieved for confidence bound value of 0.5 (table 4.7). The time it takes (number of meetings) to reach stable value of mean suitability weight followed the same pattern as in the second case (rigidity coefficient 0.75)(figure 4.10). The number of meeting to achieve stable number of competing clusters is also the same as in the second case, except slight fluctuation for confidence bound 0.25 (figure 4.11).

Table 4. 7: Model 1, case 3 result (aspects of most suitable cluster)

	Mean suitability weight	Cluster centre x-coor	Cluster centre y-coor	# of competing cluster
Baseline	0.569	23	41	17
CB=0.1	0.309	25,26,26	40,42,44	17
CB=0.25	0.416	21,22,22	33,33,34	4,5
CB=0.5	0.656	21, 23,23	30,39,40	2

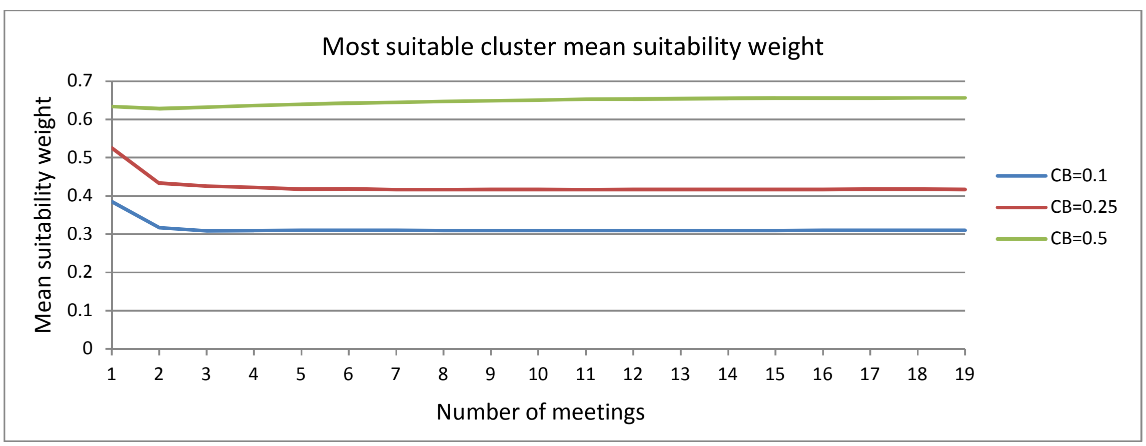

Figure 4. 10: Model 1, case 3 most suitable cluster mean suitability weight during repeated meetings

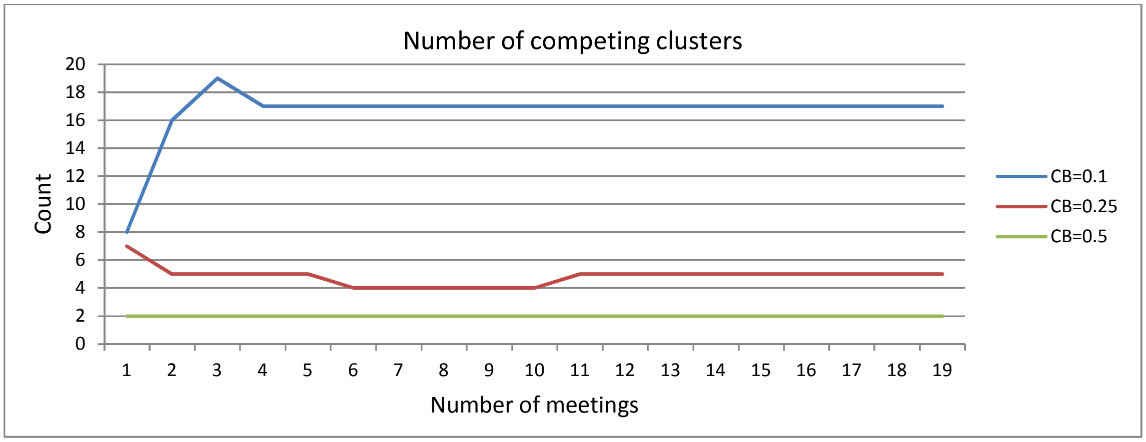

Figure 4. 11: Model 1, case 2 number of competing clusters during repeated meetings

Again the spatial location of the most suitable cluster showed shift from the baseline scenario for the case with confidence bound 0.25 and 0.5(figure 4.12). For confidence bound 0.1, the most suitable cluster at each simulation step stayed at about the same spatial location as the baseline scenario. During repeated opinion exchange the centre coordinate of the most suitable cluster for all confidence bound values three different points. However, the distance between the three points differs for each confidence bound values.

