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Comparing common connectivity metrics to agent-based simulation approach for Austrian forest landscapes.

by

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Vienna, 22 February 2021

SCIENCE PLEDGE

I declare that I have authored this thesis independently, that I have not used other than the declared sources / resources, and that I have explicitly marked all material which has been quoted either literally or by content from the used source.

Vienna, 22 February 2021

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Signature

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The basis for my thesis was built first of all on my work and interest in forest ecosystems. Secondly, I took part in the creation of a forest land-cover layer of Austria, which led to many ideas for usage in remote sensing. Research on connectivity bound these two worlds and gave lots of room to test and apply different methodologies.

I would like to thank my supervisor Dr. Gudrun Wallentin and the whole UNIGIS-Team at the Paris Lodron University Salzburg for their support throughout the creation of my thesis and the entire study programme. My thanks also go to my colleagues and superiors from the Austrian Research Centre for Forests, Natural Hazards and Landscape (BFW) for their inspiration and provided time.

I would like to thank Katharina Sachs and my brother Michael for their skillful proof-reading. I want to express my gratitude towards my family for their patience and wide-ranging support. And finally, I cannot forget to thank my fiancé Philipp. He saw me through the whole process of this thesis, both with his professional help and unfailing encouragement whenever the goal seemed to get out of reach.

Content

1. Framework of the thesis

This thesis consists of two parts, first a manuscript to be published in IJGIS and second a report of the detailed documentation of the workflow.

In the manuscript part contains the used methodological approaches and their foundations. Results and discussion of these are part of the manuscript as well. Finally, conclusions and an outlook complete the work.

The report contains a description of the applied methods including the used software and technical implementation.

Since I have put a lot of effort into my thesis, I would like to publish it in a scientific journal. For this purpose, I chose the *International Journal of Geographical Information Science*. This journal aims to publish ideas, approaches and methods. The created content is used for monitoring, prediction and decision making. Agent-based simulation as used in this thesis, is not a novel method, but not used often in papers concerning forest ecosystems in this way. As I describe a method comparison of classical GIScience research questions the choice of journal seems justified.

Author contribution

Conceptualization, Katrin Windisch; Methodology, Katrin Windisch; Validation, Katrin Windisch; Formal Analysis, Katrin Windisch; Investigation, Katrin Windisch; Resources, Katrin Windisch; Data Curation, Katrin Windisch; Writing-Original Draft Preparation, Katrin Windisch; Writing-Review & Editing, Katrin Windisch, Gudrun Wallentin; Visualization, Katrin Windisch; Project Administration, Katrin Windisch.

All authors have read and agreed to the published version of the manuscript

2. Manuscript

Comparing common connectivity metrics to agent-based simulation approach for Austrian forest landscapes.

ABSTRACT: Fragmentation influences biodiversity of forest ecosystems and is an important measure to monitor the status of forest landscapes. In this work connectivity, as opposition to fragmentation, is used to quantify a landscapes state. Three different approaches (Nearest neighbour, least cost path and Agent-based modelling) are compared and contrasted with other commonly used landscape metrics. The methods were applied to three Austrian survey areas with different forest patterns. Connecting paths were evaluated in respect to path length (travelled distances) and cumulative costs on landscape and forest patch level. A simple agent-based model, implementing correlated paths, was built to simulate agents' movements from one forest patch to the next. Figures derived from NN, LCP and ABM correlated strongly and follow the survey areas forest distribution. ABM results emphasise on short travelled distances and spread widest.

KEYWORDS: agent-based simulation, least cost path, nearest neighbour, forest connectivity

2.1. Introduction

For forest ecosystems, fragmentation is a concept that is equally important for monitoring biodiversity as it is hard to grasp and measure. The degree of fragmentation has a significant influence on biodiversity of forest habitats (Fischer and Lindenmayer, 2007). As it is difficult to provide direct measures for biodiversity, fragmentation metrics are used as proxies in forest biodiversity indices (Geburek et al., 2010).

Fragmentation can be defined either as a process or state (Franklin et al., 2002). According to Franklin et al. (2002), fragmentation can be interpreted as heterogeneity in its simplest form. In our paper, we further adhere to the definition offered by Riitters et al. (2000), who simply define fragmentation and connectivity as an opposing pair. From a process-centric view, fragmentation describes the processes that reduce and divide continuous habitat (Wilcove and Mclellan, 1986) and split large vegetation patches into multiple small vegetation patches (Saunders et al., 1991).

Even though there is a controversial discussion about the effects of fragmentation (Fahrig et al., 2019; Fletcher et al., 2018), the connectedness of forest habitat patches is relevant for species conservation, especially through ensuring the dispersal of individuals (Niculae et al., 2016; Ricotta et al., 2000; Saura and Pascual-Hortal, 2007).

Connectivity is specified as the degree to which landscape allows or hinders an individual to move between patches (Taylor et al., 1993). One way to classify connectivity is to distinguish between structural and functional connectivity. Structural connectivity represents the spatial configuration of habitat patches and functional connectivity depends on the dispersal of individuals in a landscape (Baguette and Van Dyck, 2007; Mühlner et al., 2012). Methods to quantify structural or functional connectivity are Euclidean distance and least cost path, respectively. Gaps between patches can be crossed by individuals so that patches do not necessarily have to be adjacent (Vogt et al., 2009). To measure functional connectivity by means of least cost modelling, the landscape is represented as a cost surface raster, where grid cells represent the cost to traverse the landscape in that particular cell (Etherington and Holland, 2013). Examples for movement costs are travel times, energy spent or mortality risks.

Euclidean distances are frequently quantified as nearest neighbour distance (Kindlmann and Burel, 2008). However, connectivity is not represented realistically by this measure, since animals often do not move in straight lines (Palmer et al., 2011). In contrast, least cost paths represent the optimal path between patches in terms of the selected cost criteria (Adriaensen et al., 2003; Mühlner et al., 2012). Although this approach is more realistic compared to nearest neighbour distances, it makes the simplifying assumption that the moving individual knows everything about an entire region and always chooses the optimal path (Fahrig, 2007). Least cost paths do not consider long-distance dispersal, immigration (Palmer et al., 2011) or curiosity (Simpkins et al., 2018).

Agent-based modelling (ABM) offers a highly mechanistic representation of functional connectivity. This approach is particularly well suited to model collective movement patterns of individuals in heterogeneous landscapes. Modelling connectivity thereby involves three components: 1) Movement based on an individual's constrained perception in its local environment (Castle and Crooks, 2006), 2) the adaptive movement of multiple individuals (Simpkins et al., 2018), and finally 3) the simulation of landscape connectivity resulting from the collective movement of locally constrained individuals (Palmer et al., 2011).

Comparisons of simulated movement paths by ABMs with actual radio-tracked data showed promising results. Aben et al. (2014) found that simulation of bird movement gave plausible results. Occurrence data was used by Allen et al. (2016) to validate an individual-based model for researching connectivity of subpopulations. Telemetry data (*Cervus elaphus*) was used to test the ability of common connectivity metrics to predict observations, which accentuated used paths (McClure et al., 2016).

Like in least cost path models, ABMs represent the heterogeneity of landscapes with a cost surface (Diniz et al., 2020). However, unlike least cost paths, ABMs allow to include individual behaviour principles and can also account for dynamically changing landscapes and the respective evolution of connectivity over time (Allen et al., 2016; Zeller et al., 2020). We want to give a structured comparison of functional connectivity metrics to structural landscape metrics and apply an adapted approach from Simpkins et al. (2018).

In this paper, we compare three different approaches 1) Nearest neighbour, 2) Least cost path, and 3) Agent-based modelling. We undertake these comparisons to quantify the structural and functional connectivity of forest-characterized landscapes at patch and landscape level, test their ability to predict connectivity measures and to display the influence of different forest pattern types. Each of the approaches is applied to three select landscapes in Austria that have distinctly different forest structures. The results are compared in terms of path length and accumulated costs along the derived paths and contrasted with structural landscape metrics.

2.2. Materials and Methods

In the following we outline the procedure for the three used approaches to quantify forest connectivity. NN, LCP and ABM are performed for the same forest border vectors and analysed on landscape and patch level. Additionally, common landscape metrics are calculated for the three chosen survey areas. The procedure is displayed in Figure 1.

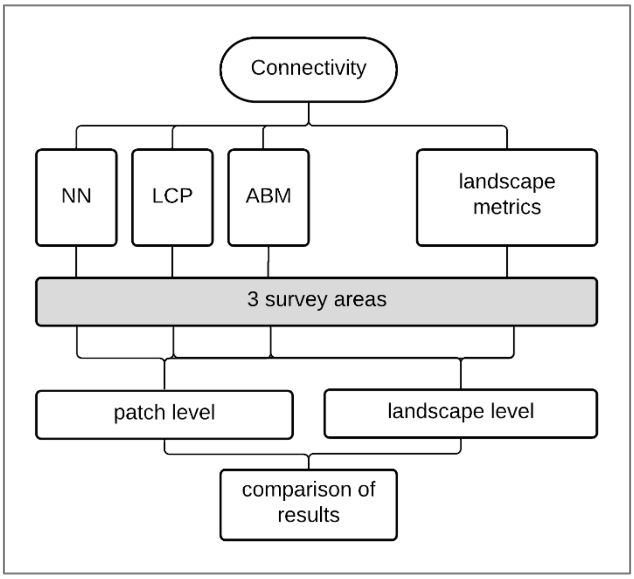

Figure 1 Applied methods

2.2.1. Nearest Neighbour

Nearest neighbour distances (NN) are calculated for forest patch vectors. The same input data as in LCP and ABM (part 2.2.8) are used. The nearest neighbouring point for each point of each forest patch is determined. The resulting line cannot cross the source patch of the starting point, only directly reachable neighbours are considered. Figure 2 shows a schematic diagram of the applied method. For each connecting line the length is calculated and the accumulated costs are derived from the corresponding cost surfaces (part 2.2.9). The calculations are performed with the help of R-package *sf* v.0.8-0 (Pebesma, 2018).

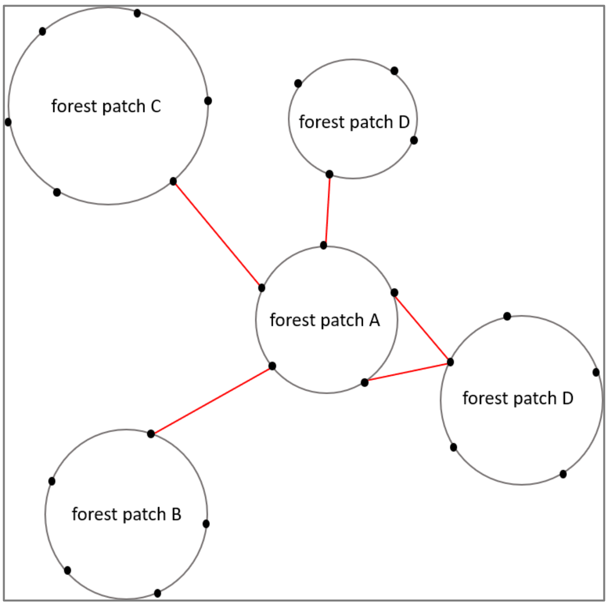

Figure 2 Schematic diagram - NN approach (circles - forest patches, black points - forest border vectors, red lines - calculated paths)

2.2.2. Least Cost Path

Least cost path metrics are determined with the same input data (chapter 2.2.8) as in the NN approach. The LCP route is calculated with Dijkstra's algorithm (Dijkstra, 1959) from processed cost surfaces. Before the cost raster can be used for LCP, a raster has to be converted to a weighted graph (Moore neighbourhood), represented as matrices. The paths are determined between single points assigned to different forest patches and forests crossings are not allowed. Lengths are calculated for these paths and extracted summarized costs for the resulting lines are obtained from the associated cost surface raster. The calculations are carried out with the help of R-package *sf* v.0.8-0 (Pebesma, 2018) and *gdistance* v.1.3-1 (van Etten, 2017).

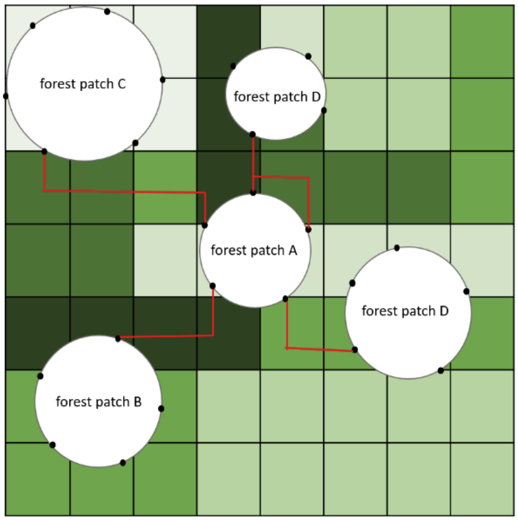

Figure 3 Schematic diagram - LCP approach (circles - forest patches, black points - forest border vectors, red lines -calculated paths, green squares – cost raster)

2.2.3. Agent-based model (ABM)

The ABM was built with the GAMA platform (Taillandier et al., 2019) and is described according to an ODD protocol (overview, design concept, details) (Grimm et al., 2010).

2.2.3.1. Purpose

The purpose of this ABM is to calculate connectivity metrics for forest patches via the dispersal of individuals from the border of forest patches. Dispersal is described mechanistically as the movement of animals from woodland patch to woodland patch through open heterogenous landscapes. Any forest cell could be a target patch for agents, except cells that belong to the agents' source patch. The model is not adapted to a specific species, but it is based on forest preferring large mammals like red deer. Movement is represented based on only few assumptions to get a straightforward and transparent dispersal model, where individuals memorize their last steps and 'die', which means they stop movement and vanish from simulation. They then leave the study area or reach the next patch or leave the study area. In addition, 'mortality' is considered when the travelled distance or accumulated costs exceeded a certain value. This threshold is orientated on other calculated measures and actual animal movement (Kie et al., 2005; Kropil et al., 2015), but since only movement between two forest patches was simulated no actual mortality (age, predation) was included in the ABM.

