Exploring Human Behaviour using Agent-Based Modelling, Neural Networks and Land Use/Land Cover (LU/LC)

"A Case Study of Flooding in the Limpopo River Basin, Xai-Xai, Mozambique"

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1. Introduction

This paper presents an agent-based model for the Limpopo River Basin Area in Mozambique. More specifically, the study focuses on the evacuation procedure of a fast flooding area in the vicinity of Xai-Xai, Province of Gaza (Figure 1).

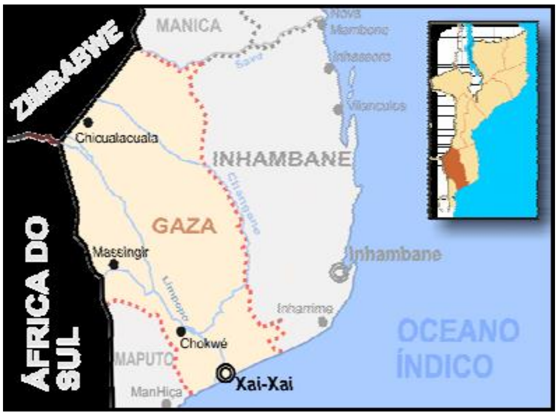


Figure 1: Province of Gaza and location of Xai-Xai
Source: Source: Koehne (2007)

The Xai-Xai area, located at the bottom of a vertical relief of 800 meters draining the land from four countries, Zimbabwe, Botswana, South Africa and Mozambique, is prone to very fast flooding. One of the worst floods in the area happened in 2000 due to the Cyclone Eline. Prior to the cyclone hitting the area, heavy rainfalls and a tropical storm brought 700mm's of rain over two days, resulting in 4 to 8 meters of flooding. The flow of the Limpopo River at Xai-Xai at the time of the storm was estimated at 10,000 m^3/sec (10 times the normal rate), breaking through dykes and resulting in flash flooding (Christie & Hanlon 2001). It is estimated that 2 million people were affected by the floods (Christie & Hanlon 2001) but at the time the British Broadcasting Corporation (BBC 2000) reported 7,000 people near Xai-Xai were trapped in trees - some up to several days - and approximately 700 perished. This was the worst flood since 1997, when the water reached 6.07m or 1.77m above flood level. Although a similar flood had occurred in 1915, which reached 5.7m or 1.4m above flood level, the area had experience bad floods quite frequently (1955, 1967, 1972, 1975 and 1981).

The reoccurrence of the natural phenomena that caused the magnitude of flooding in the year 2000 is estimated at once in 50 years and once in every 20 years for a flood of the 1977 magnitude (Christie & Hanlon 2001). A flooding event comparable to the one in 2000 occurred in January 2013 in southern Mozambique killing 36 and displacing thousands (UNITAR 2013; Appleton 2013). The major flood episode in 2000 was actually produced by 4 successive flooding events. The first was an above average rainfall in October to December 1999. This was followed by the remnant of Cyclone Connie which dropped a record rainfall between 4 and 7 of February resulting in flooding equivalent to the 1977 flood. On the 13th of February, a second crest of water came down the Limpopo River once again matching the

1977 floods. Cyclone Eline then hit on the 22nd February, causing a crest on the Limpopo River, which resulted in a flood 3m above the levels reached in 1977 on the 1st of March.

The 2000 floods, however, were a result of a long-term chain of events. During the 1990s this area suffered from drought and the hard ground in catchment areas resulted in rapid run-off; the headwaters of the Limpopo River in northern South Africa, southeast Zimbabwe and southern Mozambique had 3 times as much yearly rain (approximately 1800mm); and the dams in northern South Africa and southern Mozambique were near capacity after heavy rainfalls in October to December and could not absorb the record rainfall from subsequent cyclones, which resulted in the crests of flood water rushing down the Limpopo River (Christie & Hanlon 2001).

What transformed this event into a catastrophe was the fact the progressive flood events caught the population off guard, aided by the belief flooding could not be worse than in 1977. So when the crest of water flowing down the Limpopo River reached Xai-Xai on March 1st, water levels rose rapidly to 5.7m above 'flood level' causing people to flee to high grounds in the Xai-Xai area as well as roof tops and trees (Christie & Hanlon 2001).

It is this reality of very fast flooding that the present research investigates using an agent-based model. The objectives of the project are: a) to simulate the phenomena of a fast flooding area and evacuation behaviour; and, b) to develop a neural network designed to simulate an agent's cognitive ability to sense, learn and adapt when travelling over a landscape during a flooding episode.

Agent-based models (ABM) have been largely applied to simulate disaster processes (Dawson et al 2011; Lumbroso et al 2013). ABMs are particularly suited to disaster modelling because they allow for an understanding of disaster processes from a bottom-up approach. ABMs provide applied geographers with an understanding of how disasters affect individuals and how individual behaviours shape a pattern of collective behaviour. Such understanding is essential for disaster management, in particular for setting evacuation procedures. ABMs of disasters can help the decision making of evacuation procedures (Takahashi 2007; Brouwers &Verhagen 2003) by testing evacuation times and routes in natural disasters (Dawson et al 2011; Bakillah et al 2012; Lin & Manocha 2010) or changing of routes and procedures in buildings or urban areas (Su et al 2011; Padgham 2015; Rahman et al 2008).

The next section introduces the model and discusses the choice of methodology employed. This is followed by sections on the model implementation, results, analysis and conclusion.

2. An Agent-based Model for Limpopo Basin Flooding

The model presented here simulates a scenario of fast flooding along the lines of the one which occurred in 2000. The model is divided into two parts: the simulation of flooding and the simulation of the evacuation procedure taken by locals.

The simulation of flooding is done in a very simplistic way, as will be detailed in section 4. The environmental information used to simulate the flooding are: rain rate, run off and a digital elevation model (DEM). The DEM provides the elevation data that determines where the flooding takes place, while the rate of rain fall and run-off impacts the rate of flooding.

In areas of fast flooding like Xai-Xai, people often resort in seeking refuge on roof tops, trees, and any higher ground (Christie & Hanlon 2001). Once flooding is imminent and an area starts to flood, people start travelling to the 'safe area'. This is the behaviour the present model attempts to simulate. For the purpose of this study, a 'safe area' or shelter is either an area located in the higher grounds of Xai-Xai or any other area that is not prone to 'fast flooding'.

The model simulates the decision-making process of people when travelling towards a safe area, assuming that people evacuating do not have prior knowledge about the area and, thus, are learning about the terrain as they move. As such, the model does not include prior learning of the area as well as interaction with other people, which is another factor that can impact on people's evacuation behaviour (i.e. by going towards the neighbour's house because he knows a safe place/route).

In the model, each agent represents a single person. When moving towards a safe area, agents have the ability to sense the terrain and surrounding area they travel over. This is based on a pragmatic approach on how a person would travel over the terrain, for example, the best mode of travel is by road, followed by trails, farmland, and vegetation. The two main restrictions are that agents cannot travel across water or through buildings.

The decision-making process of agents is built upon concepts from cognitive science. In the model, the cognitive ability of an agent is its ability to sense and recognise the characteristics of the landscape around them. As part of the decision-making process inbuilt in the model, this information is used by the agent to learn about the terrain and adapt their choices in order to make the best decision to move towards the 'safe area'. In other words, agents look for a safe route away from the flooding, making decisions based on their assessment of land cover at each step. This behaviour is illustrated by the flowchart in Figure 2.

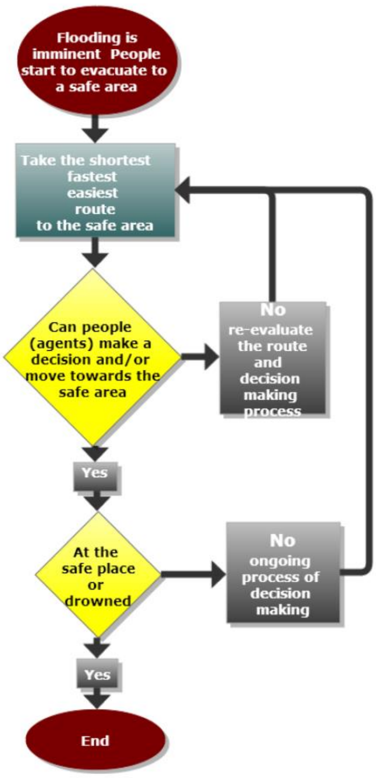


Figure 2: Flowchart of agent's behaviour

Such a decision process is central to the model and incorporates an optimal operating range of weighted information that increases the agent's ability to adapt to change. This means that if an agent has used a specific land use that has delayed his journey or made it harder, it will learn this is not a good option and improve his choices in the remaining of his path. In the model this is simulated using a neural network, which incorporates the capability of learning and adapting onto the decision-making process.

An artificial neural network is designed to work similarly to a biological neural network having artificial nodes (neurons) “linked to each other in a weighted way” forming a network (Kriesel 2005). Figure 3 illustrates the structure as data being processed through layers; input neurons that are adjusted in the hidden layer neurons, until it emerges as output neurons (Colton 2012 & 2004; Kriesel 2005). Sample data is often subdivided into training, validation and test sets. The system must first be trained with a training set – a subset of the data that will be used for learning. The validation set is used to adjust the weights and to assess the performance of the model (Ripley 1996). In this model, an agent gathers ‘input’ data about the terrain surrounding it. This information is processed through ‘hidden layers’ and emerges as ‘output’ to be used in the decision-making process as it travels over the terrain towards the ‘safe area’.