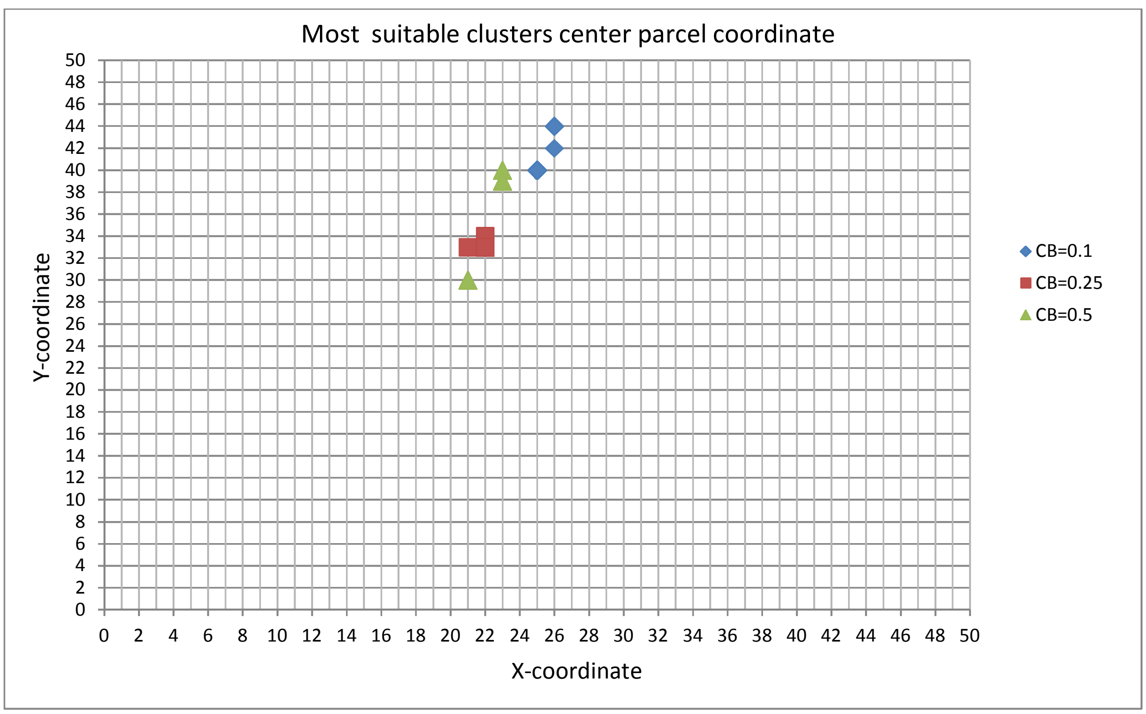

Figure 4. 12: Model 1, case 3 centre coordinates of most suitable cluster

In terms of the mean suitability weight of the most suitable cluster and number of competing clusters, the best result was observed for the largest confidence bound value (0.5) when rigidity coefficient is kept at value 0.75. However, the most suitable cluster assumed relatively different and far apart locations during repeated meeting for confidence bound 0.5 (figure 4.12). This means the most suitable cluster is spatially unstable. Therefore, it can be relatively difficult for agents to agree on where to exactly locate clusters of parcel for the intended land use. Figure 4.13 shows the stable state average suitability weight layers for the three values of confidence bound.

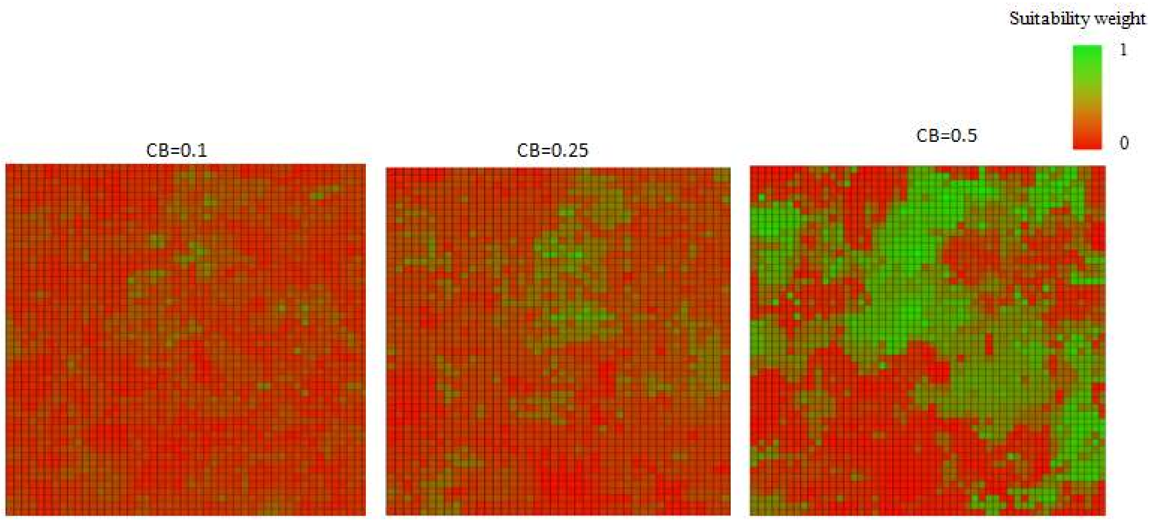

Figure 4. 13: Model 1, case 3 stable average suitability weight layers

Comparison for cases with different rigidity coefficient

So far we presented results for different values of confidence bound by keeping rigidity coefficient constant at a time. Here we present results across different value of rigidity coefficient keeping confidence bound constant at a time.

Table 4.8, 4.9 and 4.10 shows the cases with confidence bound values set respectively to values 0.1, 0.25 and 0.5 at a time and varying the rigidity coefficient. The results showed that unlike for various values of confidence bound, generally there is no significant difference among the mean suitability weight and number of competing clusters for various values of rigidity coefficient. However, very slightly decreasing pattern in the mean suitability weight could be observed with increasing rigidity coefficient for all confidence bound cases (table 4.8, 4.9 and 4.10). For confidence bound value 0.1 the number of competing clusters also increases with increasing rigidity coefficient.

The spatial location of the most suitable cluster stays almost the same with changing rigidity coefficient value for when confidence bound is kept constant.

Even though, changing values of rigidity coefficient does not significantly affect the final result in terms of the mean suitability weight of the most suitable cluster and the number of competing cluster, it seems to affect the time taken (number of meetings) to reach consensus.