2.2.3.2. Entities, state variables and scales

Simulation entities are agents, which represent moving animals from forest patch to forest patch as well as a cellular automaton, the cost raster. All moving agents have the same characteristics and starts movement from their source patch. Initially, the animal agents are located just outside the border of a source patch. The initial location is logged to start the simulation and agents have a memory to reduce turning movement of agents, since individuals are more likely to choose correlated paths (Fahrig, 2007; Simpkins et al., 2018). As state variables for the animal agents, the travelled distance, collected costs, current cost value and current cycle are listed. Additionally, every agent has a perceived area, maximum reachable cost and maximum reachable memory (chapter 2.2.3.1). The moving agents do not interact with each other, as the simulation does not represent collective movement. Instead, long-distance dispersal of solitary individuals is simulated. The cost raster has initial cost values and agents' source patch cells are marked. A cell's cost value represents the resistance of the landscape for an animal that is travelling through this landscape on a scale between 0.5 and 100 cost units. Costs describe the probability for a cell of being traversed by the agent. Through the agent's movement, cost values are updated by a movement probability matrix (chapter 2.2.4) to ensure correlated paths. These updated cost values are reset to the initial cost values after 30 timesteps. The model simulations are carried out for each forest patch and end when every agent has reached another forest patch, 'died' of maximum cost or maximum distance, or because the agent left the cost surface. Agents choose one of eight neighbouring cells (Moore neighbourhood) and moves a distance of 10 m (one cell) per timestep. One timestep in the simulation represents a few seconds. Each cost raster has a spatial resolution of 10 m by 10 m, the spatial extent depends on the survey area and ranges between 4600 and 5700 hectares.

2.2.3.3. Process overview and scheduling

The ABM is initialised with the cost surface raster of one of the three study areas and, depending on forest patch perimeter a number of animal agents are located onto forest boundary cells. In the simulation, agents move (cell by cell) until they reach the boundary of another forest patch. State variables are updated at the end of each simulation step.

2.2.3.4. Design concepts

Movement is defined by rules which describe the choices of agents. An agent chooses a cell which does not belong to its source forest patch, has not been visited and has the minimum cost value.

When an agent takes its first step, the cost values of this cell and the eight neighbouring cells are updated to ensure more directed paths (Palmer et al., 2011).

Emergence: Resulting from agent movement, the travelled distances and accumulated costs are derived.

Learning: Animal agents' memory stores the visited cells, to prevent a turn, since updated cost values (by movement probability matrices) are reset after 30 timesteps. ***Stochasticity*** is included into the ABM when an agent can choose between cells having same cost values.

Observation: Connectivity measures collected from the ABM are the travelled distance and the accumulated cost per agent, assigned to forest patch. Further analysis is carried out outside of ABM.

2.2.3.5. Initialization

The model is initialized for each forest source patch from the three core survey areas and the associated moving agents. The agent number differs according to the forest edge length of each forest patch. Therefore, patch shape and patch area influence the number of moving agents. Agents are not placed randomly in the simulation core area but positioned at the forest border. Every simulation is carried out two times for each forest patch in the core survey areas. As there is a defined number of animal agents per forest patch, replications are built in the simulation and ensure enough results.

2.2.3.6. Input data

There are three types of input data for each model simulation. Firstly, a cost surface raster is imported as TIF-file. Secondly, polygon vector data representing the source patch is imported as well. This polygon is derived from the Austrian forest layer (BFW, 2020). Each polygon was slightly geometrically simplified and for each 100 m segment or vertex (whatever comes first), a point agent is produced at the polygon's border. And in a third step, starting locations for moving agents are imported to GAMA as point vector data.

2.2.3.7. Sub-models

Set source forest: All cells overlapped by the source forest polygon are marked (*source_forest,* bool). These cells are excluded from the cells that are available for selection.

Start location: The initial positions of the moving agents are used as starting points for the agents' routes. This location is the first entry for the agents' memory. After this request the actual movement starts.

Move (Figure 4): The movement model is based on model descriptions from Bender et al. (2003), Palmer et al.(2011) and Simpkins et al. (2018). All three models are based on yet simple yet realistic movement rules. The objective for agents is to reach a target habitat patch. An agent's movement starts by detecting possible target cells, as the agent should not go to its source forest patch. Every agent has a perceived area (20 m perception distance) and if this area overlaps with one target cell (cost value <0.7, not source patch), the agent will move there, ignoring all other rules. This behaviour is implemented to prevent the agent from turning around when it is already near a target patch. Else, the agent goes to a cell that is not included in memory and has the lowest cost value. If there are no more cells left outside of memory, the cell with the lowest cost value is chosen as well. Additionally, a tendency to persist in the direction of general movement is implemented by updating the cost values of all neighbouring cells. The change factor depends on the direction of the current location (comparable Simpkins et al., 2018). This method prevents agents from travelling between the same few cells and getting 'stuck'.

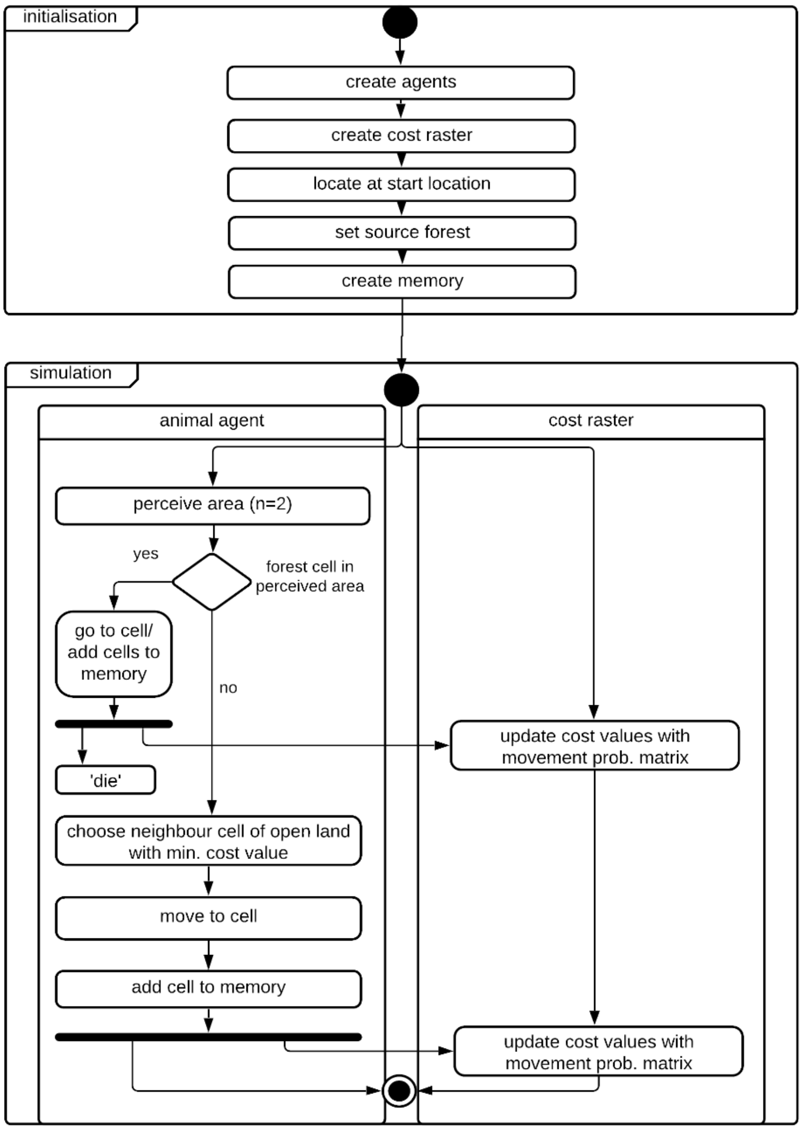

Figure 4 UML activity diagram - ABM

2.2.4. Sensitivity analysis

A sensitivity analysis was conducted to assess the impact of an animal's movement persistency on forest connectivity. Movement probability matrices (Figure 5) between subsequent timesteps were tested against the resulting paths, and analysed in respect to length and cumulative costs. The model was simulated 250 times for each movement probability matrix. The simulations were conducted for one patch in the core area of a test landscape with eight agents (patch surrounded by other patches in different sizes and distances).

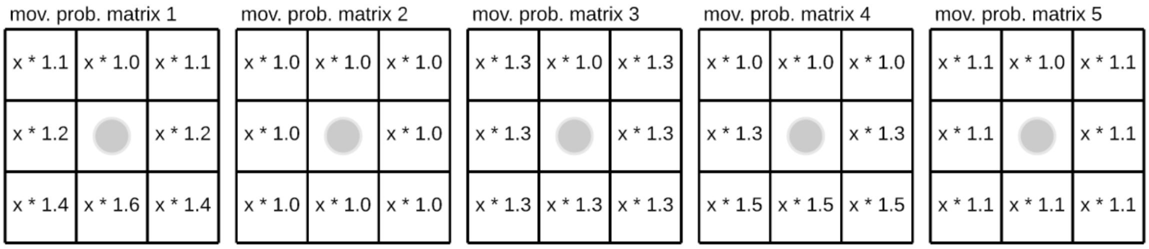

*Figure 5 Movement probability matrices for sensitivity analysis (grey circle – agent location, x * n – cost value multiplied by movement probability value)*

The movement probability matrix 2 without change values yields similar results as LCP modelling. It is therefore not considered for the actual simulations but included as comparison in the sensitivity analysis. Movement probability matrices 3 and 5 use uniform values for all neighbouring cells, except the cell ahead of the agent's location. Movement probability values of matrices 1 and 4 depend on the angle to the agent's location, whereby matrix 1 hinders from turning more effectively.

2.2.5. Landscape metrics

Since the main target of this paper is to assess forest connectivity, the study sites are investigated with respect to forest area. Additional to the three chosen approaches (Figure 1) structural measures for connectivity and fragmentation are calculated. Metrics on landscape and patch level were chosen, because results from NN, LCP and ABM are evaluated on both levels. Listed metrics are patch characteristics like minimum and maximum patch area, mean patch area, ratio between patch area and perimeter as well as mean Euclidean nearest neighbour distance (edge to edge) (Bender et al., 2003; McGarigal et al., 2012). Mean Euclidean nearest neighbour distance takes only one single nearest patch into account and should be observed in contrast to the nearest neighbour metric described in part 3.5. Splitting index (Jaeger, 2000), which describes the patch number if all patches are divided in even sized patches ($0 <= \text{index} < \text{number of cells}^2$), is determined on landscape level. Contagion (McGarigal et al., 2012; Riitters et al., 1996; Simpkins et al., 2018) ($0 < \text{index} < 100$), which is based on cell adjacencies and describes landscape clumpiness, is also calculated for the whole survey area. Splitting Index and contagion are classified as aggregation metrics. Area distribution and total forest edge (De Clercq et al., 2006;

McGarigal et al., 2012) are included in the investigation as well. A binary landscape (forest/non-forest) (comparable to Bender et al., 2003) and polygon vector data are used as basis for the analysis . The calculations are made with help of R-package *landscapemetrics* (Hesselbarth, 2019), which is based on FRAGSTATS (McGarigal et al., 2012), with RStudio v.1.2.1335.

2.2.6. Summarizing and comparing results

Measures resulting from NN, LCP and ABM are lengths and accumulated costs for single paths. These results are compared on landscape and patch level after removing outliers. This removal of whole forest patches is necessary when only very few agents from ABM simulation reached their goal and the other two approaches gave outputs in a differing higher number. Single paths from NN and LCP and single simulated paths from ABM are investigated statistically. Descriptive statistical measures (mean, median, standard deviation) are calculated for the core survey areas and distributions of lengths and accumulated costs are examined. Subsequently, a regression analysis considering these six metrics was carried out with mean and median values for each survey area and each patch. The resulting landscape numbers are contrasted with the landscape metrics mentioned before (chapter 2.2.5).

2.2.7. Survey areas

The three chosen test regions represent three different landscape types (Wrbka et al., 2005) in Austria. The first survey area is situated in southwestern Styria, where the landscape is dominated by grassland and consists of valleys formed by glaciers and hills. Forest occurs in island-shaped patches. The investigated area has a size of about 4600 hectares, including a buffer area. The second area is located in northern Austria (Waldviertel). This hilly landscape is characterised by grassland, grain cultivation and island-shaped forest patches as well. The size of survey area 2 is about 5700 hectares, including a buffer area. Finally, the location of the third study area is in one of the most densely wooded parts of Austria (political district: Lilienfeld). Characteristic for this landscape are broad ribbon-shaped forest patches. The investigated area has a size of 5200 hectares, including a buffer area. The sites were chosen because they represent diverse forest patterns and various degrees of forest density (third row Figure 6).