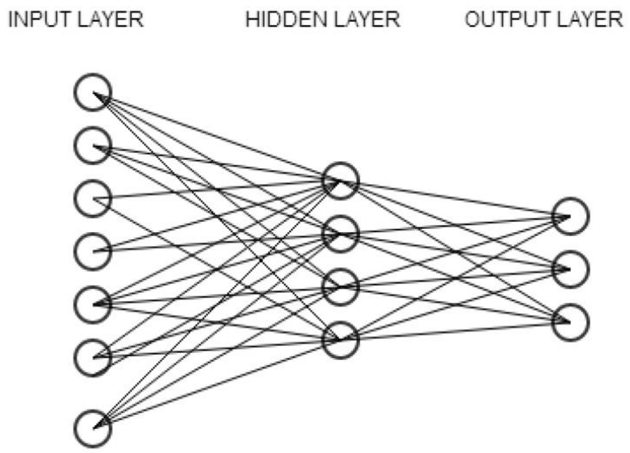


Figure 3: Conceptual model of a Neural Network. Adapted from Kriesel (2005).

The neural network developed for this study is a hybrid model, as the model required a spatio-temporal, dynamic, decision-making process. One of the requirements for this model was that training in one area should not apply to another, so the network had to be able to adapt to changing land use/land cover (LU/LC) during a flooding episode. As a result, the hybrid model included characteristics of 5 neural network types; feedforward (Ripley 1996); recurring (Kriesel 2005); stochastic (Turchetti 2004); neural-fuzzy (Kasabov 1996) and learning to rank (Li 2011). The implementation of the neural network is detailed in section 4.1.

3. Environmental Data

The landscape used in the model was built using satellite imagery. A single tile of 50cm ground resolution GeoEye -1 Satellite Imagery dated of 2009 was acquired from GeoEye through Sani-International Technology Advisors Inc covering a 140,000m square area in the vicinity of Xai-Xai, Mozambique - as shown in Figure 4. The raw imagery was acquired in four bands: red, green, blue and NIR, and joined through an imagery process in ERDAS Imagine software. This imagery was used to derive the land use/land cover information for the project having a ground resolution that provided realistic information.

Figure 4: GeoEye1 Imagery

The imagery was categorized for features such as buildings, farmland, roads, vegetation, the Limpopo River, trails and hazards; the features that were used in the process of decision-making by agents in the model. Remote sensing technology was used to assess the spectral signatures (red, green and blue) of each pixel within the imagery in order to classify the pixels for feature types and create a land use/land cover data file for the project. The following subsections detail the imagery processing and classification.

For the flooding behaviour in the model, a Digital Elevation Model (DEM) was used. The DEM obtained was an Aster GDEM 2011 Version2, 1 arc second or approximately 30m resolution. For a more realistic flooding model over the project area, the Aster DEM was interpolated and a 6m resolution version produced.

3.1 Imagery Processing and Classification

The 50cm GeoEye -1 Satellite imagery was classified using the signature editor set to classified and supervised. Each feature was outlined on the imagery that best represented the feature to be captured and the spectral signature for the patch was recorded. The rest of the imagery was then assessed using the same spectral signature.

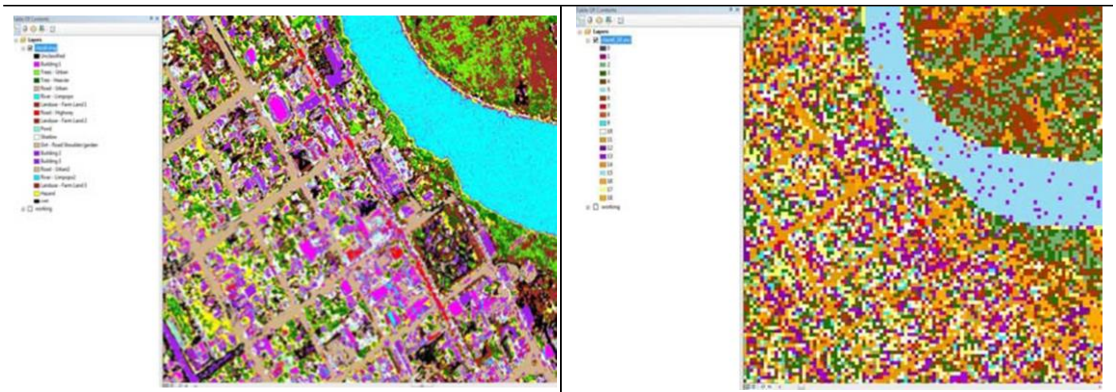
The spectral signatures of many features (red, green, blue) were assessed and categorized. It was expected that some features would have more than one spectral signature and that each one could be slightly different. For example, a road could have 3 slightly different spectral signatures due to road construction material and reflection. In Figure 5, the left side shows 19 layers in ArcMap of feature type classifications. Within the 19 layers of feature types are: Building 1, Building 2, and Building 3. The GeoEye-1 satellite imagery pixels for these 3 layer types were combined into one feature category and assigned the attribute number 20. Similarly, Road-Urban, Road-Urban2 and Road-Highway were combined to create a feature category assigned number 40. After amalgamating similar features, 19 classifications were reclassified into 9 feature categories, assigned attributes 10, 20, 30, 40, 50, 60, 70, 80 and 90 outlined on the right hand side in Figure 5.

Reclassification Categories
10 Trail/secondary road
20 Structures/buildings
30 Vegetation (dense)
40 Main roads
50 Limpopo River/water
60 Farm Land
70 Hazards
80 Building shadows
90 Unclassified

Figure 5: 19 Classification in ArcMap and Table showing the final 9 categories

3.2 Resampling the LU/LC file

The LU/LC file for the 0.5m resolution GeoEye-1 satellite image was resampled from 0.5m to 15m's using ERDAS (Figure 6). The resampled image (img) file was then converted to an ASC (ascii) file format, to be used in Repast Simphony Java platform in which the model was built.



Classification at 0.5m

Resampling at 15m

Figure 6: Resampling process - depicting the classified imagery at 0.5m on the left and how it looks when resampled at 15m on the right

4. Model Implementation

The model was developed in Repast Simphony Java and implemented in five phases, as shown in Figure 7. These phases are (1) Input (2) Training/Backpropogation and Fuzzy Logic (3) Learning to Rank and Output (4) Recurrent, and (5) Results.

In what follows, each phase will be detailed using the typical behaviour of a single agent as an example. As shown in Figure 7, the model behaviour on a typical run consists of all 5 phases. The model run will automatically stop when there are no agents present, that is, either when an agent is encompassed by flooding or when an agent has made it to the safe area. The neural network is called upon during phases 2 to 5 when land cover features are incorporated into the decision-making process. The specific behaviour of the neural network will be detailed in section 4.1.

Phase 1. Input
When a scenario is initialized, the two main data files (DEM and the classified imagery) are loaded together using the setup settings summarised in Table 1, below. These variables determine the flooding rate, location of agents, location of the safe area, amount of training, agent mobility and sensing. Figure 9 illustrates the interface on setup.

Table 1: Model Variables

Rainfall	The default is 1mm/minute. The rate can be set to any value per minute by the observer.
Run-off 3 rates are available	The default setting is 2, but can be changed by the observer. 1 - simulates the ground is not saturated, and flooding from run off is set at none 2 - simulates the ground has some saturation and contributes to flooding at a low rate 3 - simulates the ground is highly saturated and contributes to flooding at a higher rate
Agent location	The x,y location of one or more agents is set before initialization by the observer.
Agent rate of travel	Movement depends on the environment surrounding an agent. Rate of travel is pre-set at: 1 cell for feature 30 (dense vegetation), 70 (hazard),80 (building shadows), 90 (unclassified) 2 cells for feature 60 (farm land) 3 cells for feature 10 (trail) 4 cells for feature 40 (road)
Safe Area	A designated area known to be safe from flooding is set by the observer prior to initialization
Sensing (radius)	Values are pre-assigned according to the land cover the agent is on: The radial sensing values are: up to 9 cells for features 30 (dense vegetation), 70 (hazard), 80 (building shadows), 90 (unclassified) up to 25 cells for feature 60 (farm land) up to 49 cells for feature 10 (trail) up to 81 cells for feature 40 (road)
Training	Number of moves for training is set by the observer prior to initialization (the default is 5).

Phase 2. Training/Backpropogation and Fuzzy Logic Process
Once a scenario is setup and the model starts running, an agent undergoes a training process gathering data about the terrain for the agent’s first 5 moves (being the default). The brain (here represented as a neural network) of an agent undergoes a training process that sets up the initial weights for the land cover features. The knowledge base that an agent uses in this process was established by a fuzzy logic approach for feature values and rules about how an agent can move. At the end of this phase, an agent is ready to make intelligent decisions as it moves towards the safe area.

Phase 3. Learning to Rank and Output
After an agent is trained and is ready to move to a safe area, the neural network is called upon to assess an inventory of land cover information gathered by the agent. The neural network

implements a process to optimize the weights and rank the inventory of land cover features, providing an agent with the 3 best moves for decision-making (see details in section 4.1). If the 3 best moves (ranked from highest to lowest and assigned variables F1, F2 and F3) do not provide an agent with an acceptable move in accordance with model rules, a random feature will be selected and checked in accordance with model rules. A random feature is a cell an agent can select in an arbitrary direction and distance of 1 or 2 cells depending on the difficulty encountered by the agent in moving.