Table 4. 8: Model 1, case CB 0.1 result (aspects of most suitable cluster)

	Mean suitability weight	Cluster centre x-coor	Cluster centre y-coor	# of competing cluster
Baseline	0.569	23	41	17
RC=0.25	0.326	26,26	41,42	13
RC=0.5	0.318	25,26	40,41	15
RC=0.75	0.309	25,26,26	40,42,44	17

Table 4. 9: Model 1, case CB 0.25 result (aspects of most suitable cluster)

	Mean suitability weight	Cluster centre x-coor	Cluster centre y-coor	# of competing cluster
Baseline	0.569	23	41	17
RC=0.25	0.425	23,23	30,33	5
RC=0.5	0.425	22,22,23	30,33,33	5
RC=0.75	0.416	21,22,22	33,33,34	4,5

Table 4. 10: Model 1, case CB 0.5 result (aspects of most suitable cluster)

	Mean suitability weight	Cluster centre x-coor	Cluster centre y-coor	# of competing cluster
Baseline	0.569	23	41	17
RC=0.25	0.664	23,25	39,43	2
RC=0.5	0.659	21,23,23, 25	33,39,40,43	2
RC=0.75	0.656	21, 23,23	30,39,40	2

4.2.2 Model 2: All agent interaction without initial self-opinion dependence

This scenario refers to a situation where at each step of opinion exchange an agent completely abandon its current opinion and form its next opinion based solely on the opinion of others. Therefore, an agent under such scenario has rigidity coefficient zero and is totally liberal to shape its opinion based on others opinion. In doing so the agent considers all other agents opinion according to a defined weight and calculate its next opinion (in this case opinion about the suitability of a parcel of land for the intended land use purpose).

Table 4. 11: Model 2 parameters

Confidence bound (CB)	Rigidity coefficient (RC)
0.1	0
0.25	0
0.5	0

In general, the mean suitability weight of the most suitable cluster of parcels increases with increasing confidence bound. However, the rate at which it increases seem to decrease as the confidence bound increases. To investigate this behaviour separate simulations were run with other set of confidence bound values (0.35, 0.4, 0.45 and 0.55) and result included in table 4.12. The result supports the idea that the mean suitability weight of the most suitable cluster increases at decreasing rate with increasing confidence bound. More disaggregation of opinion is reflected by the increased number of competing clusters for confidence bound 0.5 as compared to the case where agents depend on their initial opinion. The number of competing clusters for confidence bound 0.5 under this model is 7 which is by far larger than the 2 in the models where agents partially depend on their own opinion.

As compared to models in which agents has some level of rigidity (as in cases of model 1), relatively poor result was achieved in terms of the mean suitability weight value of the most suitable cluster and the number of competing clusters. The larger number of competing clusters even for confidence bound value 0.5 may present difficulty for agents to reach consensus regarding where to exactly locate a cluster of parcels for the intended land use purpose.

On the other hand, the number of meetings required reaching stable values of mean suitability weight and competing number of cluster is lower than in the case of models with agents partly depend on their own opinion. For example, just two meetings were required for the mean suitability weight value to reach a stable state (figure 4.14) as compared to the minimum of 3 for the model where agents partially depend on their own opinion (model 1).
Under this model, therefore, agents may identify the most suitable cluster with fewer opinion exchanges (meetings) but they may be faced with multiple close alternatives of cluster. Therefore, it may still be difficult for them to decide the exact location of the cluster for the intended land use.

Table 4. 12: Model 2 result (aspects of most suitable cluster)

	Mean suitability weight	**Cluster centre x-coor**	**Cluster centre y-coor**	**# of competing cluster**
Baseline	0.569	23	41	17
CB=0.1	0.347	19,28	30,45	6
CB=0.25	0.556	24	42	5
CB=0.35	0.584	23	40	6
CB=0.40	0.588	23	40	5
CB=0.45	0.594	23	40	6
CB=0.5	0.601	23, 25	39,43	7
CB=0.55	0.603	23	40	7

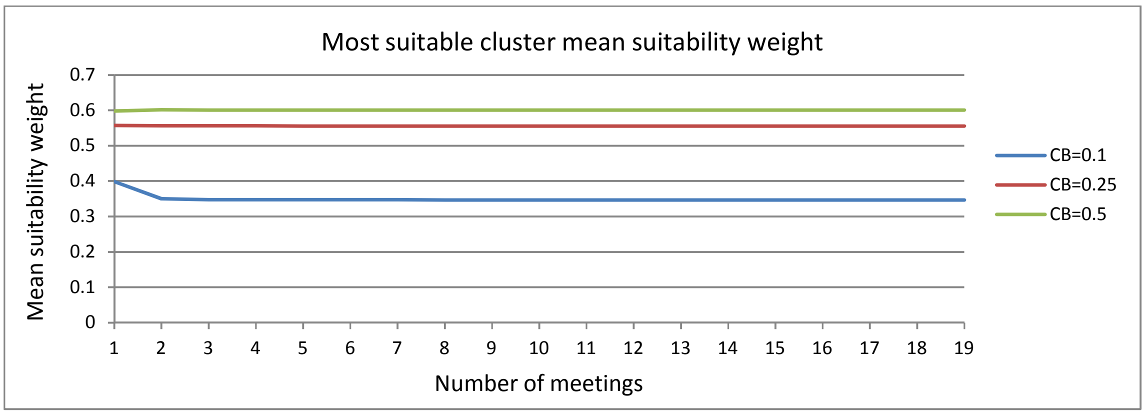

Figure 4. 14: Model 2 most suitable cluster mean suitability weight during repeated meetings