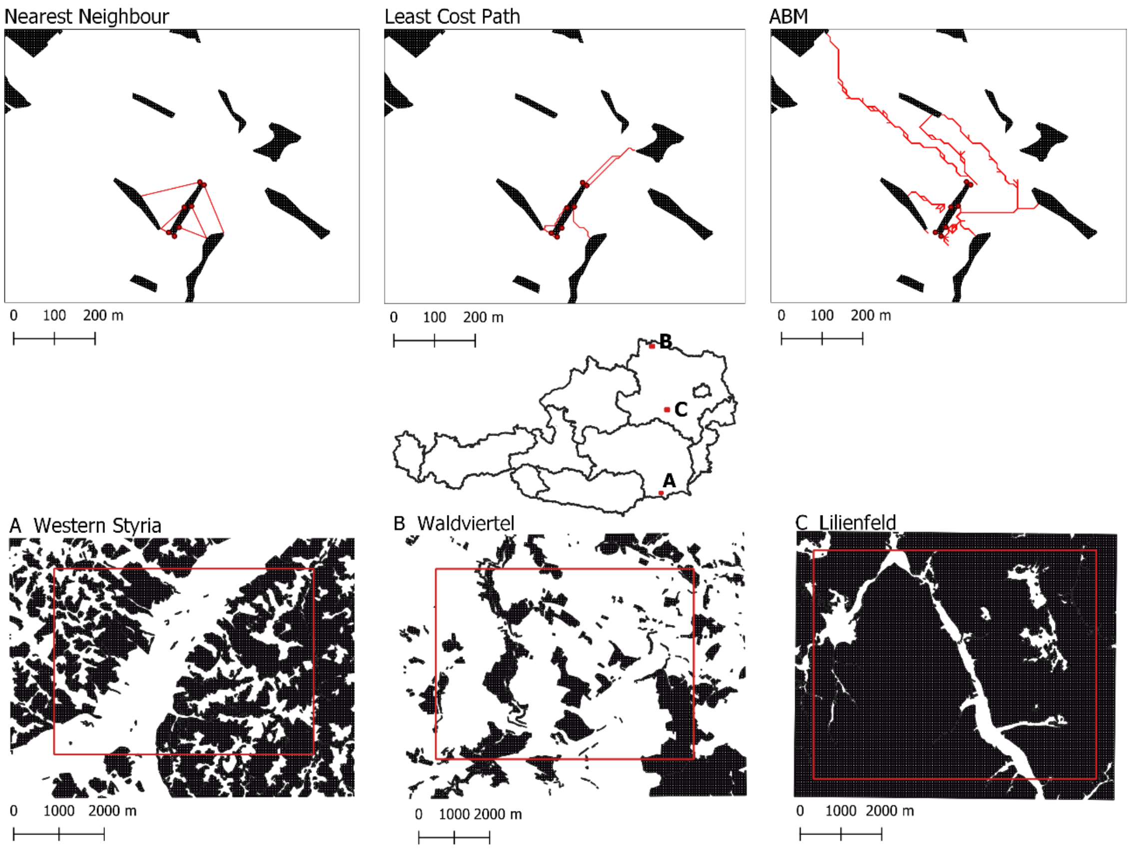

Figure 6 Overview: methods and survey areas; first row: connectivity measure approaches: nearest neighbour (NN), least cost path (LCP), agent-based modelling (ABM) example for one forest patch (red lines: calculated paths); second row: location of survey areas in Austria, third row: forest (black elements) distribution and simulation core area (red box) for 3 survey areas (A Western Styria, B Waldviertel, C Lilienfeld)

2.2.8. Forest patches and forest border vectors

The same initial situation is applied to all three approaches (ABM, NN, LCP). Forest patches are extracted from the Austrian forest layer (BFW, 2020) and slightly geometrically simplified. For each 100 m segment or vertex (whatever comes first) a point vector is produced at the polygon's border. Table 1 shows the initial numbers. Forest patches in the core survey areas and their corresponding points are chosen to calculate and simulate the different metrics for each point vector. Not each of these points lead to a result because forest crossings are prohibited. For ABM a maximum cost sum is given and an agent could 'leave' the investigated area. The core numbers display the used forest patches and start locations within the defined buffer. Survey area Lilienfeld shows a smaller aberration from the total count. In this survey area, few large forest patches represent the landscape and the border area has a smaller influence on the results; a more narrow buffer is used. Numbers with buffer include patches in the buffer zone and locations that can only be target locations for NN and LCP.

Table 1 Initial patch and forest border vector number

	Survey area Waldviertel	*Survey area Lilienfeld*	*Survey area Western Styria*
Patch number with buffer	153	71	115
Patch number within core area	47	53	39
Forest border vectors with buffer	5953	6760	15815
Forest border vectors within core area	1929	6571	2220

2.2.9. Cost raster

Cost surface raster were produced for the sites listed above. As foundation for each cost surface serves an Austrian forest layer (BFW, 2020) which is based on aerial photographs. Underlying this layer is the forest definition of the Austrian forest inventory, i.e. a minimal area of 500 m^2, minimal width of 10 m and minimal coverage of 30 % (Hauk et al., 2009). The matrix between forest patches is represented by Sentinel 2-based land cover classes from 2016 (Umweltbundesamt, 2019). Only higher ranked roads (GIP, 2016) and buffered settlement areas from the cadastral map (Bundesamt für Eich-und Vermessungswesen, 2016) were taken into account separately for more precise geometrical representation. These resulting grids have a cell size of 10 m by 10 m and each cell has a cost value between 0.5 and 100. Here it is assumed that forests stand for the lowest resistance and settlement areas stand for lowest permeability. Table 2 lists the assigned cost values to generalized land cover classes. Assigned cost values roughly follow other works that were carried out for Austria (Köhler et al., 2005; Leitner et al., 2018; Suppan and Frey-Roos, 2014).

Table 2 Cost values for produced cost surfaces

Cost values	*Land cover class*
0.5	forest from Austrian forest map
1	forest from S2-landcover
20	shrubs, reeds
30	grassland, cropland low productivity
40	grassland, cropland high productivity
50	roads, railroads, soil,
70	bare rock, water,
90	built-up area from S2-landcover
95	buffered settlement areas,
100	total barriers (motorway)

2.3. Results

Sensitivity analysis for ABM movement probability matrices resulted in the use of movement probability matrix 1, due to the highest number of target-reaching agents and most evenly distributed results. NN, LCP and ABM results for the single survey areas show differences on landscape and patch level. Results on patch level give smaller numbers for mean accumulated costs and mean travelled distances than analysis on landscape level. The numbers also display distinct differences between survey areas.

2.3.1. Sensitivity analysis

A sensitivity analysis for 250 simulations and 2000 started agents for each movement probability matrix results in different numbers of agents that reached a target forest patch. These numbers are listed in Table 3. Application of the movement probability matrix 1 gives connecting paths. Matrices 3 and 5 push agents to the straightest paths and give the highest values for mean travelled distances (Figure 7A). These two scenarios also result in the fewest target-reaching agents (Table 3). Density charts of mean travelled distance per simulation and mean accumulated costs per simulation show a positively skewed distribution for the travelled distances when using matrix 2 (Figure 7A) because paths are similar to least cost paths results. Results given by applying matrix 4 are positively skewed for mean travelled distance and mean accumulated costs as well. Considering only mean travelled distances, matrices 1, 3 and 5 their distributions look similar (Figure 7A). Taking the mean accumulated costs into account, values resulting from matrix 1 are the most evenly distributed, which is why this movement probability matrix is used for the actual simulations.

Table 3 Simulation scenarios 1-5: number of agents started and number of agents reached goal

	mov. prob. matrix 1	*mov. prob. matrix 2*	*mov. prob. matrix 3*	*mov. prob. matrix 4*	*mov. prob. matrix 5*
Agents started from source (total)	2000	2000	2000	2000	2000
Agents reached target (total)	1981	1960	1949	1982	1936

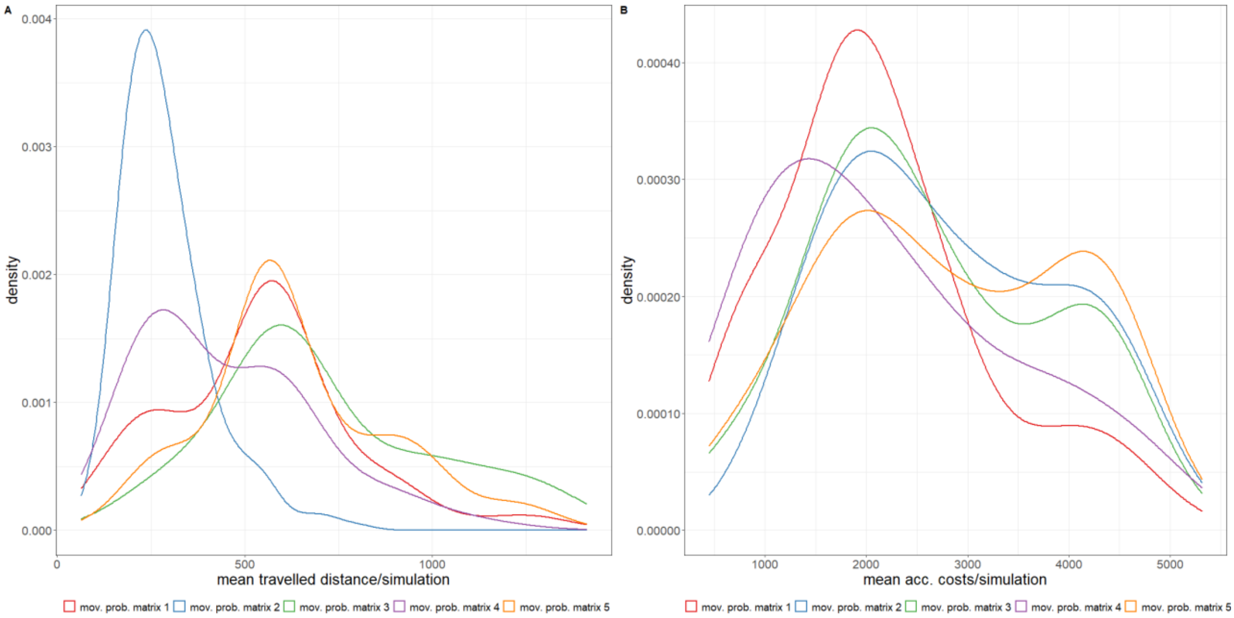

Figure 7 Density charts: mean travelled distance/simulation (A) and mean accumulated costs/simulation (B) per movement probability matrix

2.3.2. Western Styria

The three approaches on landscape level lead to quite similar results for means and medians of cumulative costs and travelled distance, by overall connecting paths, whereby the NN-approach results in the highest results for costs and the lowest travelled distances. Here, the least cost path and ABM simulation results are very much alike (see Table 4). Figure 8 displays histograms of both investigated connectivity figures for each of the three approaches.

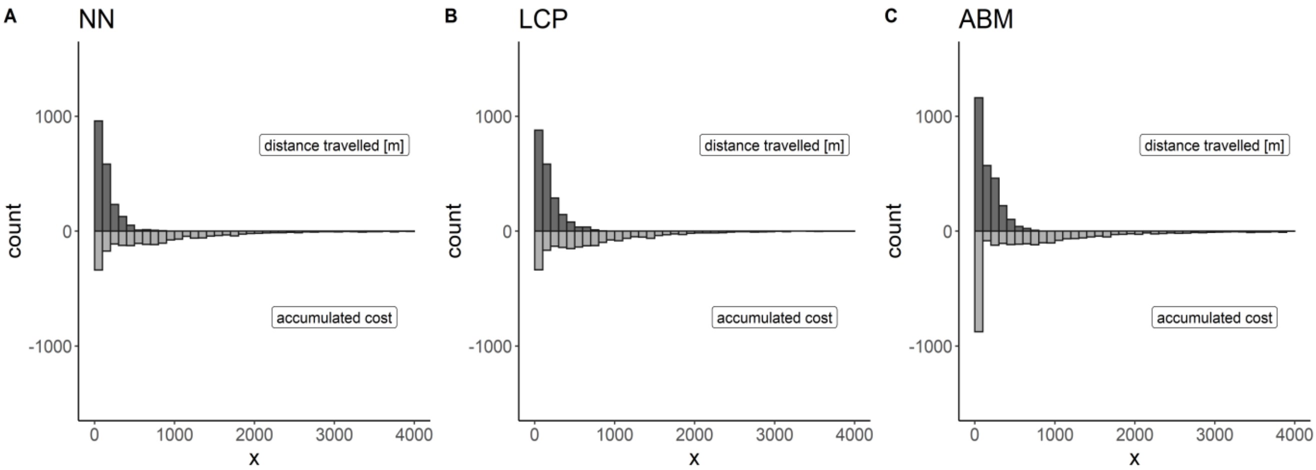

Figure 8 'Western Styria': Histograms for connecting paths: travelled distance [m] and cumulative costs (cost units) for (A) NN (n=1990), (B) LCP (n=2061) and (C) ABM (n=2592)

Analysing the results on patch level, the mean and median patch results of travelled distance and cumulative cost of the ABM simulations give the highest numbers. Comparing the medians of cumulative cost, the numbers are in a range of 73 cost units. Results of medians of travelled distance are in a range of about 35m (Table 4).

When calculating correlation coefficient *r* of medians on patch level, ABM distance (Figure 11) correlated strongly with NN distance (r=0.86) and LCP distance (r=0.78). ABMs cumulative costs are likewise highly correlated with NN cumulative costs (r=0.73) and LCP cumulative costs (r=0.70). The distance to the next neighbour patch (k nearest) shows a higher figure for *r* when correlated to ABMs mean of medians distance travelled/patch (r=0.67) than to NN- (r=0.56) or LCP-figures (r=0.49).