Phase 4. Recurrent Neural Network and Output

While an agent is travelling over the terrain, the neural network is adapting and learning, constantly assessing and re-assessing the land cover. If an agent is unsuccessful in finding a move, the neural network is called upon to undergo a more rigorous assessment that could include additional cells and/or incorporate more random moves. If a random selection does not help an agent move, the process has the option to revert back to phase 2 to undergo a re-assessment that is similar to training in order to adjust the feature weights.

Phase 5. Result

If the process proceeds to phase 5, then a move is possible. The amount an agent moves is dependent on what features it can sense. The number of cells an agent senses is determined by the radius variable and this can change automatically depending on the land cover feature it is on. For example, a sensing variable or radius of 1 (searches 9 cells) and is used for feature 30 (dense vegetation), a radius of 2 (searches 25 cells) and is used for feature 60 (farm land), a radius of 3 (searches 49 cells) and is used for feature 10 (trails), and a radius of 4 (searches 81 cells) used for feature 40 (roads). The maximum an agent can move is determined by the radius variable; for instance, an agent can move faster on feature 40 (road) by advancing 4 cells if available. After each move, the location of an agent is assessed to determine if it is at the safe area or encompassed by flooding, at which time the agent is removed from the scenario. If not, the process loops back to collect another inventory of feature data, and re-implements phases 3, 4 and 5.

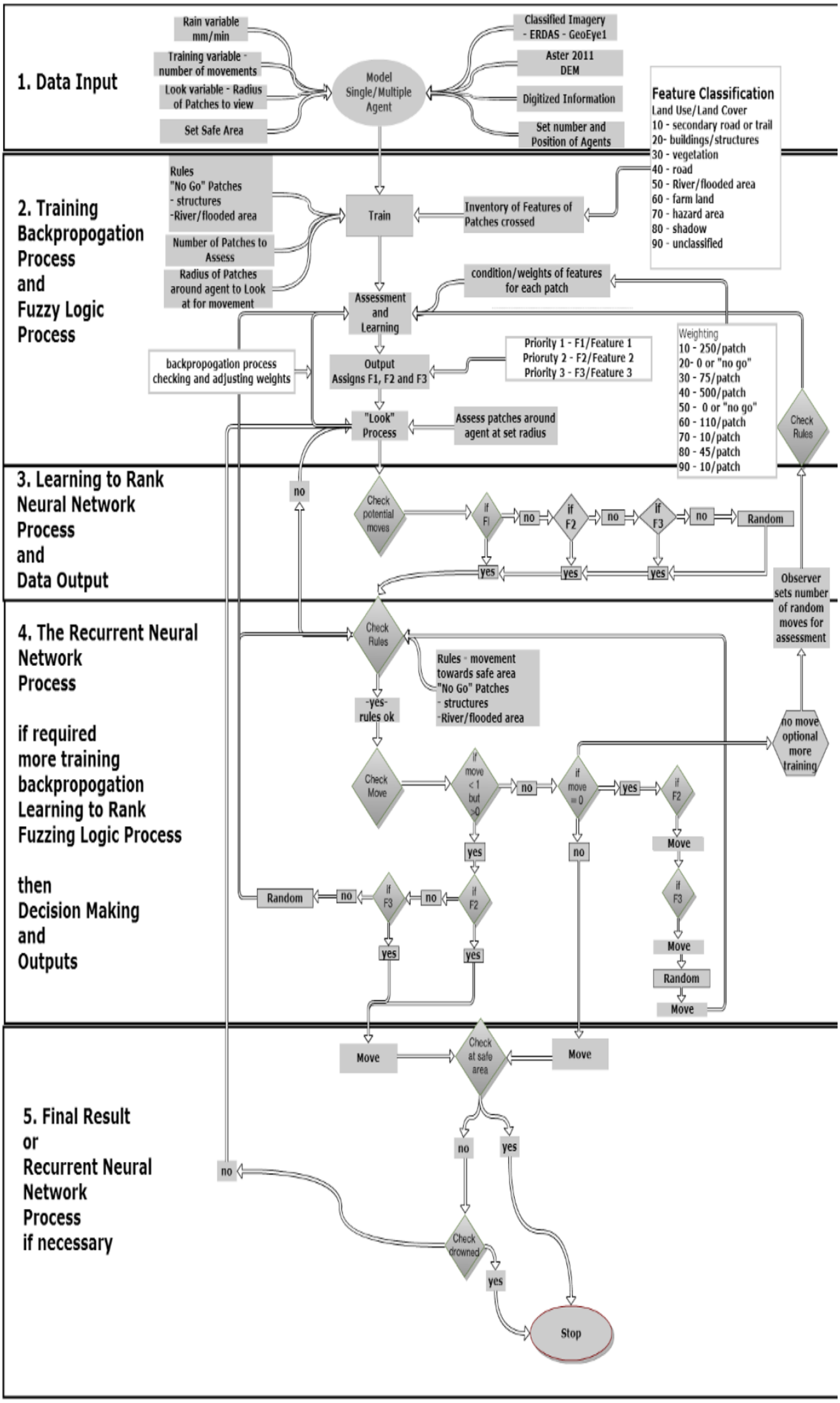


Figure 7: Flowchart of model behaviour highlighting the different stages of implementation.

4.1 Developing the Artificial Neural Network

The design of the neural network is based on a process where an agent collects data to create an inventory of information. This information is then used in a series of operations that assesses feature weights, calculates the delta error that is used in a back propagation process, optimizes the weights, and then checks the model rules to produce a list of feature outputs that is ranked from highest to lowest. The network assigns the three highest land cover features with the output variables F1, F2 and F3 for agent decision-making.

Figure 8 depicts the neural network with 21 inputs, hidden layers and 3 outputs, and describes it in 7 processes.

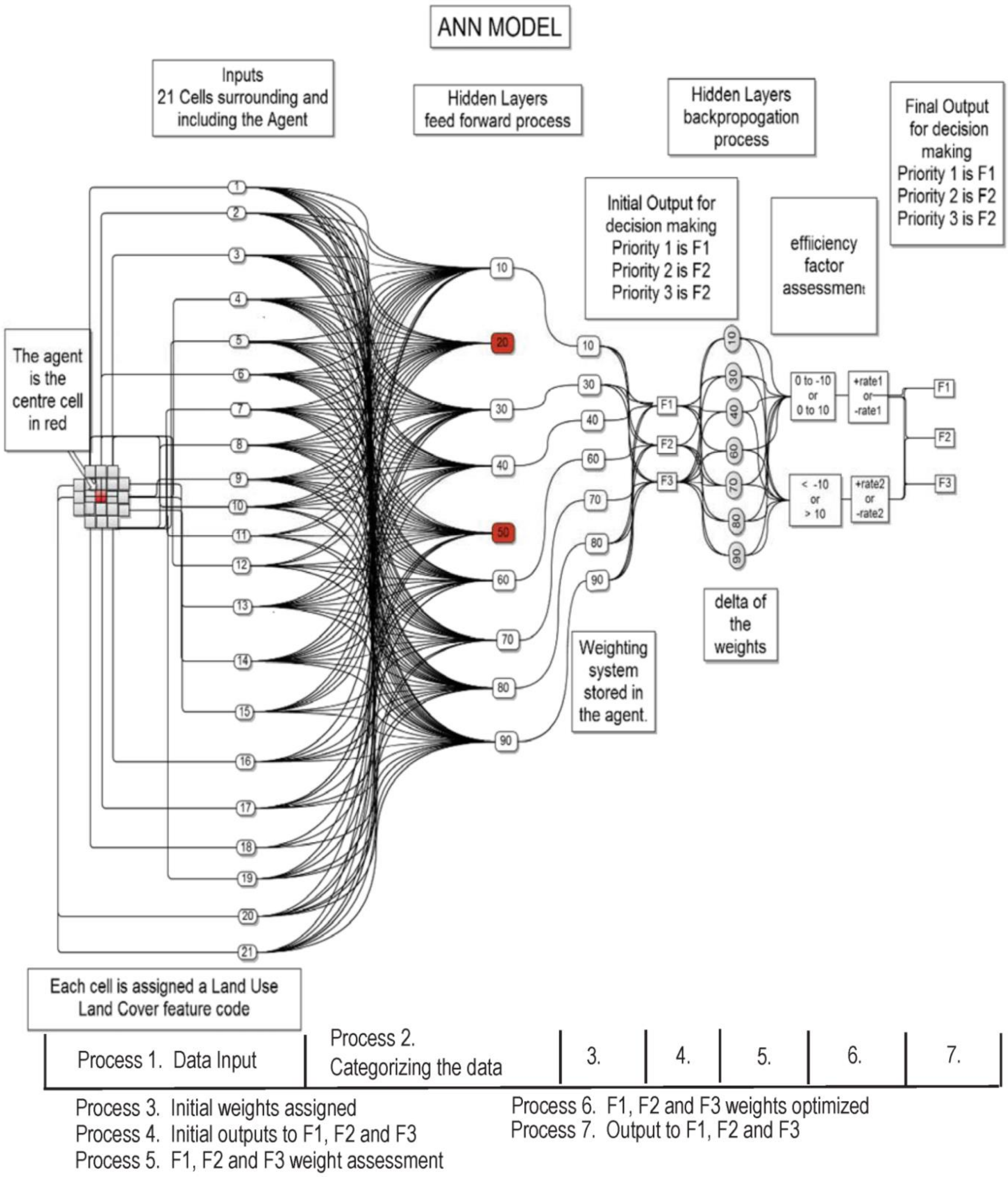


Figure 8: Outline of the Artificial Neural Network Process

In process 1, the number of cells an agent assesses depends on how far it can sense, which depends on the radius variable setting that fluctuates with the environment. As previously described in section 4;

- a radius of 1 will sense up to 9 cells;
- a radius 2, up to 25 cells;
- a radius 3, up to 49 cells; and,
- a radius 4, up to 81 cells.