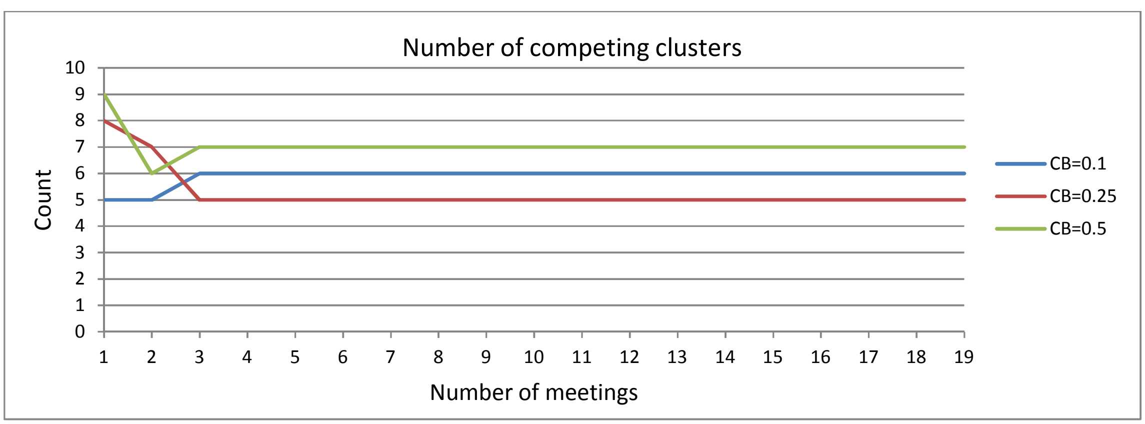

Figure 4. 15: Model 2 number of competing clusters during repeated meetings

In terms of spatial stability of the most suitable cluster only the case with confidence bound 0.1 showed significant shifts during repeated meetings. For other values of confidence bound the spatial location of the most suitable cluster was not only stable but also has not shifted significantly from the location of the most suitable cluster for the baseline scenario (table 4.12, figure 4.16).

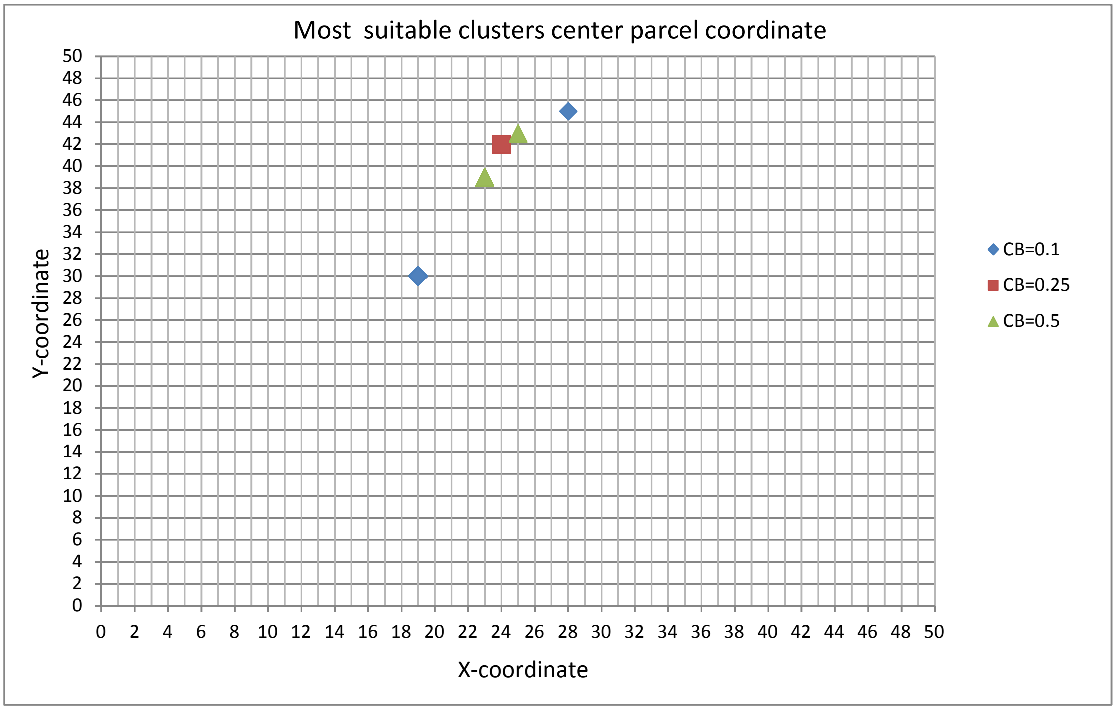

Figure 4. 16: Model 2 centre coordinates of most suitable cluster

Figure 4.17 shows the stable state average suitability weight layers for the three values of confidence bound.