Table 4 Results: survey area 'Western Styria'

	NN	*LCP*	*ABM*
Start locations (centre)	*2220*	*2220*	*4440 (sim. 1:2220/ sim 2:2220)*
number of connecting paths	*1990*	*2061*	*2592 (sim 1: 1208/ sim 2:1384)*
Landscape level			
Mean cumulative cost (SD)	*795.6 (±759.5)*	*733.2 (±669.9)*	*736.9 (±849.7)*
Median cumulative cost	*610,5*	*576,5*	*489,6*
Mean travelled distance (SD)[m]	*136.6 (±130.7)*	*160.0 (±149.3)*	*153.9 (±147.6)*
Median travelled distance e [m]	*105.7*	*123.1*	*120.7*
Patch level			
Mean cumulative cost (SD)	*605.2 (±494.5)*	*516.8 (±414.2)*	*725.1 (±582.0)*
Median cumulative cost (SD)	*547.7 (±498.5)*	*478.0 (±412.0)*	*551.5 (±627.8)*
Mean travelled distance e (SD) [m]	*106.9 (±89.3)*	*114.3 (±96.3)*	*163.0 (±133.5)*
Median travelled distance (SD) [m]	*96.1 (±87.5)*	*103.3 (±95.7)*	*131.2 (±140.7)*

2.3.3. Waldviertel

Analysing the results of survey area *Waldviertel* on landscape level, the mean cumulative cost and mean travelled distance (all connecting paths) for ABM simulations give the lowest numbers. The differences between the three approaches are more pronounced than the differences in survey area *Western Styria*. Mean costs are in a range of about 650 cost units (Table 5, landscape level). Figure 9 shows histograms of all connecting paths of NN-, LCP- and ABM-approach for both investigated connectivity figures. In compared results on patch level, the number of mean cumulative cost is in a range of about 620 cost units (Table 5, patch level), ABM give the highest results.

Numbers of travelled distances do not show a variation that wide. Median distances on landscape and patch level of NN and LCP give similar numbers, ABM values differ from NN- and LCP-figures (Table 5).

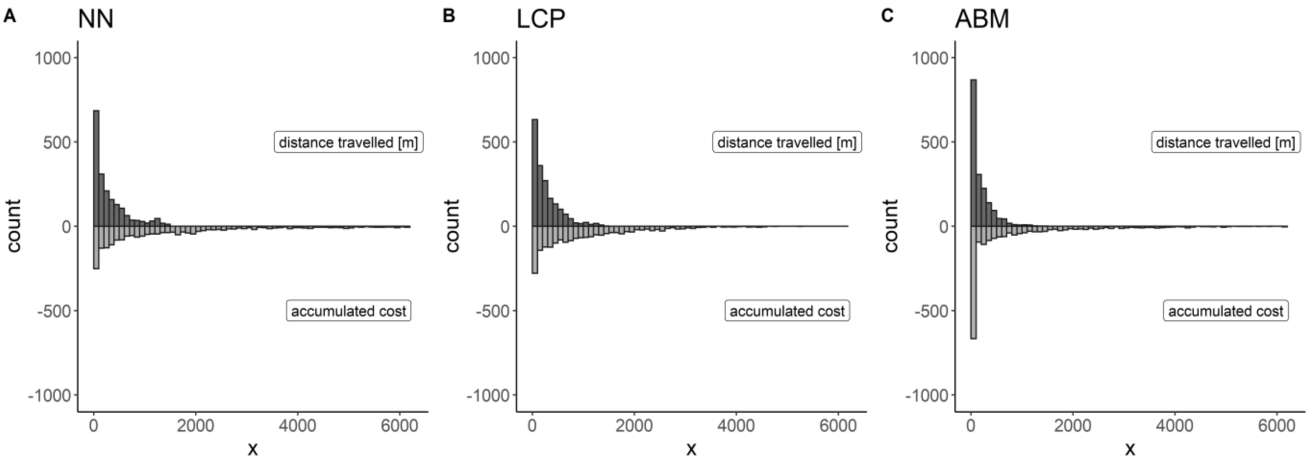

Figure 9 'Waldviertel': Histograms for connecting paths: travelled distance [m] and cumulative costs (cost units) for NN (n=1810), LCP (n=1877) and ABM (n=1779)

On patch level medians (Figure 11C) of ABM travelled distance correlated significantly (sig. level 0.05) with NN distance (r=0.37) and LCP distance (r=0.44). ABMs accumulated costs also significantly correlate with NN cumulative costs (r=0.54) and LCP cumulative costs (r=0.54). The distance to the next neighbour patch (k nearest) shows a lower correlation coefficient for ABMs median distance travelled (r=0.28) than to NN- (r=0.4) or LCP-figures (r=0.4).

Table 5 Results: survey area 'Waldviertel'

	NN	LCP	ABM
Start locations (centre)	1929	1929	3858 (sim.1: 1929/sim. 2: 1929)
number of connecting paths	1891	1877	1779 (sim. 1: 842/sim. 2: 937)
Landscape level			
Mean cumulative cost (SD)	1471.5 (±1543.4)	968.9 (±939.6)	810.5 (±1136.1)
Median cumulative cost	880.5	700	323
Mean travelled distance (SD)[m]	309.3 (±338.8)	270.6 (±273.0)	182.7 (±212.2)
Median travelled distance e [m]	180.3	184.9	104.9
Patch level			
Mean cumulative cost (SD)	1030.1 (±621.7)	721.6 (±433.9)	1258.9 (±862.3)
Median cumulative cost (SD)	738.1 (±554.0)	601.5 (±375.8)	963.2 (±947.3)
Mean travelled distance e (SD) [m]	214.5 (±121.6)	187.0 (±102.7)	277.5 (±162.5)
Median travelled distance (SD) [m]	157.7 (±110.2)	157.2 (±90.5)	210.4 (±173.1)

2.3.4. Lilienfeld

ABM simulations carried out for the most densely wooded survey area *Lilienfeld* results in lower numbers of mean cumulative cost and travelled distance (landscape level) than calculated metrics for NN and LC and all other survey areas (Table 6).

As in survey areas *Western Styria* and *Waldviertel,* mean cumulative costs and mean travelled distances on patch level show a reverse image. NN and LCP mean and median travelled distances per patch give similar results. In contrast, ABM simulations give higher numbers (Table 6).

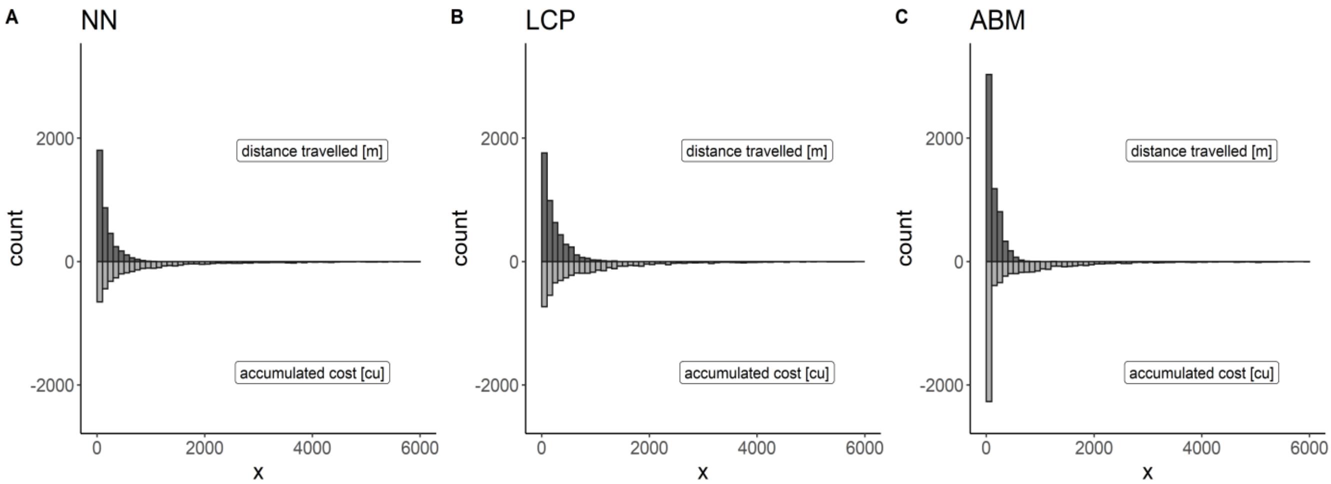

Figure 10 'Lilienfeld': Histograms for connecting paths: travelled distance [m] and cumulative costs (cost units) for NN (n=3767), LCP (n=4623) and ABM (n=5629

When calculating Pearson's r of medians on patch level (Figure 11A), ABM travelled distance correlated significantly (sig. level 0.05) with NN travelled distance (r=0.57) and LCP travelled distance (r=0.44). ABMs cumulative costs also significantly correlate with NN cumulative costs (r=0.57) and LCP cumulative costs (r=0.46). The distance to the next neighbour patch (k nearest) shows a lower correlation coefficient when correlated to ABMs median travelled distance per patch (r=0.69) than to NN- (r=0.24) or LCP-figures (r=0.13).

Table 6 Results: survey area 'Lilienfeld'

	NN	*LCP*	*ABM*
Start locations (centre)	*6571*	*6571*	*13142 (sim. 1: 6571/sim. 2: 6571)*
number of connecting paths	*3767*	*4623*	*5629 (sim. 1: 2654/sim. 2: 2975)*
Landscape level			
Mean cumulative cost (SD)	*933.6 (±1129.1)*	*898.3 (±1017.4)*	*682.0 (±1012.8)*
Median cumulative cost	*500.5*	*551.0*	*240.8*
Mean travelled distance (SD)[m]	*164.1 (±167.1)*	*221.8 (±220.0)*	*130.0 (±133.3)*
Median travelled distance e [m]	*106.9*	*152.4*	*84.9*
Patch level			
Mean cumulative cost (SD)	*335.2 (±336.4)*	*255.2 (±271.7)*	*489.5 (±410.6)*
Median cumulative cost (SD)	*261.1 (±257.4)*	*221.7 (±233.4)*	*272.2 (±302.0)*
Mean travelled distance e (SD) [m]	*64.3 (±51.80)*	*63.8 (±61.8)*	*118.8 (±78.2)*
Median travelled distance (SD) [m]	*56.2 (±46.5)*	*54.2 (±57.5)*	*85.2 (±64.4)*

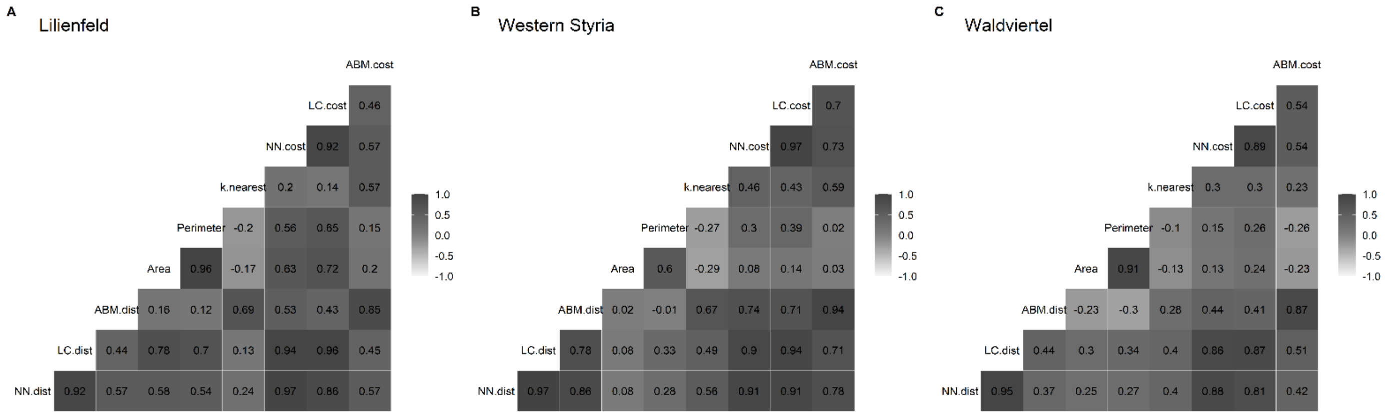

Figure 11 Correlation matrices of survey area core areas: NN.dist - NN median travelled distance/patch, LC.dist - LC median travelled distance/patch, ABM.dist - ABM median travelled distance/patch, NN.cost - NN median cum. cost/patch, LC.cost – LC median cum. cost/patch, ABM.cost – ABM median cum. Cost/patch, Area – patch area [ha], Perimeter – patch perimeter [m], k.nearest - Euclidean nearest neighbour distance/patch

2.4. Discussion

2.4.1. Distribution of connecting paths

Figures determined by all connecting paths for one survey area suggest that the ABM approach gives the lowest numbers. Looking at histograms from chapter 2.3 even though ABM simulations gave more connecting paths (absolute numbers due to two simulations), an emphasis can be found on short travelled distances and low numbers of cumulative cost in single connecting paths. In survey area *Waldviertel* there are fewer connecting paths (Table 5) from ABM (n=1779) than from NN (n=1891) or LCP (n=1877). However, a lot of these paths are found for low cumulative cost figures and short travelled distances, which means that up to a travelled distance to 100 m ABM gives 867 paths, NN gives 685 paths and LCP gives 630 paths. In this regard, survey area *Waldviertel* shows more pronounced relative differences, which can be explained by low forest percentage and long distances between forest patches. In contrast, connecting paths found in survey area *Western Styria* (Table 4) result in 1161 paths (ABM), 960 paths (NN) and 877 paths (LCP) of travelled distances up to 100 m. This can be explained by the fact that an agent reaches a close target in ABM simulations more often. The longer the agent's paths get, the higher the chances are that the agent reaches the survey area's border and 'dies'. Due to this bias towards low values, averaged figures per patch give more robust figures for comparison, than figures determined by all connecting paths. Each forest patch is a potential stepping stone that contributes to forest connectivity. By comparing averaged figures each patch is taken into account equally. Distributions of median travelled distances and cumulative costs on patch level in each survey area are displayed in Figure 12. Over all patches and survey areas these medians have a wide range. NN median cumulative cost/patch range from 1.5 (*Lilienfeld*) to 2467 (*Waldvierte*l), LCP median cumulative cost/patch range from 1.5 (*Lilienfeld*) to 1565.5 (*Waldviertel*) and ABM median cumulative cost/patch range from 0.5 (*Lilienfeld*) to 3515.5 (*Waldviertel*), which gives an impression of the differences between survey areas and patches.