In process 2, the inventory of LU/LC data is assessed and categorized into the numeric variables shown in Table 2.

Table 2: Numeric Variables Assigned to Features

10 (trails)	40 (roads)	70 (hazards)
20 (structures)	50 (water)	80 (building shadows)
30 (dense vegetation)	60 (farm land)	90 (unclassified)

The categorized inventory of data will be used in the next process for weight assignment and movement associated with each cell. Features 20 (structures) and 50 (water) are not utilized for movement, as they are considered ‘no go’ cells.

The knowledge base on (LU/LC) feature weights is a pre-assigned percentage of 1000 based on a pragmatic approach and trial runs. The percentage value is later used to optimize the weights in process 6 that determines the final output in process 7.

- feature 10 was set at 250 (25%);
- feature 30 at 75 (7.5%);
- feature 40 at 500 (50%);
- feature 60 at 110 (11%);
- feature 70 at 10 (1%);
- feature 80 at 45 (4.5%);
- feature 90 at 10 (1%).

In process 3, the weights are summed for of all the features (in the inventory) and stored. After the total weights for each feature are assessed during process 4, they are ranked from highest to lowest, with the three highest features assigned variables F1, F2 and F3.

In process 5, the delta error is determined using the percentage of the total weights compared to the knowledge base for each feature. The delta error is used to determine the (optimization) efficiency value called ‘r’ and categorized in one of three ranges; (1) less than -10; (2) -10 to +10 or (3) greater than +10.

Depending on the category of the delta weights, each value has a learning factor of rate 1 or rate 2 to either reduce the weight or increase it to its optimal value. In process 5, if the ’r’ value was between -10 and 10, rate 1would be used, utilizing a small increase or decrease of the weights to approach the optimal value of 0. If the ’r’ value has less than -10 or greater than 10, rate 2 would be applied to increase or decrease the weights at a greater rate into the range between -10 and +10. If more adaptation is required, the observer could increase the learning rate. The formula for adjusting the weights was +/- (rate1 or rate2) x (the features initial assigned weight).

When all the weights have been adjusted, in process 6 the output features are ranked from highest to lowest and once again the three highest are assigned the variables F1, F2 and F3.

5. Model Interface

The landscape of the model is composed by a 470 x 470 matrix of 15m cells containing two layers of information: land cover and DEM as illustrated in Figure 9.

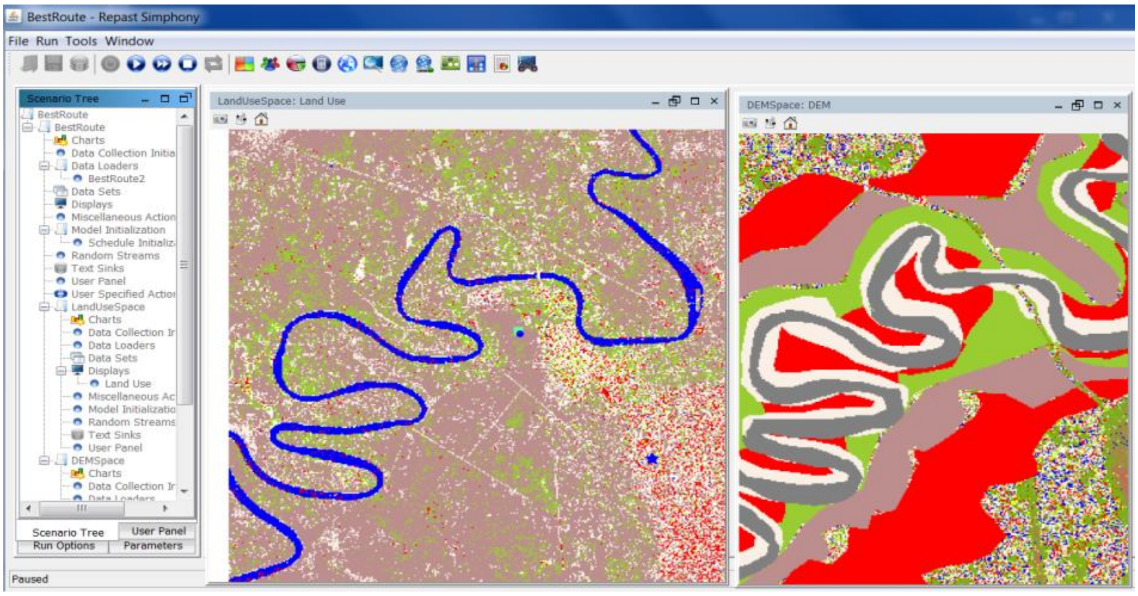


Figure 9: Model Interface showing Land Use (left) and DEM layers (right).

The user can set the model parameters using the interface (see Figure 10). These are: number of agents, rainfall in mm/minutes, and option for printing to an output file. The example shown in Figure 10 has 1 safe area, shown as a pink star, 20 agents represented by purple dots, and the flooded area in blue.

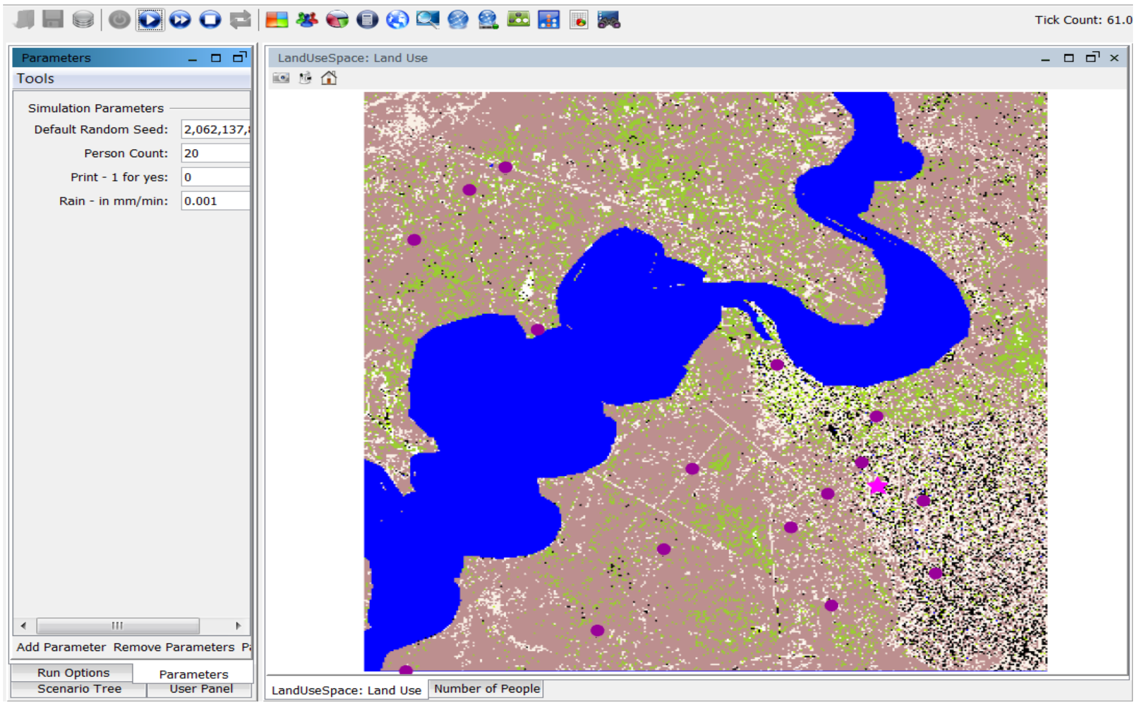


Figure10: shows 20 agents during a flooding scenario in the Land Use layer.

6. Scenarios and Analysis

Three scenarios are presented to demonstrate how the model worked. Scenario 1 tests the decision-making process over rural and urban land use/land cover. Scenario 2 tests the agent’s ability to make difficult decisions, such as to find a bridge in order to get to a safe place. Finally, scenario 3, tests the ability of multiple agents to face different levels of difficulty in decision-making.

In all scenarios, the rain rate is set at a value between 0.5 and 1mm per minute, a value that simulates the year 2000 flood, and run off rate that is moderate (a value of 2 – maximum value is 3) increasing the rate of flooding greater than the accumulation of rain. The location and number of agents was selected to provide a cross section of information that would demonstrate how the model worked over 3 scenarios.

Data was collected for each scenario and used to evaluate the agent’s ability to successfully travel the environment and find a safe place or inability to escape the flooding. The data is organized into 4 charts and 1 table that are described in Table 3. Charts A, B and C in figures 14, 16 and 18, depict the values for (1) feature weights variables (wt10 to wt90), (2) optimization variables (r10 to r90), and (3) feature selection variables (F, F1, F2 and F3).