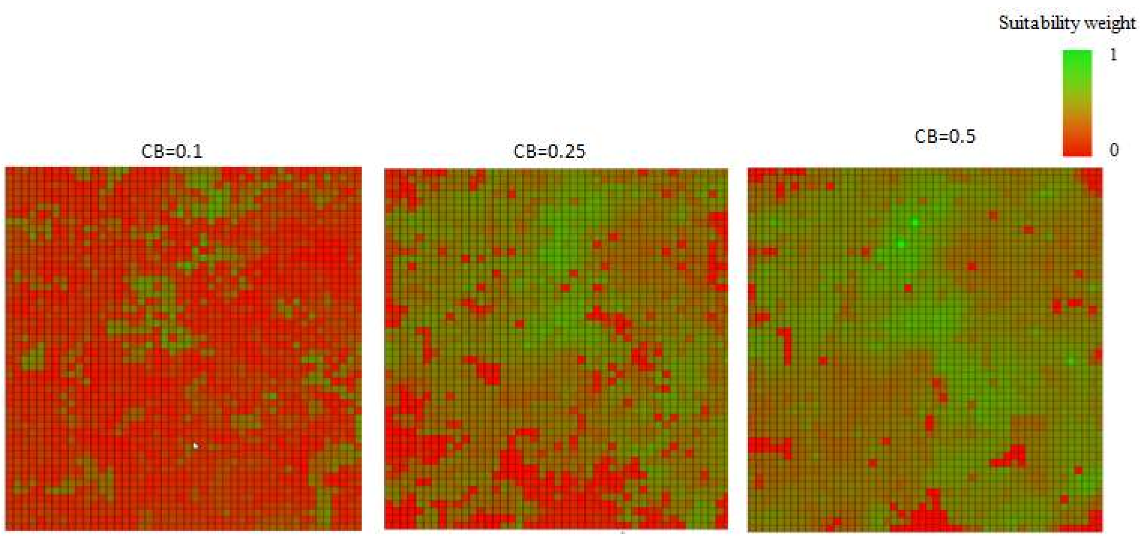

Figure 4. 17: Model 2 stable average suitability weight layers

4.2.3 Model 3: Pair wise interaction

Dependence on initial opinion in this case is implicit in the that fact that when agents interact pair wise, the next value for the agents opinion is the average of the two interacting agents if their opinion difference is within a specified confidence bound range. If their opinion difference is greater than the confidence bound the agent maintains its current opinion. Cases with confidence bound values 0.1, 0.25 and 0.5 were considered.

As compared to the 'all agents interaction' (model 1 and model 2) it is difficult to reach stable value of mean suitability weight for the most suitable cluster. For example, as can be seen from figure 4.18 the mean suitability weight for confidence bound 0.5 has kept increasing even after about 20 meetings. For the same confidence bound the number of competing cluster has kept on decreasing even about 20 meetings (figure 4.19). Therefore, even though theoretically consensus may be reached among agent as to which cluster to choose and its exact location after large number of meetings, it may not reflect the real world practice where agents do not meet and exchange idea beyond few number of times.

However, the mean suitability weight of the most suitable clusters is high for lower confidence bound (table 4.13) as compared to 'all agents interaction' models.

Table 4. 13: Model 3 result (aspects of most suitable cluster)

	Mean suitability weight	Cluster centre x-coor	Cluster centre y-coor	# of competing cluster
Baseline	0.569	23	41	17
CB=0.1	0.570(slightly increasing)	23	42	16
CB=0.25	0.580(little fluctuation)	23	30,40	13
CB=0.5	Unstable (increasing)	23, 25	39,43	Unstable (decreasing)

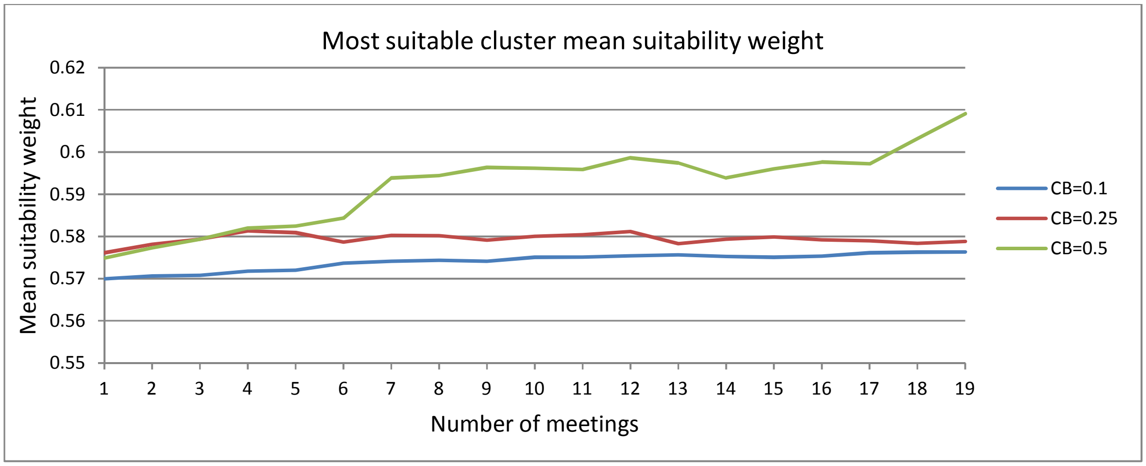

Figure 4. 18: Model 3 most suitable cluster mean suitability weight during repeated meetings