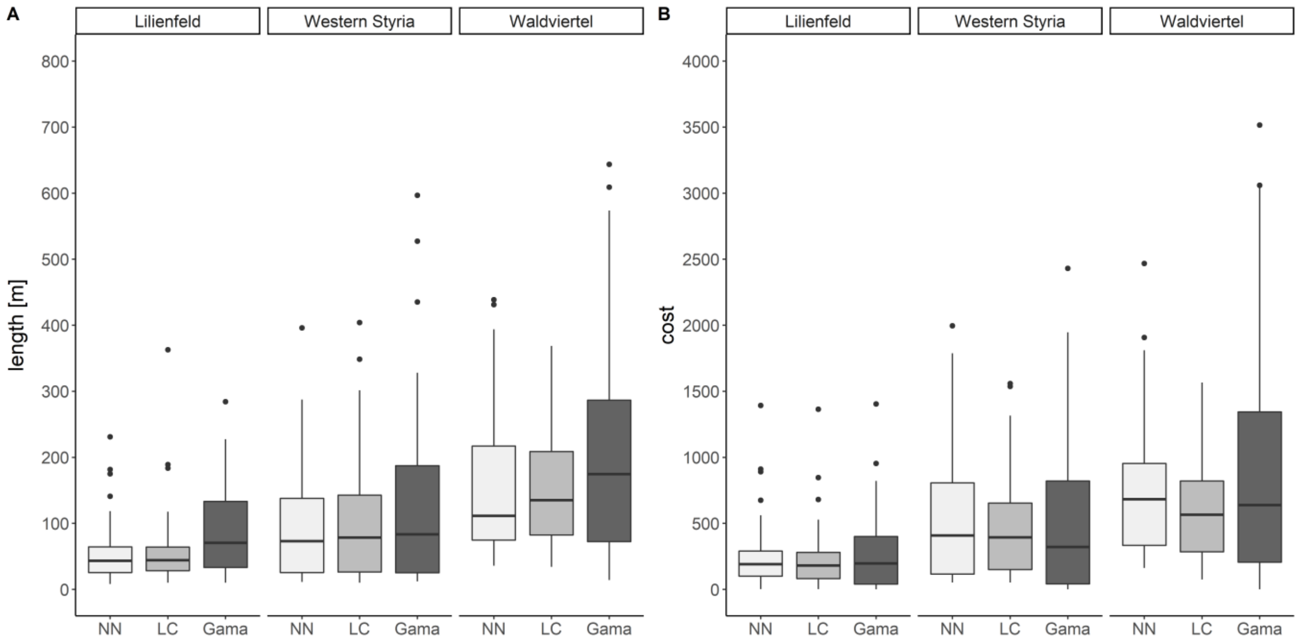

Figure 12 Boxplot median travelled distance per survey area and approach, (B) Boxplot Median cumulative costs per survey area and approach on patch level

High correlation between nearest neighbour travelled distances and least cost paths travelled distances (0.92<r<0.97, Figure 11) suggests that least cost path length is not a good indicator for connectivity, since it is not representing the cost raster well enough (Etherington and Holland, 2013). Cumulative costs for least cost paths travelled distances combine information of path length and cost surface. Correlation coefficient *r* for median cumulative costs/patch (LCP and ABM) and median travelled distance/patch (NN) also indicates high correlation (Figure 11). For instance, survey areas' *Western Styria* correlation coefficient for NN median travelled distance per patch and LCP/ABM cumulative cost per patch gives 0.91/0.78.

If the difference between the survey areas' ABM figures is statistically ensured, it can be tested by a *Student's t-test*. Comparisons of mean values for ABM accumulated cost per patch between all survey areas concluded in rejection of the null hypothesis (*Western Styria*/*Waldviertel* t= -3.33, *Western Styria/Lilienfeld* t= 2.28, *Lilienfeld/Waldviertel* t=-5.80, P≤0.05). The differences can be considered secure.

2.4.2. Comparison to landscape connectivity metrics

When analysing the distributions of calculated median figures on patch level for NN, LCP and ABM (Figure 12) these are following the forest pattern (Table 7) of the different survey areas. For the survey area with buffer *Lilienfeld* for instance, forest percentage is 86.5 %, contagion 65.3 and edge density 36.2 metres per hectares. Mean Euclidean nearest neighbour distance for the survey area with buffer *Lilienfeld* (33.6 m (±15.8 m)) and the core survey area core (15.4 m (±16.8 m)) give the lowest numbers. The median travelled distances on patch level for the three investigated approaches give the lowest values of all survey areas; but ABM results are more widely scattered around the median value (Table 8). These results are to expected since in this densely wooded survey area, forest edge density is quite low. Since there are few extended patches, paths to neighbouring patches should be shorter. ABM median travelled distances on patch level differ more distinctly from NN and LCP median travelled distances, than median cumulative costs of NN, LCP and ABM differ from each other. Connecting paths resulting from NN- and LCP-approach not only have pre-set start locations but also a defined set of target locations to 'choose' from (start locations from neighbouring patches). As ABMs agents are free to move past a forest patch, when it is not perceived by the agent, this contributes to this difference.

Table 7 Landscape metrics of survey areas incl. buffer

	Survey area Lilienfeld	*Survey area Western Styria*	*Survey area Waldviertel*
forest percentage [%]	86,5	46.2	20.5
forest patch number	71	115	153
mean forest patch area (SD) [ha]	102.5 (±433.7)	18.7 (±92.5)	7.7 (±29.3)
mean Euclidean nearest neighbour distance (SD)	33.6 (±15.8)	64.9 (±69.5)	71.1 (±79,6)
contagion	65,6	37,6	56.4
total forest edge [m]	188580	393380	239890
Edge density [m/ha]	36.2	84.7	41.8
Splitting index	3.2	21.2	235.8

Table 8 Survey area core area metrics – median connectivity figures on patch level

	Survey area Lilienfeld	*Survey area Western Styria*	*Survey area Waldviertel*
Patch number core area	53	39	47
Mean patch area (SD) [ha]	63.4 (±17.5)	2.3 (±2.7)	9.1 (±296.8)
Median patch area [ha]	0.2	0.9	1.4
Mean patch perimeter (SD) [ha]	2413.5 (±9313.2)	1826.2 (±2478.0)	1562.5 (±1899.8)
Mean (Euclidean nearest neighbour distance/patch) [m] (SD)	15.4 (±16.8)	42.9 (±85.6)	85.8 (±129.7)
Median travelled distance NN (SD) [m]	56.2 (±46.5)	96.1 (±87.5)	157.7 (±110.2)
Median travelled distance LCP (SD) [m]	54.2 (±57.5)	103.3 (±95.7)	157.2 (±90.5)
Median travelled distance ABM (SD) [m]	112.5 (±64.36)	164.9 (±140.7)	210.4 (±173.1)
Median cumulative costs NN (SD) [m]	261.1 (±257.4)	547.7 (±498.4)	738.1 (±554.0)
Median cumulative costs LCP (SD) [m]	221.7 (±233.4)	478.0 (±412.0)	601.5 (±375.8)
Median cumulative costs ABM (SD) [m]	272.2 (±302.0)	551.5 (±627.8)	935.6 (±947.3)

Maximum figures for travelled distance calculated on landscape level (ABM *Western Styria* 917.7 m, ABM *Lilienfeld* 1257.1 m, ABM *Waldviertel* 1400.5 m) depend on survey area size, but the computation results can be compared to actual movement data from other works when keeping the investigated species and home range in mind. These studies often have dispersal or differences between seasons in mind (Kropil et al., 2015), but also investigate movement in respect to habitat patch structure (Kie et al., 2005) or even test connectivity models with movement data (McClure et al., 2016). All three studies address *Cervus elaphus* in North America and Europe, which is a wildliving, widespread ungulate in Austria. McClure et al., 2016 observed from monitoring 10 (fall) and 12 (spring) individuals a mean movement of 26.7 km in 6.7 days and 25.2 km in 5.6 days. In another study from North America (Kie et al., 2005), scientists monitored movement lengths every two hours and found a variation in vector length between about 17 m/min and about 70 m/min, which would result in a total vector length between 2040m to 8400 m in two hours. A study on red deer in the Western Carpathians (Kropil et al., 2015) found shifts between seasonal home ranges for resident animals of only 1463 ± 1665 m. These values differ from each other but show that travelled distances from ABM could be travelled by *Cervus Elaphus*, considering that forests are not the only cover they use when moving long distances.

2.4.3. Restrictions

Even though connectivity can be quantified by ABMs and other metrics, these methods have limitations. Connectivity measures and cost surfaces should be verified by actual movement data (Diniz et al., 2020; Grimm et al., 2005). Most methods to estimate connectivity measures depend on cost surfaces, therefore generation of cost surfaces and choice of cost values have a high influence on the obtained metrics (Simpkins et al., 2017; Zeller et al., 2012). In respect to cost surfaces, improvements, especially by using a defined species, could be made. However, cost values were developed by studies carried out for Austria and generalized for our comparison of methods.

Movement decisions used by our ABM are simplified to get a generalized and reproducible model and ignore certain important aspects of animal movement. Interactions between agents and possible disturbance from humans are not considered, because the model simulates animal movement as long-term-dispersal of solitary individuals. It is assumed that no agent knows the used landscapes or gets familiar with its environment (McClure et al., 2016). In addition, temporal variation in behaviour, daily (Kie et al., 2005) or seasonal (Fattebert et al., 2019), as well as environment (Allen et al., 2016; Zeller et al., 2020) are not taken into account. Since forest connectivity was the main goal for this paper, simplifications may be allowable, however, a plausibility test with telemetric data would have been desirable.

2.5. Conclusions and Outlook

In conclusion, ABMs simulation results are an addition to usual connectivity metrics and open up a lot of possible enhancements and opportunities to explore animal movement. Preferably, future investigations are supported by actual movement data. But if movement data are non-existent or only available to a limited extent, ABM data can provide an addition or alternative, especially when a species-specific cost surface and movement model is developed. Implementing behaviour aspects of individuals, like learning by experience and from other individuals, could be a focus of future works.

The described method for three approaches was feasible for small scale applications like the selected survey areas, but is not practicable on a large scale. Presumably, high path density and small cost surface resolution could be changed for other applications, without too much loss of information.

Additionally, the work shows that ABM, as well as NN and LCP, predict differences in forest connectivity for various landscapes. For this work, we found that, for generalized applications, NN and LCP results were sufficient.

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3. Report

3.1. Overview

The empirical work of this thesis was conducted by following procedure. Three methodological approaches were used to quantify forest connectivity. 1) Nearest neighbour (NN), 2) Least cost path (LCP) and 3) Agent-based modelling (ABM) were performed for the same forest border vectors and analysed on landscape and patch level. The calculations were carried out for three chosen survey areas with various forest cover and density. Additionally, common landscape metrics were calculated for the three chosen survey areas. The procedure is displayed in Figure 13. For a better understanding of the work process at first the generation of input data is outlined and then the applied methods are described in detail.

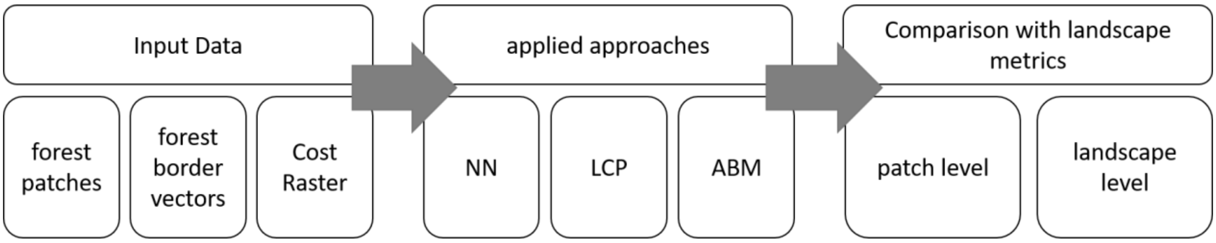

Figure 13 Workflow

3.2. Survey areas

To quantify connectivity three chosen test regions, represent different forest pattern types. One survey area is situated in south-western Styria and the other two in Lower Austria. In southwestern Styria the landscape is dominated by grassland and consists of valleys formed by glaciers and hills. Forest occurs in island-shaped patches. The second area is located in northern Austria (Waldviertel). This hilly landscape is characterised by grassland, grain cultivation and island-shaped forest patches as well. Finally, the location of the third study area is in one of the most densely wooded parts of Austria (political district: Lilienfeld). Characteristic for this landscape are broad ribbon-shaped forest patches. The sites were chosen because they represent diverse forest patterns and various degrees of forest density. Table 9 gives information about the survey areas area [hectares], forest percentage and patch number. Every test area includes a buffer area, to avoid bias effects at borders. Area location, forest distribution and core areas are displayed in Figure 14.