Chart D in figures 14, 16 and 18, and Tables 4, 5 and 6 displays statistical analysis about the decision-making process used to assess how well the neural network worked and if there is evidence of adaption and path dependence. Linear regression calculations were performed on the data for the R^2 statistic (also called the correlation coefficient), providing a measure on how good the fit is or the correlation between the resultant values and the predicted values (Fox 2008). In this study there are no predicted values therefore the results (feature selections ‘F’) are compared to the preferred values, which are the ranked feature selection variables F1, F2 and F3. The usual statistical value for R^2 is a value between 0 and 1, with a value closer to 1 indicating that a greater proportion of the variance is accounted for by the model (Mathworks 2012). For all the tick values, the R^2 assessment is based on the top three feature values (variables F1, F2 and F3) compared to the actual feature selected by the agent. R^2 values are also provided for the optimization value ‘r’ (for each feature) with respect to its corresponding feature weight, providing an indication on how well the agent could adapt and learn.

Root Mean Square error (RMS) (also known as the fit standard error, the standard error of regression and the standard deviation of the residuals) was calculated on the same data used for R^2. RMS is an estimate of the standard deviation of the random components in the data. A value closer to 0 indicates a fit that is more useful for prediction (Mathworks 2012). In this study, RMS was used to indicate how well scenario results compared with the results of the optimal operating range. RMS should be used in conjunction with the R^2 values to help assess how well the model performed.

Table 3: Description of Figures for each scenario:

Figures 14, 16 and 18, Chart A	A line chart showing the weight variables (wt10, wt30, wt40, wt60, wt70, wt80 and wt90) value for each feature during a scenario.
Figures 14, 16 and 18, Chart B	A line chart showing the ‘r’ variable (r10, r30, r40, r60, r70, r80, r90) indicating how efficient the weighting process was during a scenario. The target value of ‘r’ is 0 and the optimal operating range is -10 to + 10.
Figures 14, 16 and 18, Chart C	A line chart showing the ranked feature output, F1, F2 and F3 (described in section 4) and the feature the agent selected (F) during a scenario.
Figures 14, 16 and 18, Chart D	A bar chart showing the standard deviation (SD) and mean value of ‘r’ (the optimized value of each feature weight).
Tables 4, 5 and	A table that depicts the R^2 (at the 95% confidence interval) for the

6	correlation of features the agent selected ‘F’ with ranked feature values F1, F2 and F3, and the R^2 for the correlation of the optimization value of each feature ‘r’ with the weights for features 10 (trails), 30 (vegetation), 40 (roads), 60 (farmland), 70 (hazards), 80 (building shadows) and 90 (unclassified). The table also includes corresponding RMS values.

In what follows, each of the scenarios will be described and analysed.

6.1 Scenario 1 – One Agent Rural/Urban Area

In scenario one an agent was placed in a rural area just outside the lower urban area of Xai-Xai.

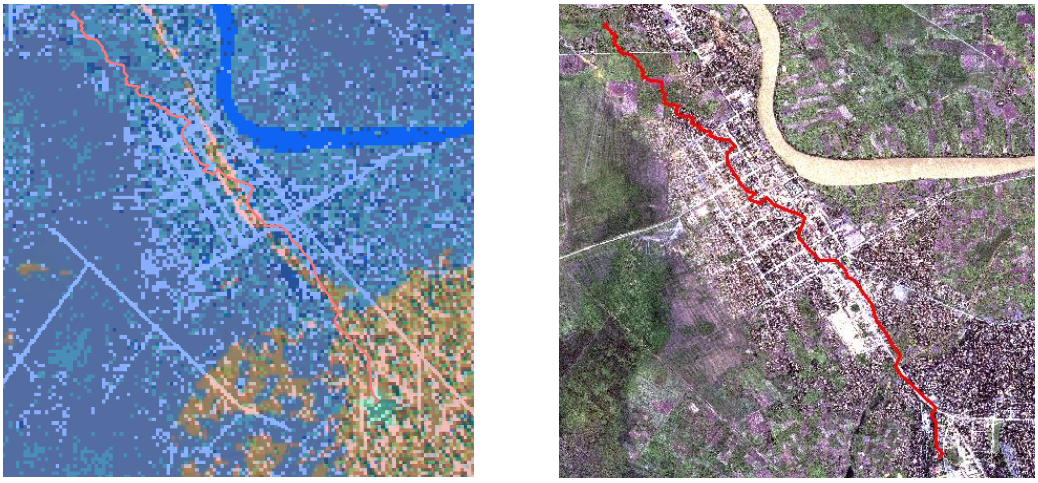


Figure 13: Scenario 1 - Illustration showing the flooding and route taken by the agent in Repast Simphony Java (left). The coordinates of the route in Repast Simphony Java were converted and overlayed on GeoEye1 0.5m imagery using ArcGIS (right). The agent commenced at the upper left, travelled via the red line to the ‘safe area’ near the bottom right.

During scenario 1, the agent travelled across farm land, then various roads within lower Xai-Xai, and across a mix of rural/urban terrain to the ‘safe area’ in the upper area of Xai-Xai. The scenario time was 110 ticks (representing minutes) with a rain fall of 1mm/minute, incurring a flood level of 3 meters. Although the flooding occurred quickly, the agent avoided the flooded areas and made it to the safe area.

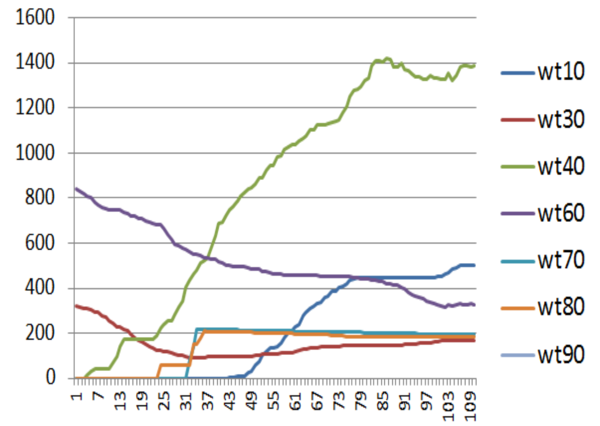


Chart A:

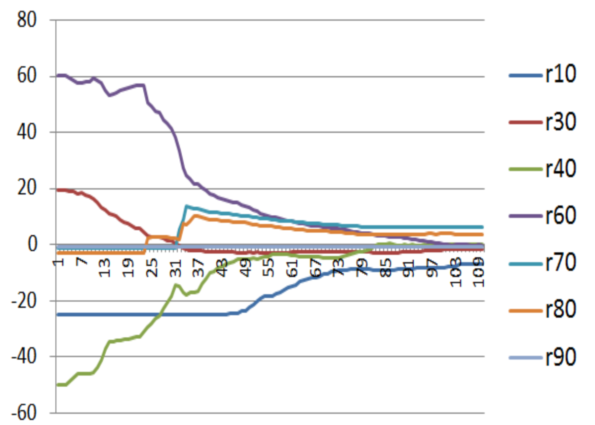


Chart B:

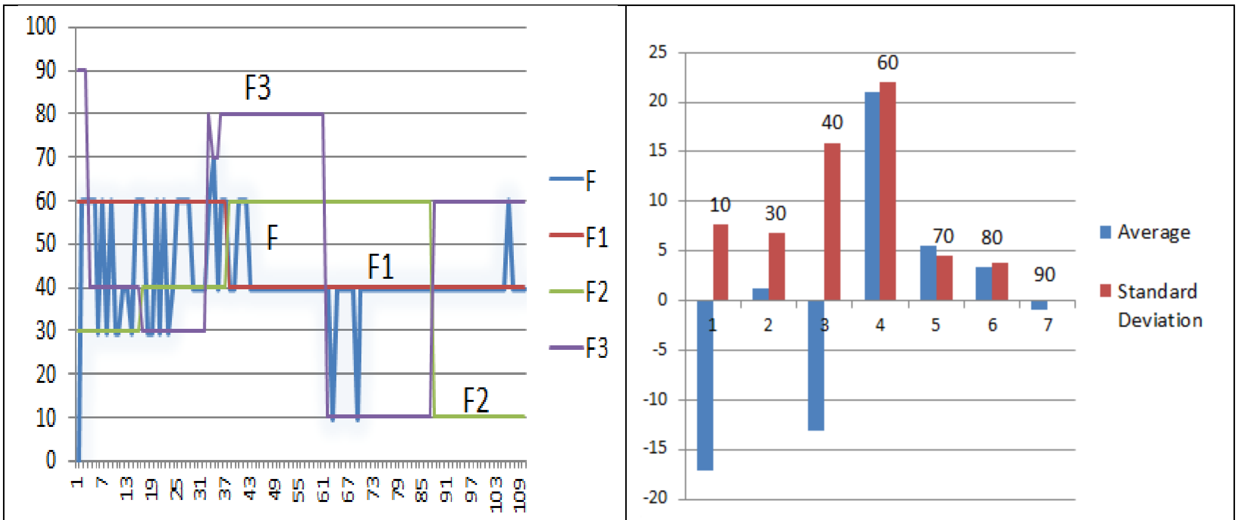


Chart C: **Chart D:**

Figure 14: Scenario 1, Chart A**:** Illustration of the Weights (wt) indicating how the agent interacted with the environment during the scenario and the values of the feature weights at each 'tick' interval that would be used in the ranking process; Chart B**:** Optimization values (r) of the weights for each feature; Chart C**:** Feature selections F (actual) and ranked features F1, F2 and F3; Chart D: standard deviation and mean of the 'r' values.