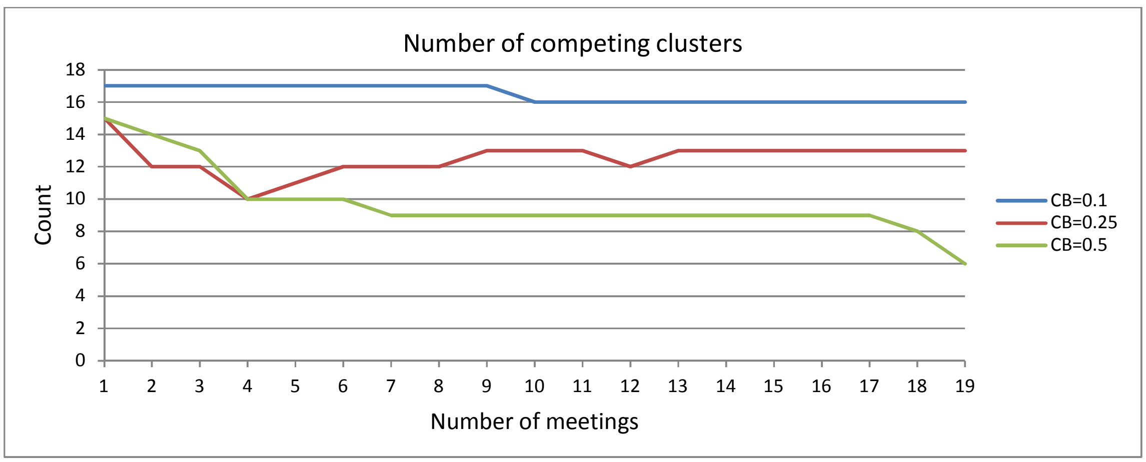

Figure 4. 19: Model 3 number of competing clusters during repeated meetings

The case with confidence bound 0.1 and 0.5 yielded spatially stable most suitable clusters whereas fluctuation is observed for the case with confidence bound 0.25

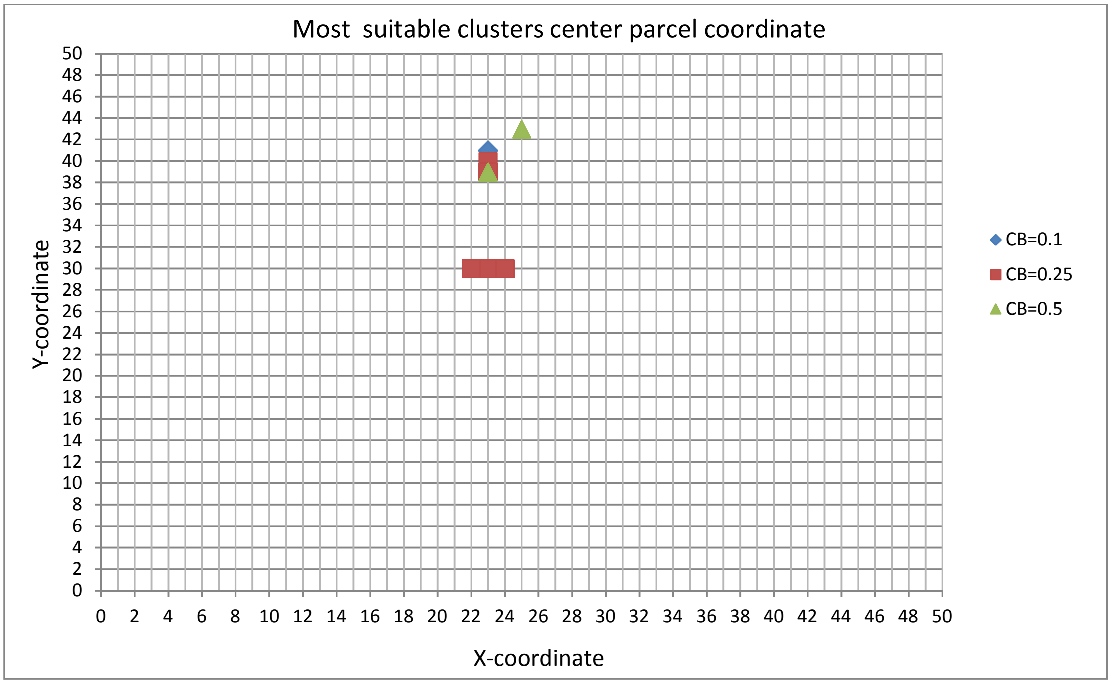

Figure 4. 20: Model 3 centre coordinates of most suitable cluster

The fact that the mean suitability weight of the most suitable clusters is high even for lower confidence bound added to the fact that there is large number of competing clusters for lower confidence bound could be because agents only interact with one agent at a time. Thus, the shift in opinion may take long time and hence suitability weight assigned to a parcel may not rapidly change. In figure 4.21 the maps for confidence bound 0.1 and 0.25 does not seem to be significantly changed from the baseline map.