Table 9 Survey area information

	Survey area Lilienfeld	*Survey area Western Styria*	*Survey area Waldviertel*
Area with buffer [ha]	5210	4645	5710
Area core area [ha]	3890	2350	3910
Forest percentage [%]	86,5	46.2	20.5
Forest patch number with buffer	71	115	153
Forest patch number within core area	53	39	47

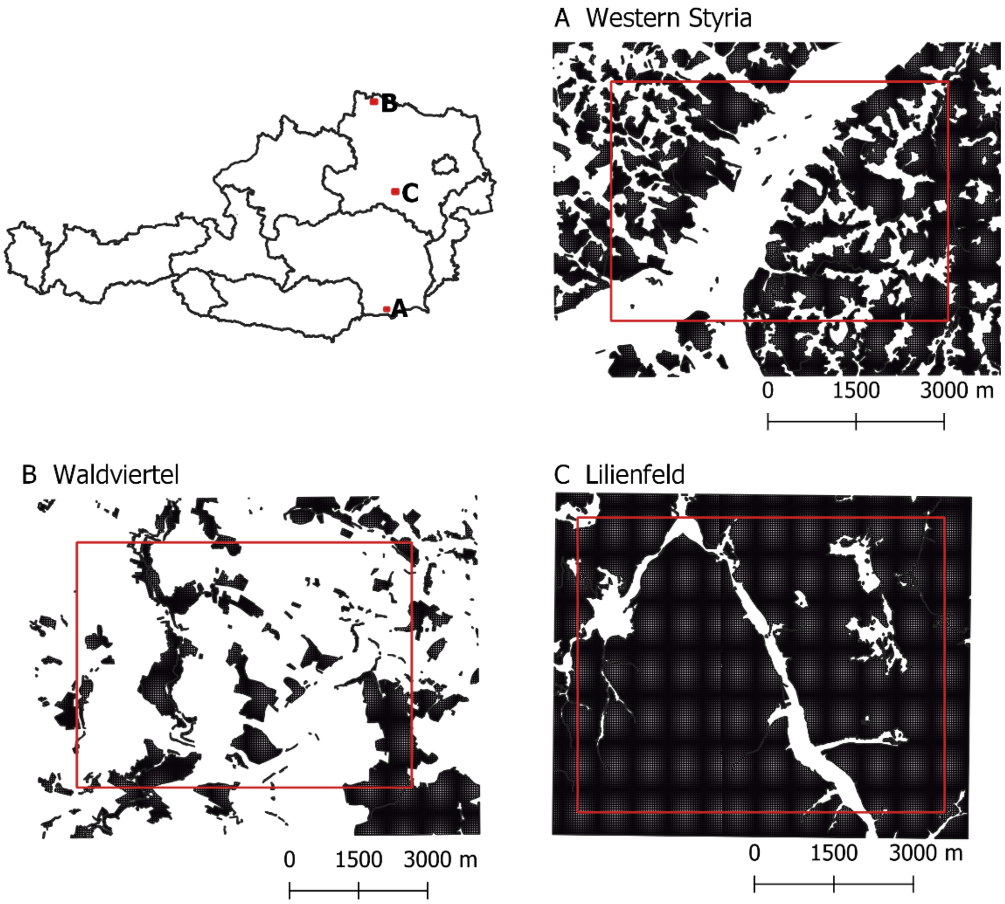

Figure 14 top left: location of survey areas in Austria, top right and second row: forest (black elements) distribution and simulation core area (red box) for three survey areas (A Western Styria, B Waldviertel, C Lilienfeld)

3.3. Forest patches and forest border vectors

To generate input data for all three approaches (ABM, NN, LCP), forest patch polygons were extracted from the Austrian forest layer (BFW, 2020), slightly geometrically simplified and for each 100 m segment or vertex (whatever comes first) a point vector was produced at the polygon's border. For the simplification and production of point vectors R-package *sf* v.0.8-0 (Pebesma, 2018) was used. Each forest patch and each forest border vector were assigned a unique ID. In the following a code-snippet with comments to understand the point generation is included.

```
point_vectors<-st_segmentize(polygons_simplified, dfMaxLength=100)%>% ##vector every 100m
  st_coordinates() %>% ##get coordinates
  as.data.frame() %>%
  dplyr::select(X, Y) %>%
  st_as_sf(coords = c("X", "Y"))##create sf object with geometry
```

Forest patches in the core area of survey areas and their corresponding points were chosen to calculate and simulate the different metrics for each forest border vector. Not each of these points led to a connecting path (see chapter 3.5, 3.6 and 3.7). Table 10 shows the initial numbers of patches and vectors. The core area numbers display the used forest patches and start locations within the defined buffer. Numbers with buffer include patches and point vectors in the buffer zone. Figure 15 shows the resulting polygon and point geometries with each survey areas core area.

Table 10 Initial patch and forest border vector number

	Survey area Waldviertel	*Survey area Lilienfeld*	*Survey area Western Styria*
Patch number with buffer	153	71	115
Patch number within core area	47	53	39
Forest border vectors with buffer	5953	6760	15815
Forest border vectors within core area	1929	6571	2220

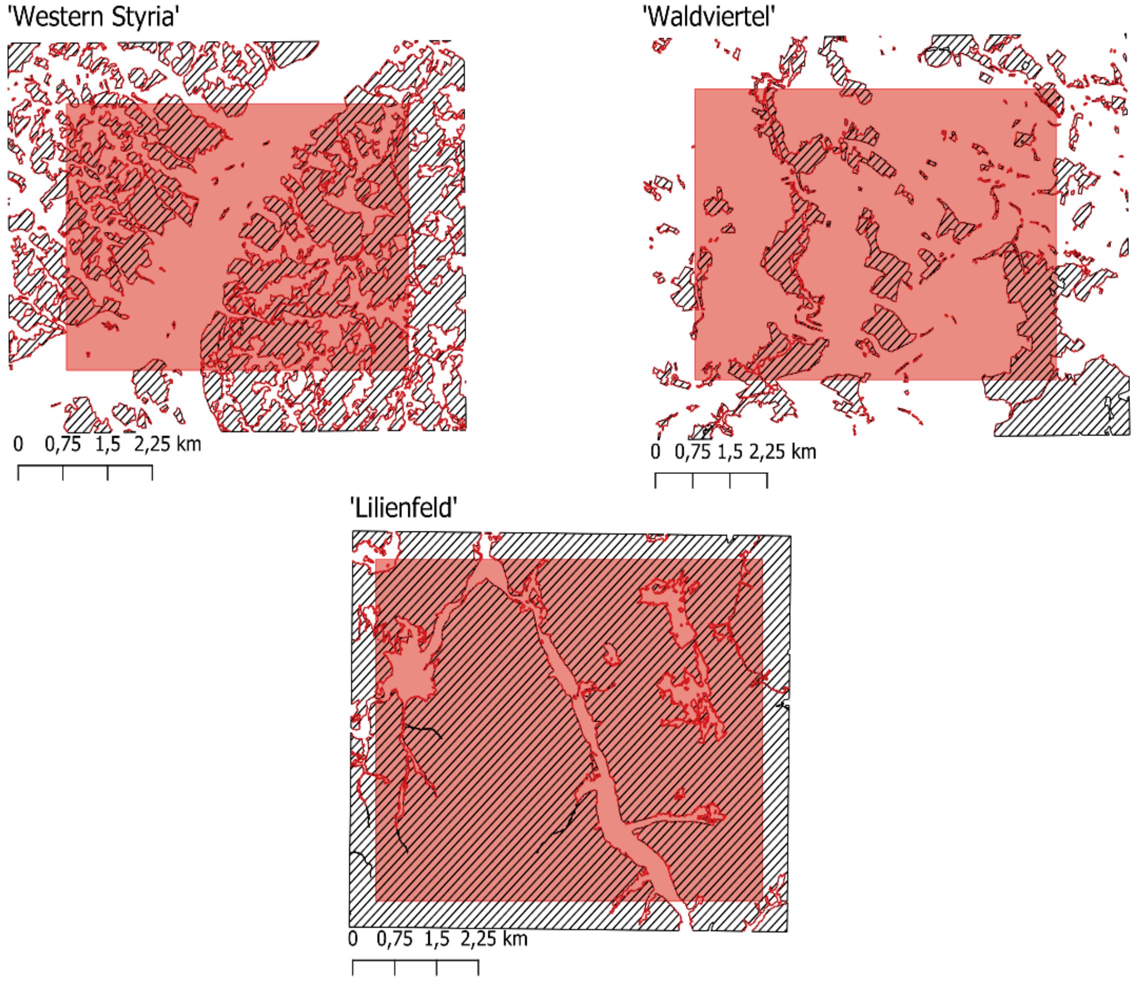

Figure 15 Forest border vectors (red points) at forest patches with core area for survey areas

3.4. Cost raster

Cost surface raster were produced for the sites listed above. As foundation for each cost surface served the Austrian forest layer (BFW, 2020). Underlying this layer is the forest definition of the Austrian forest inventory, i.e. a minimal area of 500 m², minimal width of 10 m and minimal coverage of 30 % (Hauk et al., 2009). The polygon geometries initially were produced automatically with aerial photographs and normalized digital surface models and afterwards edited manually. The matrix between forest patches is represented by Sentinel 2-based land cover classes from 2016 (Umweltbundesamt, 2019). Only higher ranked roads (GIP, 2016) and buffered settlement areas from the cadastral map (Bundesamt für Eich-und Vermessungswesen, 2016) were taken into account separately for more precise geometrical representation. These resulting grids have a cell size of 10 m by 10 m and each cell has a cost value between 0.5 and 100, where it is assumed that forests stand for the lowest resistance and settlement areas stand for lowest permeability. Table 11 lists the assigned cost values to generalized land cover classes.

Table 11 Cost values for produced cost surfaces

Cost values	*Land cover class*
0.5	forest from Austrian forest map
1	forest from S2-landcover
20	shrubs, reeds
30	grassland, cropland low productivity
40	grassland, cropland high productivity
50	roads, railroads, soil,
70	bare rock, water,
90	built-up area from S2-landcover
95	buffered settlement areas,
100	total barriers (motorway)

The creation of costs raster was carried out mainly with R-package *raster* v.2.9-22 (Hijmans, 2019). At first the survey extent was determined and stored in a polygon. With help of this extent a part of the Sentinel 2-based land-cover map (Umweltbundesamt, 2019) was extracted (function: *raster::crop*). With help of a matrix relating to Table 11 the different land cover classes were converted to cost values (function: *raster::reclassify*). Now raster cells overlapped by higher ranked roads (GIP, 2016) are reclassified (function: *raster::rasterize*). These roads are represented as line geometries, so they have to be buffered (5 m, function: *sf::st_buffer*) upfront. For building polygon geometries (Bundesamt für Eich-und Vermessungswesen, 2016) the same steps were implemented. At first a 10 m buffer for each polygon was generated, these building polygons were used to reclassify the raster concluding from reclassifying roads. In the end, forest polygons were included in the raster in the same way. The resulting raster (Figure 16) were exported to TIF-files (datatype: FLT4S, EPSG: 31287). Pixel counts for each cost value class and each survey area are shown in Table 12.

Table 12 Pixel counts cost values - survey areas

Cost value	*Waldviertel – Pixel count*	*Lilienfeld – Pixel count*	*Western Styria – Pixel count*
0.5	117594	450858	214758
1	8322	3844	9490
20	1909	1744	2252
30	275342	3378	100201
40	111667	35258	92272
50	33264	3885	11908
70	578	9	77
90	633	170	285
95	25125	10984	33233

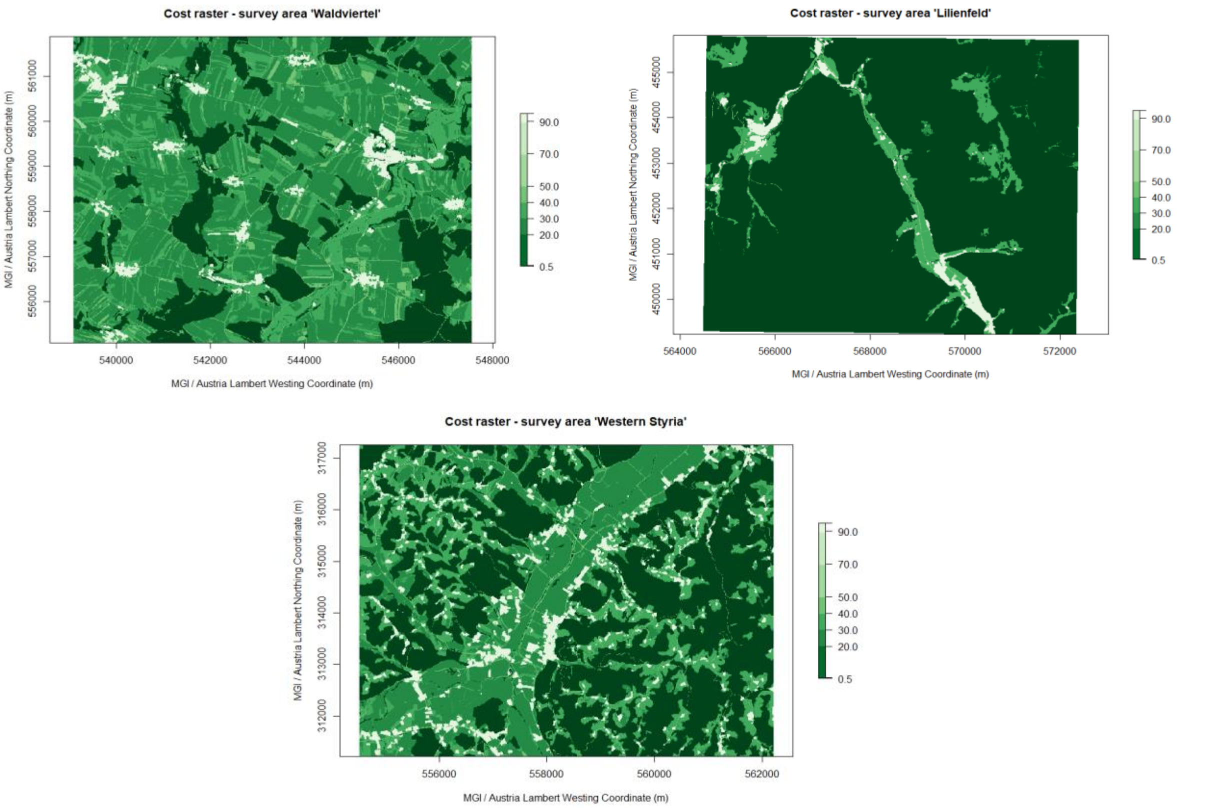

Figure 16 Cost raster survey areas with buffer (changed from Umweltbundesamt (2019), BFW (2019), GIP (2016), Bundesamt für Eich- und Vermessungswesen (2016))

3.5. Nearest Neighbour

Euclidean nearest neighbour distances (NN) are calculated for forest border vectors (chapter 3.3). The nearest neighbouring point for each point of each forest patch is determined. The resulting line cannot cross the source patch of the starting point, only direct reachable neighbours are considered. For each connecting line the length is calculated and the cumulative costs are derived from the corresponding cost surfaces (chapter 3.4).