Comparing Figure 13 to Figure 14A, the highest weight for the agent as it travelled through the rural area (from approximately 0 to 30 tick minutes) was feature 60 (farm land). Entering the urban area of Xai-Xai it had to adapt as demonstrated by a spike in feature 40 (roads) and feature 10 (trails). In Figure 14A, the three highest feature weights for the agent at each 'tick' correspond to the feature variables F1, F2, and F3 that were used in the decision-making process (Figure 14C).

Figure 14B illustrates the optimization process and how it initially struggled to bring the weights for land cover features 60 (farmland) and 40 (roads) within the optimal values. Mid-way through the scenario all the weights were operating close to the preferred range of +/- 10.

In Figure 14C, the actual feature selection made by agents, indicated by the line 'F', depicts feature F1 was selected most of the time, with some F2, F3 and a few random selections. When the agent was in the rural area, the selection process was more erratic whereas in the urban area, feature 40 (road) was the main selection.

The standard deviation (SD) of optimization values 'r' for land cover features 60 (farmland), 40 (roads) and 10 (trails) showed they were slightly outside the preferred operating range, as illustrated in Figure 14D, and their corresponding mean values were close to or greater than 10. The mean values for all other features were within +/- 10. (The variable 'r' was described in the beginning of this section).

Table 4: Scenario 1, Illustration 5 - Regression Analysis showing R^2 (at the 95% confidence interval) for the correlation of features the agent selected with ranked feature values F1, F2 and F3, and the R^2 for the correlation of the optimization value of each feature 'r' with the weights of features 10 (trails), 30 (vegetation), 40 (roads), 60 (farmland), 70 (hazards), 80 (building shadows) and 90 (unclassified). The table also includes corresponding RMS values

Feature 1 F1 R^2	0.93	RMS	11.8
Feature 2 F2 R^2	0.75	RMS	21.9
Feature 3 F3 R^2	0.73	RMS	22.6
R^2 10	0.99	RMS	17.4
R^2 30	0.73	RMS	29.1
R^2 40	0.88	RMS	171.0
R^2 60	0.94	RMS	35.9
R^2 70	0.87	RMS	34.0
R^2 80	0.81	RMS	35.5
R^2 90	1.0	RMS	0

Table 4, indicates the R^2 values for output features F1, F2 and F3 with the feature selection 'F' were approaching 1 in the order of F1, F2 and F3. The RMS values were approaching 0 in the order of F1, F3 and F2. This suggests the model was selecting features in the preferred order, with a stronger selection correlation for F1 features; F2 and F3 being approximately the same.

The R^2 for land cover features 10 to 90 (explained at the introduction of section 6) suggests the weights were adjusting and operating well (all over 0.7). The RMS values supported R^2 except for feature 40. Generally, the values show that the model was working well with the agent adapting to the environment.

6.2 Scenario 2 – One Agent Extreme Travel

In this scenario one agent was placed in a rural area on the westerly side of the Limpopo River, presenting a challenge for the agent to find a way across the river in its effort to get to the 'safe area'. The scenario time was 311 tick/minutes with a flood level of 1.5m and rainfall of 0.5mm/minute. The flooding was moderate and the agent made it to the 'safe area' as shown by the agent's route taken in Figure 15.

Figure 15: - The illustration shows the flooding and route taken by the agent in Repast Simphony Java (left). The coordinates of the route in Repast Simphony Java were converted and overlayed on GeoEye1 0.5m imagery using ArcGIS (right).

Figure 15 illustrates that the agent travelled across farm land to the river. It then found the bridge, crossed over to Xai-Xai, taking various roads before reaching the 'safe area'.

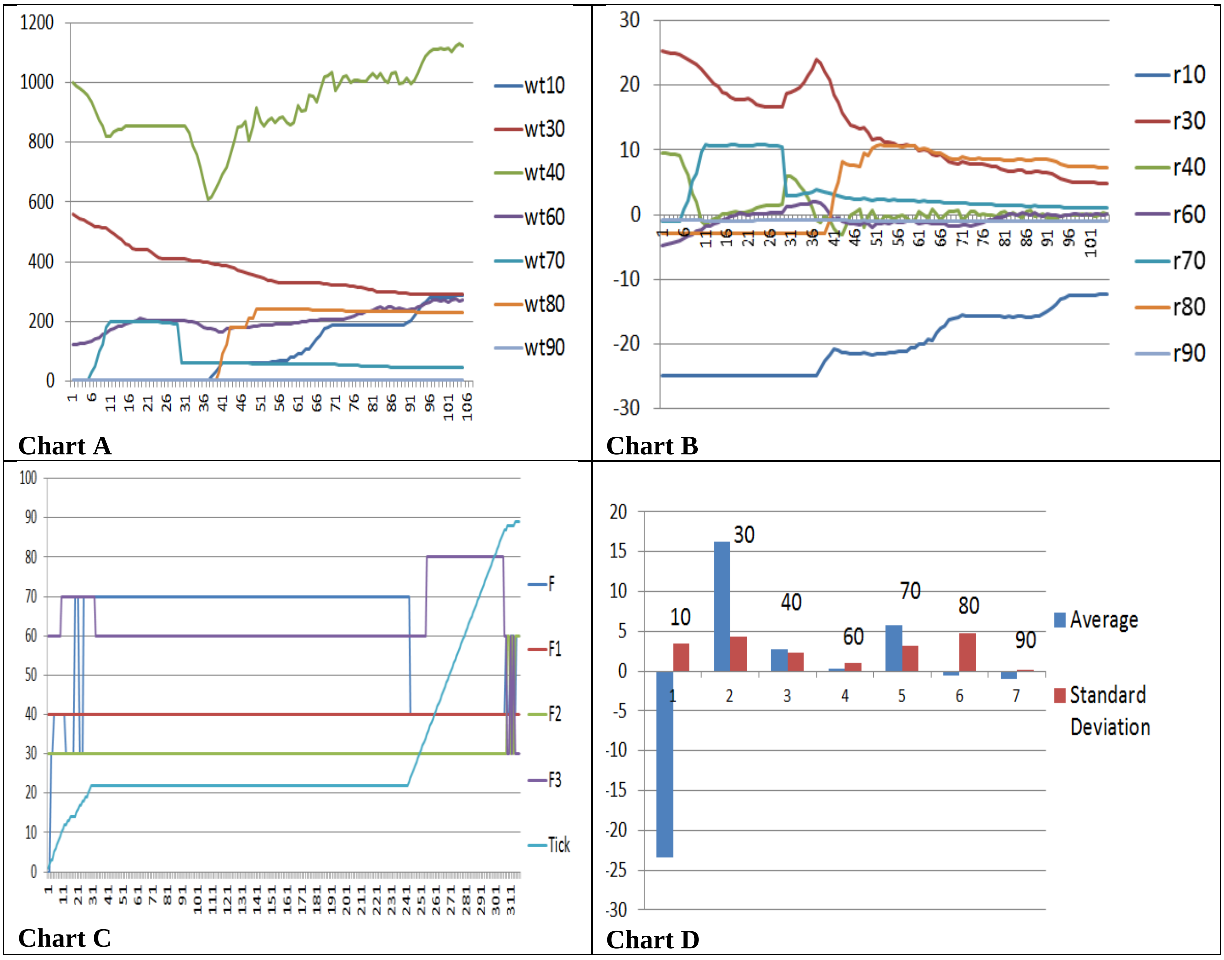


Figure 16: Scenario 2, Chart A: Weights (wt) of the features 10, 30, 40, 60, 70, 80 and 90; Chart B**:** Optimization values (r) of the weights for each feature; Chart C**:** Feature selections F (actual) and ranked features F1, F2 and F3, and Tick line for agent progress; Chart D**:** Standard Deviation and Mean of the 'r' values**.**

Figure 16A illustrates the weight for feature 40 (roads) was highest for the entire scenario. The weight for feature 30 (vegetation) was higher in the rural area, but when the agent travelled from lower Xai-Xai through a transitional area (rural/urban) to the upper area, the weights for 10, 30, 60, 70 and 80 were converging.

In Figure 16B, the 'r' value for land cover features 10 and 30 indicates the process struggled to achieve the optimal operating range of +/- 10. Levels for all the weights improved as the scenario progressed.

Figure 16C illustrates selections were made on features F1, F2 and F3 as the agent travelled across the rural area until it discovered the river. Making a series of random selections while adapting to the terrain, the agent travelled along the river, found and crossed the bridge. It then travelled through lower Xai-Xai, with the main selection on F1, roads (40). Near the end of the scenario while crossing over an area of rural and urban land cover, between lower and upper Xai-Xai, a series of selections on features F1, F2 and F3 were made. The selections by the agent suggest it adapted to the terrain by selecting the best available land cover features while travelling to the 'safe area'.

The majority of the land cover features with the exception of features 10 and 30 had a mean 'r' value within +/- 10. All the features had a SD within +/- 10 as shown in Figure 16D.

In Table 5, the R^2 values for the correlation of the features selected by the agent 'F' with F1, F2 and F3 were approaching 1 in the order of F1, F2 and F3, and the RMS values were approaching 0 in the same order. This suggests the decision-making process was working well as the agent made selections on features in the preferred order.