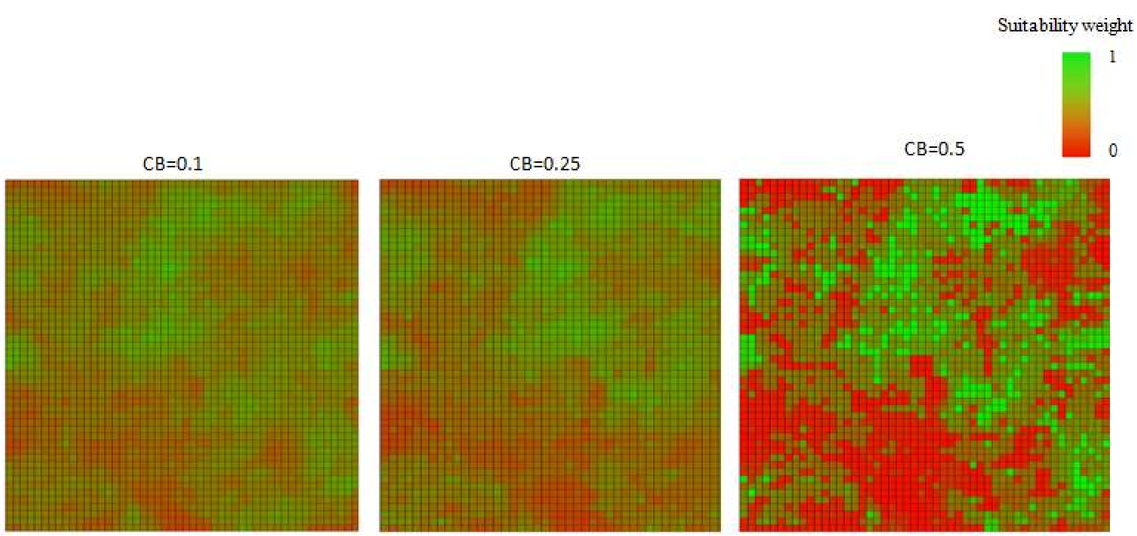

Figure 4. 21: Model 3 stable average suitability weight layers

5. Discussion and conclusion

The objective this study was to investigate how exchange of opinion in agent based land use decision making influences the process of land use choice by decision makers and how best choice can be made. Three models of opinion dynamics were studied. Model 1 refers to a case where at each time step (meeting) all agents interaction but agents partially depend on their own current opinion to form their next opinion. Model 2 refers to a case where at each time step all agents interact and agents totally relay on opinions of other agents to form their next opinion. Model 3 refers to a case where at each time step an agent interacts and exchanges opinion with only one agent. Within each model different combinations of model parameters (confidence bound and rigidity coefficient) were considered. Confidence bound values of 0.1, 0.25 and 0.5 and rigidity coefficient 0.25, 0.5 and 0.75 were iteratively used. Results were compared for the different models and model parameters. Comparison was also made with the baseline scenario where model of opinion dynamics was not applied at all.

The baseline scenario resulted in large number of competing clusters (17). This indicates that in the absence of opinion exchange it is difficult to reach consensus regarding where a land has to be allocated for the intended purpose. This is logical because as long as agents do not exchange opinion they cannot come to a common opinion regarding where to locate a unit of land for the intended purpose. If there is no opinion exchange agents rely totally on their own initial opinion which they form according to their own view of the features of the land under consideration.

For model 1 higher value of confidence bound yielded higher value of mean suitability weight of the most suitable cluster and lesser number of competing clusters. This is true as compared to results for lower values of confidence bound as well as the baseline scenario. This might be related to the fact that at higher confidence bound agents have higher tolerance to the difference in their opinion. Therefore, for higher confidence bound agents are willing to negotiate and exchange opinion even despite relatively big difference in their opinion. This willingness to exchange opinion may lead to better consensus and faster decision making regarding the land choice.

Similarly, higher values of confidence bound yielded higher value of mean suitability weight for model 2. This is true as compared to results for lower values of confidence bound as well as the baseline scenario. However, the number of competing clusters stayed the same and relatively higher for different values of confidence bound in the case of model 2. Moreover, for model 2 the mean suitability weight increases at much more decreasing rate than in model 1. On the other hand, the number of meetings required to make decision is fewer for model 2 than model 1. Under model 2, therefore, agents can identify the most suitable cluster with fewer opinion exchanges (meetings) but they may be faced ambiguity to choose from multiple close alternatives of suitable clusters. This suggests that complete absence of rigidity (completely volatile opinion) may end up in multiple alternative suitable clusters and obstruct the process of land choice and hence it may imply that some level of rigidity in opinion is required for better result.

For model 3 it would take very large number of meetings to identify the stable mean suitability weight and number of competing clusters. For example, even at simulation step 20 (after 20 meetings) the means suitability weight of the most suitable cluster appeared to rapidly increase for confidence bound 0.5. This could be because agents interact only with one other agent at a time, and hence it would take more time to reach consensus with all agents about the land use choice. In the real world scenario it could be impractical to hold such large number of meetings (opinion exchange) to make land use choice. However, the mean suitability weight of the most suitable clusters is high for lower confidence bound as compared to model 1 and model 2.

The most suitable cluster for the case of confidence bound 0.1 assumed about the same location as the baseline scenario for all cases of rigidity coefficient. This holds true for confidence bound value of 0.5 at rigidity coefficient 0.25. But at higher values of rigidity coefficient the spatial location of the most suitable cluster for confidence bound 0.5 appeared to be relatively unstable.

Variations in the values of rigidity coefficient were not reflected in significant variation in the mean suitability weight of the most suitable cluster and the number of competing clusters. However, rigidity coefficient appeared to affect the number of meetings (opinion exchange) required to make decision. For lower rigidity coefficient relatively fewer meetings were required as compared to higher rigidity coefficient values. This makes sense because if agents are very conservative (very rigid) they tend to adhere to their own opinion and repeated meeting (negotiations) are required to come to consensus. Also cases with confidence bound 0.5 resulted in relatively higher spatial fluctuation of the most suitable cluster for higher values of rigidity coefficient. Therefore, at higher rigidity coefficient agents may face difficulty in reaching decision about the exact location of the most suitable cluster.

It was observed in general that confidence bound is the most important parameter that determines the effectiveness of opinion exchange among decision makers in the process of selection of a land unit for an intended purpose. Effectiveness in this case refers to how best the selected land unit (cluster of parcels) is in terms of suitability for the intended purpose. The best land unit (the most suitable cluster of parcels) would have the largest mean suitability weight and small number of competing clusters. Also effectiveness refers to the number of meetings to get the most suitable cluster. Large value of confidence bound led to more effective result. Rigidity coefficient appeared to affect the number of meeting required to reach decision. Smaller rigidity coefficient yielded better result in this aspect.