The calculations were performed mainly with the help of R-package *sf* v.0.8-0 (Pebesma, 2018). These calculations for connecting paths (function: *sf::st_nearest_points)* were conducted for single forest patches (Figure 17). At first forest border vectors were filtered by forest patch ID to avoid paths between vectors of the same patch. Length [m] was calculated in course of NN path calculations. The cumulative costs along the connecting paths were extracted from the cost raster in another working step (*function: raster::extract*). In the following the developed R-code is inserted and commented.

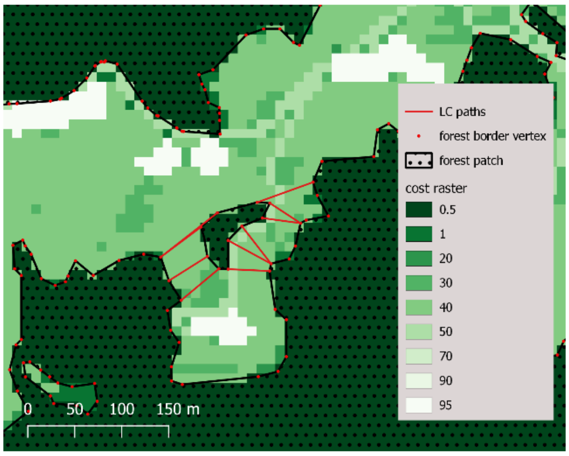

Figure 17 Connecting paths (NN) for patch 101 Western Styria

In the first part the working directory is set and required packages are loaded. Also, a cluster to use parallelize the process and use multiple cores is created.

```
setwd("D:/") #set working directory

#required packages

require(sf) #https://CRAN.R-project.org/package=sf

require(raster) #https://CRAN.R-project.org/package=raster

require(tidyverse) #https://www.tidyverse.org/

#https://CRAN.R-project.org/package=tidyverse

#require(rgdal) #https://CRAN.R-project.org/package=rgdal

require(dplyr) #https://CRAN.R-project.org/package=dplyr

library(doParallel) #https://CRAN.R-project.org/package=doParallel

library(foreach) #https://CRAN.R-project.org/package=foreach


clu<-makeCluster(nCores) #used cores

registerDoParallel(clu)
```

In the first for-loop the vectors are filtered by patch-ID. This filtering results are written to a data frame with the source vectors and another data frame with the possible target vectors.

```
for (x in (unique(patch_id_list[[1]]))){#list of unique patch IDs within core area

  source_vectors<-filter(core_vectors, core_vectors$patch_id==x) #subset source vectors

  target_vectors<-filter(all_vectors, all_vectors$patch_id!=x) #subset target vectors
```

Now the resulting paths are calculated for the above chosen patch. The calculations are carried out parallel for single point vectors. At first all connections between all point vectors are created by the function *st_nearest_points*. Now the forest crossing paths are detected and excluded. After computing the paths lengths, the shortest line geometry for each forest border vector is selected. If there are no non-forest crossing paths NA values are possible.

```
resulting_paths<-foreach (i=1:nrow(source_vectors),.combine=c, .packages="sf")%dopar%{

  nn<-st_nearest_points(source_vectors[i,], target_vectors) #all paths

  nn_sp<-as_Spatial(nn) #as Spatial

  nn_sf<-st_as_sf(nn_sp) #Spatial as sf

  #filter crossing paths

  nn_cross<-nn_sf[poly_forest_patches, , op = st_crosses] #geometries crossing forest
patches

  nn_cross<-as_Spatial(nn_cross)

  nn_cross<-st_as_sf(nn_cross)

  nn_ex_cross<-nn_sf[!(nn_sf$geometry %in% nn_cross$geometry),] #exclude crossing paths

  #calculate lengths

  nn_ex_cross$length=st_length(nn_ex_cross)#calculate length as attribute

  nn_length<-nn_ex_cross[order(nn_ex_cross$length),]#order by path length

  nn_head<-head(nn_length,1)#get shortest path

  if (dim(nn_head)[1]==0){

    return(NA)

  }

  else{

    nn_source<-st_join(nn_head,source_vectors, join=st_intersects ) #attach ID source
vector

    nn_target<-st_join(nn_source,target_vectors, join=st_intersects ) #attach ID target
vector

    nn_target_sp<-as_Spatial(nn_target)

    return(nn_target_sp)

  }

}
```

In the end the NA-values are negated and the geometries are combined. As last step for each forest patch an ESRI-shapefile is written to the chosen working directory.

```
  res_paths<-Filter(Negate(anyNA), resulting_paths) #negate NA entries

  nn<-do.call(rbind, res_paths) #bind rows

  nn<-st_as_sf(nn)

  nn<-unique(nn) #drop duplicated geometries/rows

  st_write(nn, sprintf("nn_patch_%d.shp", x) ,driver="ESRI Shapefile", update=TRUE) #write
geometries to shapefile

  gc()

}

stopCluster(clu)
```

3.6. Least Cost Path

Least cost path metrics were determined with the same input data (chapter 3.3) as in NN approach. The LCP connecting paths were calculated with Dijkstra's algorithm (Dijkstra, 1959) from processed cost surfaces (chapter 3.4). Before the cost raster could be used for LCP, a raster had to be converted to a weighted graph (Moore neighbourhood), represented as matrices (function: *gdistance::transition*). The connecting paths were determined between single points (function: *gdistance::shortestPath*) assigned to different forest patches and forests crossings were not allowed (Figure 18). Lengths were calculated for these paths and in a second working step summarized costs are extracted for the resulting lines from the associated cost surface raster (function: *raster::extract*).

Calculations were carried out mainly with the help of R-package *sf* v.0.8-0 (Pebesma, 2018) and *gdistance* v.1.3-1 (van Etten, 2017). These calculations were performed in a similar manner as NN, as connecting paths for forest border vectors correspond to one particular forest source patch. In the following the developed R-code is inserted and commented.

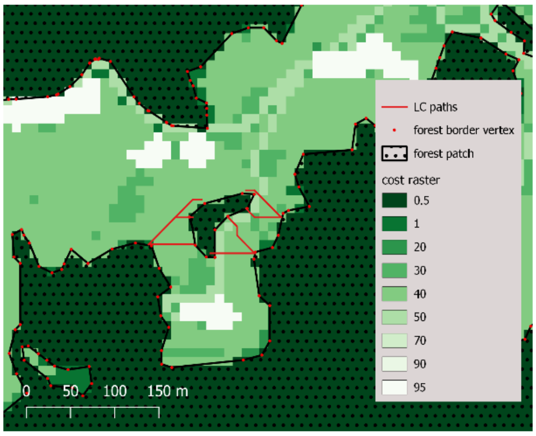

Figure 18 Connecting paths (LCP) patch 101 survey area Western Styria

For LCP calculations also a working directory is set and the required packages are loaded to the workspace in RStudio v. 1.2.1335. These calculations are carried out in parallel as well. In a first step the imported cost raster is transformed to a transition raster (*gdistance::transition*).

```
setwd("D:") #set working directory

#required packages

require(sf) #https://CRAN.R-project.org/package=sf

require(raster) #https://CRAN.R-project.org/package=raster

require(tidyverse) # https://CRAN.R-project.org/package=tidyverse

# https://www.tidyverse.org/packages/

require(rgdal)# https://CRAN.R-project.org/package=rgdal

require(dplyr) # https://CRAN.R-project.org/package=dplyr

require(gdistance) # https://CRAN.R-project.org/package=gdistance

library(doParallel) # https://CRAN.R-project.org/package=doParallel

library(foreach) # https://CRAN.R-project.org/package=foreach


##produce resistance raster (weighted graph)

raster_trans<-transition(raster, function(x) 1/mean(x), 8)#transtion matrix, 8 directions

raster_trans<-geoCorrection(raster_trans)


cl<-makeCluster(nCores)#used cores

registerDoParallel(cl)
```

The for-loop subsets the imported forest border vectors into one data frame with source vectors in the survey areas core area and into a second data frame with all possible target vectors in the survey area including the buffer area.

```
##connecting paths - LCP

for( x in (unique(patch_id_list[[1]]))){

  source_vectors<-core_vectors[core_vectors$patch_id==x,]#subset source vectors

  target_vectors<-all_vectors [all_vectors$patch_id!=x,]#subset target vectors
```

The foreach-loop is carried out in parallel for each forest border vector. With *gdistance::shortestPath* like in NN-calculations all connecting paths are determined. Again, all forest-crossing paths are detected and excluded. From the remaining paths the shortest one for each vector is stored. Afterwards the source and target patch IDs are attached to the resulting line geometries.

```
  resulting_paths<-foreach (i=1:nrow(source_vectors),.combine=c)%dopar%{

    lc<-gdistance::shortestPath(x=raster_trans, origin=source_vectors [i,],
goal=target_vectors, output="SpatialLines")# get lest cost paths

    lc_sf<-sf::st_as_sf(sho_path)#as sf

    lc_sf$length<-sf::st_length(lc_sf)#get path lengths[m]

    lc_cross<-lc_sf[poly_forest_patches, , op = sf::st_crosses]#geometries crossing forest
patches

    if (dim(lc_cross)==0){

      return(NA)}

    else{

      lc_cross<-sf::as_Spatial(lc_cross)

      lc_cross<-sf::st_as_sf(lc_cross)

      lc_sf_cross<-lc_sf[!(lc_sf$geometry %in% lc_cross$geometry),]#exclude crossing paths

    }

    lc_sf_cross$length=sf::st_length(lc_sf_cross)

    lc_length<-lc_sf_cross[order(lc_sf_cross$length),]#order by path length

    lc_head<-utils::head(sp_length, 1)#get shortes path

    if (dim(lc_head)==0){

      return (NA)
```

```
    }
    else{
      if (as.numeric(lc_head$length, units="m")==0){#assign meter as unit
        return(NA)}
      else{
        join_source<-sf::st_join(lc_head,as(source_vectors,"sf"),
join=sf::st_nearest_feature )#attach ID source vector
        join_target<-sf::st_join(join_source,as(target_vectors,"sf"),
join=sf::st_nearest_feature )#attach ID target vector
        lc_sp<-as(join_target, "Spatial")#as Spatial
        return (lc_sp)
      }
    }
  }
```

The results of the foreach-loop are filtered by NA values. The other entries are combined and again for each forest patch an ESRI-shapefile is written to the chosen working directory.

```
  res_paths<-Filter(Negate(anyNA), resulting_paths)#negate NA entries
  list_paths<-do.call("rbind", res_paths)#bind rows
  list_paths<-as(list_paths, "sf")#as sf
  st_write(list_paths, sprintf("lc_patch_%d.shp", x ),driver="ESRI Shapefile")
  gc()
}
```

3.7. Agent-based model (ABM)

The ABM was built with the GAMA platform (Taillandier et al., 2019). The model code is inserted and commented in the following. Figure 19 shows the simulation for patch 101 of survey area Western Styria through individual simulation steps.

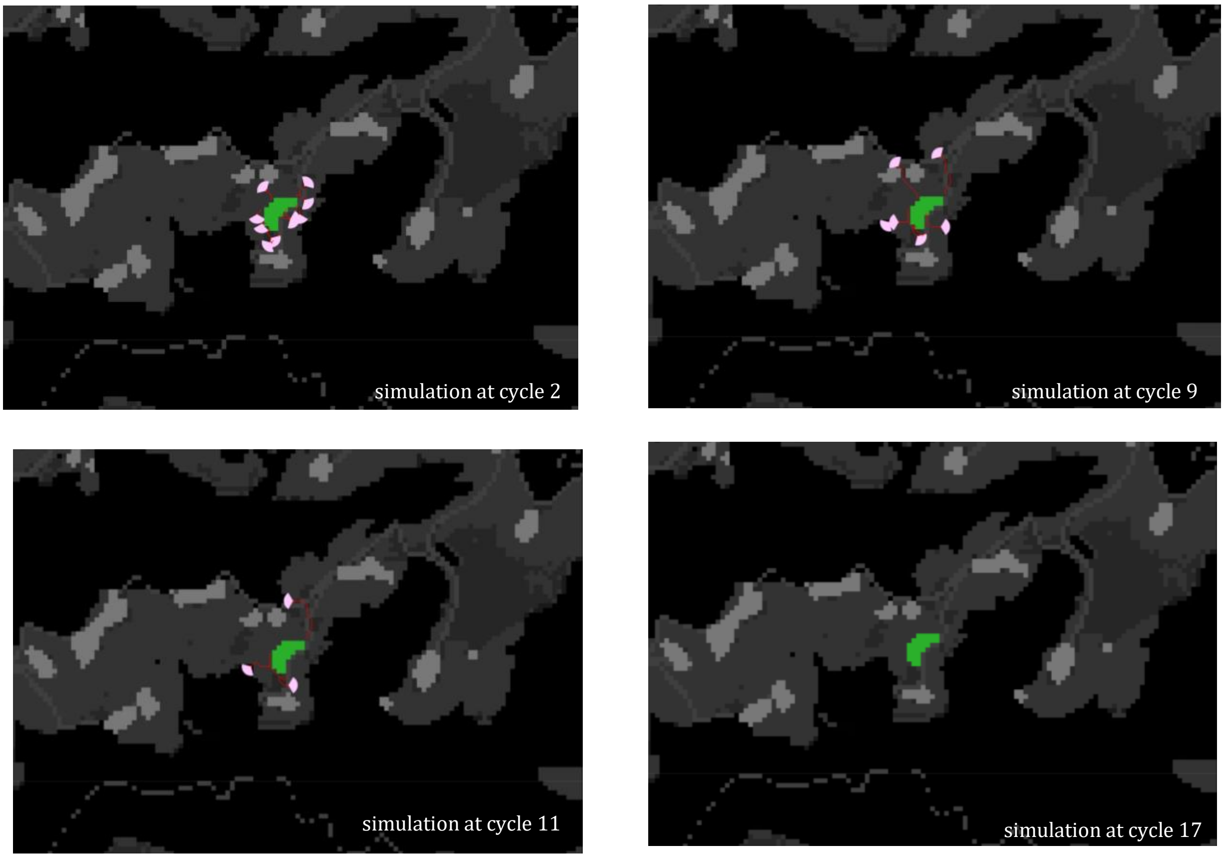

Figure 19 Screenshots GAMA simulation patch 101, 'Western Styria' (green: forest source patch), red: animal agents' paths, lilac: agents perceived area

The purpose of this ABM is to calculate connectivity metrics for forest patches via the dispersal of individuals from the border of forest patches. Dispersal is described mechanistically as the movement of animals from woodland patch to woodland patch through open heterogenous landscapes. Any forest cell could be a target patch for agents expect cells that belong the agents source patch. Movement is represented based on only few assumptions to get a straightforward and transparent dispersal model, where individuals memorize their last steps and 'die' (stop movement and vanish from simulation), when they leave the study area or reach the next patch or leave the study area.