Table 5: Scenario 2, Illustration 5 - Regression Analysis showing R^2 (at the 95% confidence interval) for the correlation of features the agent selected with ranked feature values F1, F2 and F3, and the R^2 for the correlation of the optimization value of each feature 'r' with the weights of features 10 (trails), 30 (vegetation), 40 (roads), 60 (farmland), 70 (hazards), 80 (building shadows) and 90 (unclassified). The table also includes corresponding RMS values

Feature 1 F1 R^2	0.97	RMS	14.8
Feature 2 F2 R^2	0.92	RMS	17.8
Feature 3 F3 R^2	0.89	RMS	20.6
R^2 10	0.99	RMS	5.76
R^2 30	0.88	RMS	16.5
R^2 40	0.04	RMS	73.4
R^2 60	0.16	RMS	19.1
R^2 70	0.99	RMS	5.40
R^2 80	0.99	RMS	9.45
R^2 90	1.0	RMS	0

R^2 for the optimization value 'r' in relation to the weights for features 10, 30, 60, 70, 80 and 90 indicates the process was operating well for those features having values over 0.88. The R^2 value for feature 40 was low and RMS was much higher than the rest suggesting improvement could be made to keep the 'r' value for 40 within the optimal operating range.

6.3 Scenario 3 – 25 Agents: 15 Urban/10 rural

In this scenario 15 agents were placed in various locations in the lower urban area of Xai-Xai and 10 in the rural area. The whole area flash flooded to an elevation of 3m within 70 tick/minutes. The flooding trapped all the rural agents and 10 of the urban agents, only 5 made it to the safe area as indicated in Figure 17.

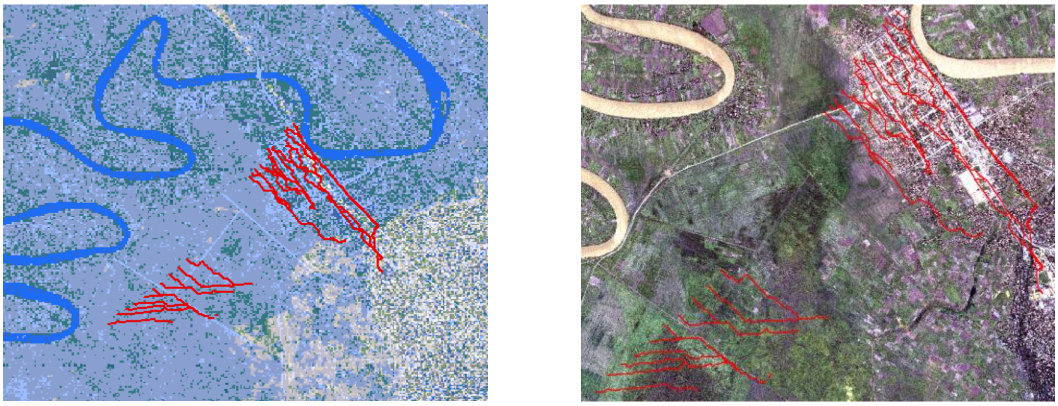


Figure 17: - Illustration showing the flooding and routes taken by the agents in Repast Simphony Java (left). The coordinates of the routes in Repast Simphony Java were converted and overlayed on GeoEye1 0.5m imagery using ArcGIS (right).

The results indicate that roads (40) and secondary roads/trails (10) were being utilized as the primary source of travel when it was available; however, the use of trails and rural features for travel was not fast enough to keep the agents ahead of the flooding.

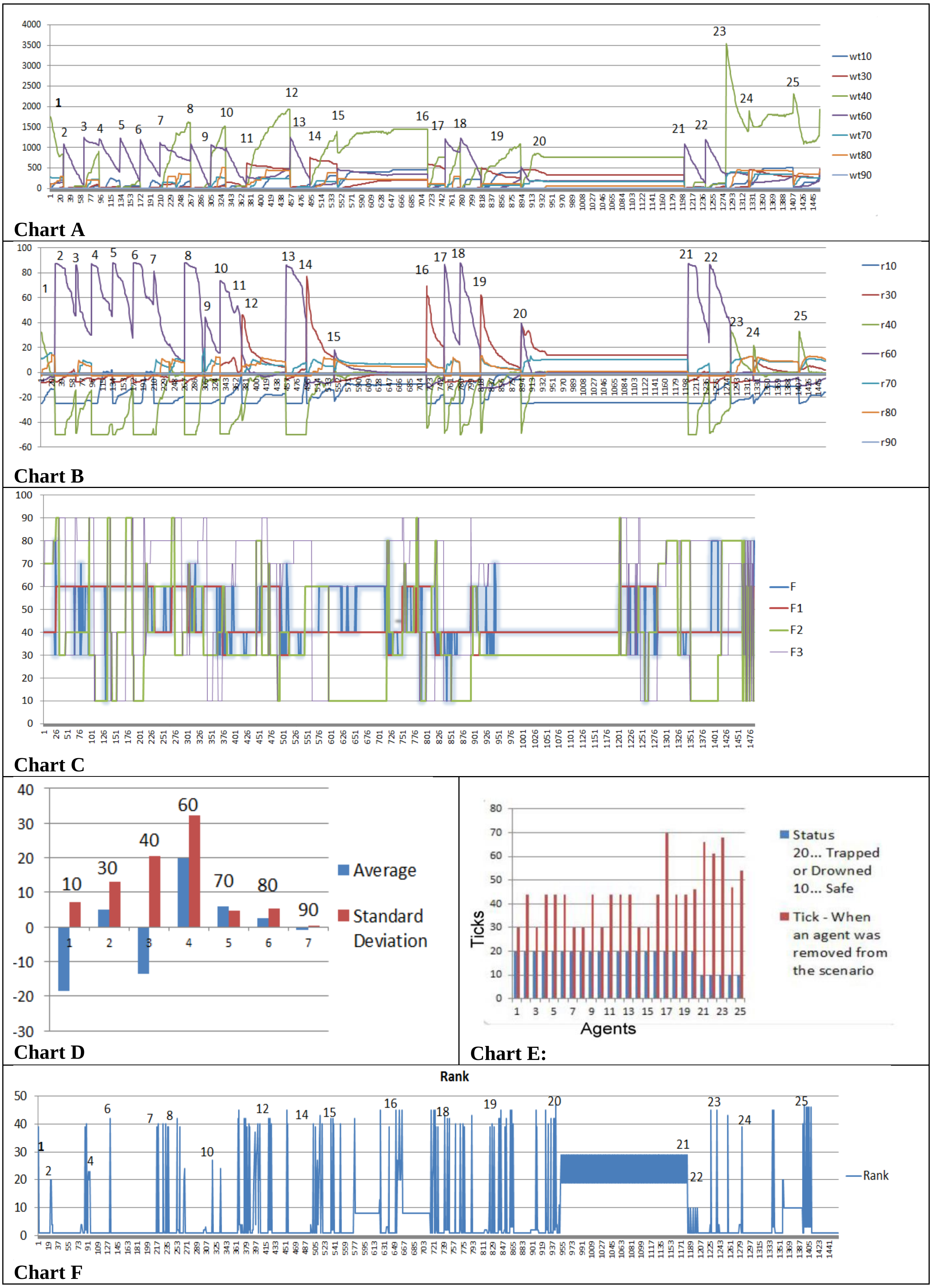


Figure 18: Scenario 3, Chart A; Weights (wt) of the features 10, 30, 40, 60, 70, 80 and 90 for 25 agents; Chart B: Optimization values (r) of the weights for each feature; Chart C: Feature selections F (actual) and ranked features F1, F2 and F3; Chart D: Standard Deviation and Mean of the 'r' values; Chart E: Illustration indicating when and why an agent was removed from the scenario; Chart F: Illustration of the level of decision

making each agent made during the scenario. The number on top represents the agents (1 to 25) with the level of decision making noted on the vertical axis.

Figure 18A shows the individual weights for the 25 agents. As with the 2 previous scenarios, agents displayed the capability of assessing the land cover and making decisions on an individual basis. Every agent in Figure 18A depicts a unique set of weights. Urban agents favoured feature 40 (roads) where feature 60 (farmland) was favoured for rural agents.

The optimization process appeared to work well for all the agents. As the scenario progressed, all 'r' values improved towards the optimal range of +/- 10 (See Figure 18B).

Figure 18C indicates feature F1 was selected most often, with fewer selections made on F2 and F3, and some random selections. Generally, the 25 agents performed similar to the individual scenarios.

Figure 18D indicates the 'r' values for features 10, 30, 40 and 60, also being the features the agents selected most often, struggled to be within the preferred range of +/- 10. The values could be improved by adjusting the learning rate impacting how fast optimization of the weights occurs.

When an agent was removed from the scenario, a value of 10 or 20 was assigned to the file output indicating whether the agent made it to the 'safe area' or was trapped. For example, in Figure 18E, agents 1 to 20, were all trapped, indicated by the value 20 on the blue bar, and agents 21 to 25 made it to the safe area, indicated by the value 10. The corresponding red bar indicates at what point in the scenario the agent was removed. The last agent to be removed was number 17 at 70 ticks.

Figure 18F indicates the level of decision making required for each agent. Many agents travelled through the scenario using the first decision-making process, while many had to dig deeper to the max level of 47. Agent 20 got stuck in a decision-making loop (indicated by the blue bar) until it was able to move forward. This figure indicates that many agents struggled to find a viable decision at some point during the scenario.