Accordingly, the best result was observed for model 1 with the largest confidence bound value (0.5) when rigidity coefficient is kept at value 0.25. Agents were able to identify a cluster with the highest mean suitability weight (0.664) than in the case of lower confidence bound values within the same model and other models. The number of competing clusters was very small (only 2) relative to the other confidence bound cases. Moreover, the most suitable cluster for this case has stable spatial location and was identified just after few meetings (3 to reach stable mean suitability weight and 1 for number of competing cluster). An interesting observation about this best scenario (confidence bound of 05 and rigidity coefficient 0.25) was that the spatial location of the most suitable cluster did not shift significantly from the location of the most suitable cluster for the baseline scenario (the scenario without opinion dynamics). This may imply that the location of parcel cluster to be chosen for the intended land use is determined more by the initial suitability weight each agent assign to the parcels within the input land unit. In other words, it may imply that instead of the opinion dynamics model and the parameters of the models, the rules based on which agents form their initial opinion about the suitability of a land unit for the intended land use determine the location of the final cluster chosen.

In general, the application of opinion dynamics (exchange of opinion among decision makers) significantly affects the process of land use choice and how best and fast the choice can be made.

References:

Bousquet F. , C. Le Page, 2004. Multi-agent Simulations and Ecosystem Management: a review, Ecological Modelling vol. 176, pp:313–332

Crooks, A. T. (2012), The Use of Agent-Based Modelling for Studying the Social and Physical Environment of Complexity and Planning, Systems, Assemblages and Simulations, Ashgate, Burlington, VT, pp. 385-408.

Dawn C. Parker, Steven M. Manson, Marco A. Janssen, Matthew J. Hoffmann & Peter Deadman, 2003. Multi-Agent Systems for the Simulation of Land-Use and Land-Cover Change: A Review, Annals of the Association of American Geographers, 93:2, 314-337

Dawn C. Parker, Thomas Berger, and Steven M. Manson, 2001. Agent-Based Models of Land-Use and Land-Cover Change, Report and Review of an International Workshop October 4–7, 2001, Irvine, California, USA

Deffuant Guillaume, David Neau, Frederic Amblardand, Gerard Weisbush, 2000. Mixing beliefs among interacting agents, Advances in Complex Systems, vol. 3, issue 01 no. 4

Dyke Van Parunak, Robert Savit, Rick L. Riolo, 1998. Agent-Based Modeling vs. Equation-Based Modeling: A Case Study and Users' Guide, Proceedings of Multi-agent systems and Agent-based Simulation

Federico E. Bert, Guillermo P. Podesta, Santiago L. Rovere, Angel N. Menendez, Michael Northd, Eric Tatara, Carlos E. Laciana, Elke Weber, Fernando Ruiz Toranzo, 2011. An Agent Based Model to Simulate Structural and Land Use Changes in Agricultural Systems of the Argentine Pampa, Ecological Modelling vol. 222 , pp: 3486– 3499

Francesca Ceragioli, Paolo Frasca , 2012. Continuous and discontinuous opinion dynamics with bounded confidence, Nonlinear Analysis: Real World Applications, vol. 13, pp: 1239-1251

Hegselmann R., Krause U.,2002. Opinion Dynamics And Bounded Confidence Models, Analysis, And Simulation, Journal of Artifical Societies and Social Simulation (JASSS) vol.5, no. 3.

Hegselmann R., Krause U.,2005. Opinion Dynamics Driven by Various Ways of Averaging, Journal of Computational Economics, vol. 25, pp: 381–405

John Wainwright and James D.A. Millington, 2010. Mind, the gap in landscape-evolution modeling, Earth Surface Processes And Landforma, vol. 35, pp:842–855

Lorenz Jan , 2007. Continuous Opinion Dynamics under Bounded Confidence: A Survey, International Journal of Modern Physics Vol. 18, No. 12, pp:1819 - 1838

Mahamadou Belem, Raphaël J. Manlay, Jean-Pierre Müller, Jean-Luc Chotte, 2011. CaTMAS: A multi-agent model for simulating the dynamics of carbon resources of West African villages: Ecological Modelling, vol. 222 pp: 3651– 3661

Nicholas Magliocca, Elena Safirova, Virginia McConnell, Margaret Walls, 2011. An economic agent-based model of coupled housing and land markets (CHALMS), Computers, Environment and Urban Systems, vol. 35, pp:183–191

Quang Bao Le, Soo Jin Park, Paul L.G. Vlek, Armin B. Cremers, 2008. Land-Use Dynamic Simulator (LUDAS): A multi-agent System model for Simulating Spatio-temporal Dynamics of Coupled human–landscape system. I. Structure and Theoretical Specification, Ecological Informatics, vol. 3, pp: 1 3 5 – 1 5 3

Robin B. Matthews, Nigel G. Gilber, Alan Roach, J. Gary Polhill, Nick M. Gotts, 2007. Agent-based land-use models: a review of applications, Landscape Ecol, vol. 22 pp:1447–1459

Shepard D., 1968. A two-dimensional interpolation function for irregularly-spaced data, ACM '68 Proceedings of the 1968 23rd ACM national conference, pp: 517 - 524

Soham Biswas, Parongama Sen 2009. Model of binary opinion dynamics: Coarsening and effect of disorder, American Physical Society, Physical Review. E, Vol.80, Issue 2