Table 6: Scenario 3, Illustration 5 **-** Regression Analysis showing R^2 (at the 95% confidence interval) for the correlation of features the agent selected with ranked feature values F1, F2 and F3, and the R^2 for the correlation of the optimization value of each feature 'r' with the weights of features 10 (trails), 30 (vegetation), 40 (roads), 60 (farmland), 70 (hazards), 80 (building shadows) and 90 (unclassified). The table also includes corresponding RMS values

Feature 1 F1 R^2	0.92	RMS	13.3
Feature 2 F2 R^2	0.65	RMS	28.8
Feature 3 F3 R^2	0.76	RMS	23.7
R^2 10	0.63	RMS	98.4
R^2 30	0.70	RMS	104
R^2 40	0.69	RMS	342
R^2 60	0.61	RMS	201
R^2 70	0.64	RMS	67.4
R^2 80	0.84	RMS	55.8
R^2 90	1.0	RMS	0.0

The R^2 and RMS values in Table 6 indicate F1, F2 and F3 were approaching 1 and 0 respectively, in the order of F1, F3 and F2 suggesting agent selection on F2 should have been better. As a result, agents might have been able to move faster if output feature F2 was the preferred alternate when F1 was not available and possibly less agents being trapped by the flooding.

The R^2 for all the feature weights indicated the adjustment was working well with values all over 0.61. The RMS for feature 40 (roads) was somewhat higher as it struggled to achieve the optimal operating range, suggesting this process affecting adapting and learning should be examined.

7. Model's Evaluation

The evaluation process of agent-based models is comprised of calibration, verification, and validation (Manson 2003). Manson et al (2012) describe *calibration* as the adjustment of model parameters to fit with desired results; *verification* as a way to ascertain whether the model runs according to design and intention, i.e. by running the model with data to determine if output data are in line with expectations and, finally, *validation* as the process in which the model outputs are compared with real-world data. Although validation is an important part of an agent-based model's evaluation, it is also one of its greatest challenges (Crooks et al 2012). In the case of the present study, validation would require real world information which was not available for this project. Therefore, the evaluation of the model focuses on verifying the process of a calibrated ABM and how well the output data met with expectations.

The two parts of the model (flooding and evacuation behaviour) were evaluated separately. The flooding model was calibrated to simulate the flooding that took place in Xai-Xai in 2000 derived from the book 'Mozambique and the Great Flood of 2000' by Christie and Hanlon (2001). In order to replicate this behaviour, the amount of rainfall used for the model scenarios (presented in section 6) was set between 0.5 to 1 mm per minute (6 cm/hr) in the medium to severe range.

By and large, the manner in which the flooding occurred in the model was consistent with the flooding experienced in the area as outlined in the three scenarios presented in section 6. The flooding model could have been more realistic if a higher resolution and more accurate DEM had been used. The flooding model also lacked other considerations such as hydraulics and mitigation measures, which would allow for a more realistic outcome. Still, the model did provide a realistic flooding environment for the agents to interact with, which satisfied the objectives of the project.

The evacuation behaviour was evaluated using a combination of three different methods: visual assessment of the agent's route, statistical analysis and assessment of the output from the neural network. Those were used to evaluate the decision-making process for each scenario presented in section 6.

For conducting the visual assessment, the routes produced by agents in the model were reproduced using environmental data in ArcGIS. This was done by converting the coordinates of the routes and overlaying them on GeoEye1 0.5m imagery using ArcGIS. The routes taken by agents in the Repast Simphony Java model were then visually compared with the same routes produced in ArcGIS.

The assessment of the routes selected by the agents were performed for all three scenarios (see Figures 13, 15 and 17) and presented significant similarities to the ArcGIS routes. Thus, the results of visual assessment suggest that agents make decisions about the terrain in a similar manner to a person. The fastest features to travel over, such as roads, are taken when available and cells with structures and water are avoided. All the scenarios verified that the process was meeting expectations as agents made decisions similar to humans as they moved towards the safe area. An example is the agent's behaviour in scenario 2, which demonstrates characteristics of human decision-making when the agent found and crossed the bridge as it travelled to the safe area, however, some decisions were poor ones, in part due to lack of information about the area and cells that could not be sensed. In addition, the resampling process degraded features that contributed to agents getting trapped.

The statistical analysis evaluation was conducted using linear regression by calculating the R^2 and RMS statistic. R^2 provided information to evaluate the correlation between feature outputs and features the agent selected while RMS or root mean square error provided an estimate on how well scenario results of the feature weights compared with the optimized results.

The statistical analysis yielded interesting results that provides us with an insight into human decision-making using a hybrid model of neural networks. When the neural network was working well, R^2 and RMS could be both high and low. An R^2 value that was closer to 1 suggested the decision making process was operating well, whereas a low (closer to 0) statistic suggested adapting and learning was taking place. The reverse was seen for RMS and therefore both values were evaluated together. Scenarios that required lots of adapting often accomplished by random moves showed a lower correlation of optimal weights 'r' with the actual weights. Scenarios that did not require as much adapting and less random moves, showed a higher value. Correlation of the features indicated F1 was the preferred selection with F2 and F3 being a close 2nd and 3rd option. In scenarios where little adaptation was required and few random selections were made, the R^2 value was 1 and RMS 0.

In each scenario the operation of the neural network was assessed (presented in section 6) using Charts A to D, in Figures 14, 16 and 18. Chart C shows the output of the neural network, being the 3 features (variables F1, F2 and F3) that were provided to each agent for selection at each tick interval, and the actual selection (variable F) that was made. Chart C shows that the decision-making process often resembled the human characteristic of 'panic'. This occurs when an agent is trapped by flood water or by buildings and the feature selection line (F) 'zig-zags' between various selections. For example, in Scenario 1 (see Figure 14C), between ticks 1 to 37, the feature selection line jumps between different features as the agent moved through the rural area as it encountered various land cover. In all scenarios, agents experienced areas that had fewer problems in decision-making thus having a 'calm' appearance as a result of less feature selection activity (see Figure 16C, between ticks 241 to 301). In this example, the period of calm occurred after a series of random selections and weight adjustment as the agent searched for and found the road to cross the bridge over the Limpopo River. Scenario 3, provides additional information on the level of decision making (Figure 18E) encountered by each agent. If no problems were encountered by an agent the 1st level would be sufficient, however, if an agent encountered severe difficulty in making an acceptable decision, up to 47 decision levels could be tried. The chart indicated each agent experienced a unique level of difficulty in making decisions.

Travel time by an agent to the safe area, using an average walking rate of 4km/hr (according to Cavagna et el 1976) was considered reasonable. The distance from lower Xai-Xai to the safe area (in the upper area) is approximately 3 km's. If an agent did not get trapped, the travel time was approximately 60 tick minutes to the safe area and approximately 110 tick minutes when commencing in the rural area, about 4 km's from the safe area. Travel time in each scenario took into consideration what type of terrain the agent was travelling over as the rate of travel over roads was approximately 2 ½ times faster than over rural areas.

8. Conclusions

The model was successful in simulating a fast flooding area, thus providing a framework to study evacuation behaviour as well as developing a neural network to simulate an agent's cognitive ability to sense, learn and adapt when travelling over a landscape during a flooding episode.

The evaluation of the model (presented in section 7) suggested agents did demonstrate cognitive abilities and human characteristics, it was not possible to perform a full validation of the model due to lack of data. It is well known that validating human behaviour is very difficult to achieve and, in fact, it is considered as one of the main challenges of ABMs, as highlighted by Kennedy (2012). Thus, further calibrating the learning rate to improve decision-making and progress of an agent during a flooding episode may not necessarily improve the results as not all people learn at the same rate. In other words, without obtaining data on real human behaviour, further calibration of the model is likely to be a fruitless effort to improve decision-making results.

The evaluation process demonstrated there is potential for using this design of hybrid model of neural networks on further research about the evacuation behaviour of people in the fast flooding area of Xai-Xai, which can be possibly extended to other geographic areas where models integrate human decision-making and land use/land cover. The architecture in Repast Simphony Java is flexible and adaptable, such that further steps could be taken to improve the model with more land cover/land use features, improved DEM, a larger knowledge base of information, other decision-making processes, and increased agent movement. Further development of the model could also involve the participation of local groups providing essential data for model calibration and validation.

While there are challenges in agent-based modeling when integrating human decision-making with the complex phenomenon of fast flood and changing land use/land cover, this study highlights the potential of using a hybrid model of neural networks for decision-making in ABM's.

The model presented here is the first steps towards a tool which can effectively inform decision-making on evacuation procedures in the Limpopo River Basin Area in Mozambique. By allowing for a better understanding of how individuals behave when evacuating the area during fast-flooding events, the model can inform of practitioners in the development of an effective disaster management plan. The model can be particularly helpful in informing the stages of preparedness and response. Once the model is fully developed and validated, different evacuation routes can be tested and the safer routes identified. This can inform the development of a safe evacuation procedure as part of the preparedness plan future events to be implemented by local authorities together with the local population. Similarly, based on the evacuation behaviour of individuals, critical areas for rescue can also be identified, which can be part of the response plan for the disaster. Priority areas for rescue can be identified which allow emergency services to have an effective action plan. This knowledge can hopefully be transferable to other areas of fast-flooding and inform evacuation procedures and policies elsewhere.

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