Table 13 shows the logged state variables for the moving animal agents (GAMA code: *species start*) and the cellular automaton (GAMA code: *grid cell*).

Table 13 ABM - state variables

state variable: moving agent	*comment*
int(self)	initial number
cycle	current simulation cycle
length(agents)	remaining number of agents
costSum	cumulative costs [cost units]
costCollect	cost value of current cell [cost units]
distance	travelled distance [m]
state variable: cost raster	*comment*
init_value	initial cost value
resistance_value	mutable cost value

3.7.1. GAMA-Model Code

```
/***
* Name: MoveFromShape
* Author: Windisch
* Description: Forest connectivity
***/
```

In a first step the required input data is loaded. The cost raster is inserted as TIF-file. Agent locations at the forest border and source forest patch are loaded as ESRI-shapefile. The survey border is also integrated as shapefile. The source forest patch and forest border are casted to geometries for further usage. In this global section the storage for the mean travelled distance per simulation and the mean cumulative costs is set and a reflex to update these values is created after the global initialisation of the model. Also, the perception distance is defined and the number of agents is casted to an integer value.

```
model MoveFromShape
global{
	file raster <-file("D:/.../raster_survey_area.tif");/*input raster)*/
	file shape_file_source <-file("D:/.../source_vectors.shp");/*input agent 
locations)*/
	file shape_source_forest<-file("D:/.../poly_source_forest.shp");/*input source 
forest)*/
	geometry source_patch<-shape_source_forest;
	geometry shape <- envelope(envelope(raster))/*size and shape of environment*/;
	file border <-file("D:/.../border_survey_area.shp");/*input survey areas border as 
shape*/
	geometry boundary<-border;
	float mean_cost;
	float mean_dist;
	list<cell> memory;
	//list<geometry> shpGeom <- []; optional: store results in shape
```

```
//perception distance
float perception_distance <- 20.0;
int nb_agent;
```

Initial the cell values of the imported raster are queried and used for visualisation. The initial cell values are stored (*init_value*) and resistance values are created from the grid for the model. Cells overlapped by the source patch geometry are set to *source_forest =TRUE*. Now the agents are created at their location imported from the shapefile *shape_file_source*.

```
init {
ask cell {
        int val<-int(grid_value);
        color <- rgb(val, val, val);
}
ask cell{
        init_value<-grid_value;/*store initial grid value*/
}
ask cell{
        resistance_value<-grid_value;/*store resistance value*/
}
 ask cell{
        source_forest<-false;/*all cells source forest = false*/
}

create start from:shape_file_source{       /*create animal agents (species start)*/
  location<-(one_of(shape_file_source)).location;
  nb_agent<-length(start);
        }
}

    reflex mean_dist{ /*reflex store mean travelled distance and mean accumulated costs*/
ask start{
        mean_dist<-  mean(distance_travelled);
        mean_cost<-  mean(costSum);
        }
}
```

The following reflex was created to stop the simulation when all agents reached their goal or stopped the simulation in another way.

```
//pause when species start empty
 reflex stop_simulation when: empty (start) {
 do pause;
```

```
    }
        }
```

The next part contains every information about the moving animal agents (*start*). All variables are defined in the beginning. The memory is defined as list which stores all visited cells. The variables *costSum, costCollect* and *distance_travelled* store the cumulated costs, the currents cell cost value and the distance travelled until this point of the simulation. *My_cell* describes the current location, *start_location* records the first visited cell and *path* stores geometry of the agents' path for visualization. The points *source* and *goal* store the last and first position of an agent in a point to calculate the travelled distance.

```
species start skills: [moving]{
        list<cell> memory;
        float costSum<-0.0 ;
        float costCollect <- 0.0;
        float maxCost<-4000.0;
        float distance_travelled;
        cell my_cell;
        cell start_location;
        path my_path;
        point source;
        point goal;
        geometry perceived_area;
```

At first the agents and their locations are initialized and the first location is added to the memory.

```
        //initialize start location
        init{
                ask start{
                my_cell<-location;
                start_location<-location;
                memory<<my_cell;
                }
        }
```

To visualize the agents during the simulation an aspect has to be defined. The agents are displayed as red square and the paths as red lines.

```
        //draw agent and path
        aspect default{
                draw square (4) color: #red;
                if (my_path!= nil) {
                draw my_path.shape color: #red;
                }
        }
```

After the agents are initialized the source forest cells are set by an *agents_overlapping* function. Colours of cells, where source_forest is true, are updated to green by a reflex described later on.

```
//set source forest
reflex set_source_forest when:start_location!=0 {
        //set source patch<-overlap shape
        list<cell> source_forest_cells<-agents_overlapping(source_patch);
        ask source_forest_cells{
                source_forest<-true;
        }
        ask cell{
        do update_color_green;
        }
        }
```

The reflex *basic move* describes the movement behaviour of the animal agents. Source forest cells are excluded from the selectable cells. If a possible target cell is within the perceived area the agents immediately move to this cell. Else the agents choose one of the cells which is not in memory with the lowest resistance value. Each visited cell is added to memory.

```
//basic move
reflex basicMove {
        list<cell>target_cells<-cell where(each.source_forest=false);
        list<cell>target_forest<-target_cells where(each.resistance_value<0.7);
        geometry target<-target_forest;
        if perceived_area  overlaps one_of(target_forest){
                do goto target:target speed:50.0;
        }
        else{
        list<cell>possible_cells_1<-my_cell.neighbors
where(each.source_forest=false);
        list<cell> possible_cells <- possible_cells_1 where (not (each in memory));
        if not empty(possible_cells) {
        my_cell <-possible_cells with_min_of (each.resistance_value);
        location<-my_cell.location;
        memory<<my_cell;
        }
        else{/*all neighbour cells in memory*/
        my_cell<-possible_cells_1 with_min_of (each.resistance_value);
        location<-my_cell.location;
        memory<<my_cell;
        }
        }
}
```

To maintain the agent's persistency to move in correlated paths a movement probability matrix is applied. Neighbouring cells resistance values according to the current location are changed by values from this matrix.

```
//apply movement probability matrix, change grid_value per direction
reflex changeCost  {
        list<cell> changeCell<- my_cell.neighbors sort_by (self direction_to each);
        if my_cell in memory {
                ask changeCell where ((self direction_to each)=90){
                        resistance_value <- resistance_value *1.2;
                }
                ask changeCell where ((self direction_to each)=45){
                        resistance_value <- resistance_value *1.1;
                }
                ask changeCell where ((self direction_to each)=135){
                        resistance_value <- resistance_value *1.4;
                }
                ask changeCell with_min_of(self direction_to each){
                        resistance_value<-resistance_value*1;
                }
                ask changeCell with_max_of(self direction_to each) {
                resistance_value <-resistance_value*1.6;
                }
        ask cell{ /*optional: update color of cost value*/
        do update_colour;
}
}
}
```

Each step of the simulation the variables *costCollect* and *costSum* are updated.

```
//summarize costs
reflex sumCost{
        costCollect<-my_cell.resistance_value;
        costSum<-costSum+costCollect;
}
```

The perceived area is also displayed in the simulation. See also *aspect perception.*

```
reflex update_perception {
        perceived_area <- (cone(heading-60,heading+60) intersection world.shape)
intersection circle(perception_distance);
        list<cell>obstacle<-cell where(each.source_forest=true);
        if (perceived_area != nil) {
                perceived_area <- perceived_area masked_by (obstacle);
}
}
```

Like stated before between *source* and *goal* the travelled path is created. The length of this path is stored in the variable *distance_travelled*.

```
	//draw path between start location and current location
	reflex draw_path{
		ask start{
	source <- memory[0].location;
	goal <- last(memory).location;
	my_path <- path_between(memory, source, goal);
	distance_travelled<- my_path.shape.perimeter with_precision 2;//path length,
travelled distance of start
```

The next part shows possibilities to store the simulations results. A shapefile with all paths or a Text- respectively CSV-File can be written to save the simulations output.

```
	//optional save result as shape-file or txt-fileor csv-file
	/*shpGeom <- shpGeom + my_path.shape;
	save shpGeom to: "D:/.../path_all.shp" type:"shp" ;*/
	}
	}

	//Save results for every cycle, for every agent as TEXT or CSV
	/*reflex save_result when:my_cell.grid_value<=0.8{
	 save ("cycle: "+ cycle +"; nb_start: "+ length(start) +"; ID: "+int(self)
	     + "; costSumStart: " + max (self.costSum with_precision 2)  +"; CostCollect: "+
max(self.costCollect with_precision 2)+"; distance: "+ start max_of(self.distance_travelled
with_precision 2))
	 to: "results.txt" type: "text" rewrite:false ;
		}*/

    reflex save_result_csv when:my_cell.grid_value<=0.7{
	 save [cycle, length(start), int(self), max (self.costSum), max (self.costCollect),
max(self.distance_travelled)]
	 to: "D:/.../results_self_.csv" type: "csv" rewrite:false ;
		}
```

The following four reflexes describe how agents stop their movement (*die*). An agent can either reach a forest cells, reach maximum costs or maximum memory or leaves the survey area entirely.

```
	//die when forestpixel is reached
	 reflex stop when: my_cell.grid_value<=0.7{
	write("reached goal");
	do die;
    }
```

```
        // die when maxcost
     reflex stop_max when:costSum>=maxCost{
        write ("reached maximum cost");
        do die;
     }
     //die when maximum memory
      reflex stop_max_mem when:length(memory)>=150{
        write ("reached maximum memory");
        do die;
     }

     //die at survey area border
     reflex stop_border when: perceived_area overlaps boundary{
        write ("touched border");
        do die;
     }

    //draw perceived area
    aspect perception {
        if (perceived_area != nil) {
                      draw perceived_area color: #plum;
               }
        }
}
```

Now the cost raster is described as cellular automaton. The raster cells change colour when they overlap with the source forest patch (action *update_color_green*) or change their colour according to the movement probability matrix. Every 30 cycles the resistance values are reinitialized (reflex *re_init*)

```
grid cell file: raster neighbors: 8 {
       float resistance_value;
       float init_value;
       bool source_forest;

       action update_colour{
              color <- rgb([int(resistance_value),
int(resistance_value),int(resistance_value)]);
       }

       action update_color_green {
       if source_forest=true{
              color <- rgb([34, 139,34]);
              }
       }
```

```
		reflex re_init when: every(30#cycle){		/*re-initialize cost values*/
		resistance_value<-init_value;
		}
	}
```

Finally, two different types of experiments are created. At first a single execution of the model is implemented (*Simulation: Agents from Shapefile*). Secondly a batch experiment can be executed (*Batch: Simulation from Shapefile*). This way numerous simulations with the same initial situation can repeated. Additionally, a CSV-File containing mean cumulative costs and mean travelled distances is written.

```
//Simulation: Agents from Shapefile
experiment mySimulation_shape type:gui{

	reflex compacting when: every(10#cycle) {
		do compact_memory();
	}

	output{
		inspect "Location" value:start attributes:["location"] type:table;
		inspect "Memory" value: start attributes:["memory","costSum","costCollect",
"distance_travelled"] type:table;
		display myMap type: opengl{
			grid cell lines: #transparent;
			species start aspect:default;
			species start aspect:perception;
		}
	}
}

// Batch Simulation from Shapefile
experiment mySimulationBatch type:batch repeat:2 until:empty(start){

	reflex compacting when: every(10#cycle) {
		do compact_memory();
	}

	 reflex save_results  {
  ask simulations{
		save [self.name ,self.mean_dist, self.mean_cost] to:
"D:/windisch_mt/Testgebiete_Waldkarte/tg_wstmk/center/gama/results/result_batch_poly42.csv"
type: "csv" rewrite:(int(self)=0)?true:false;
    }
  }
```

```
	output{
		display myMap type: java2D{
			grid cell lines: #transparent;
			species start aspect:default;
			//species start aspect:perception;
		}
	}
}
```

3.8. Sensitivity analysis

A sensitivity analysis was conducted to assess the impact of an animal’s movement persistency on forest connectivity. Movement probability matrices between subsequent time steps are tested against the resulting paths and analysed in respect to length and cumulative costs. The model is simulated 250 times for each movement probability matrix. The simulations were conducted for one patch in the core area of a test landscape with eight agents (patch surrounded by other patches in different sizes and distances). Movement probability matrix 2 without change values effects similar results like LCP modelling and therefore not considered for the actual simulations but included as comparison in the sensitivity analysis. Movement probability matrices 3 and 5 use uniform values for all neighbouring cells except the cell ahead of the agent’s location. Movement probability values of matrices 1 and 4 depend on the angle to the agent’s location, whereby matrix 1 hinders from turning more pronounced.

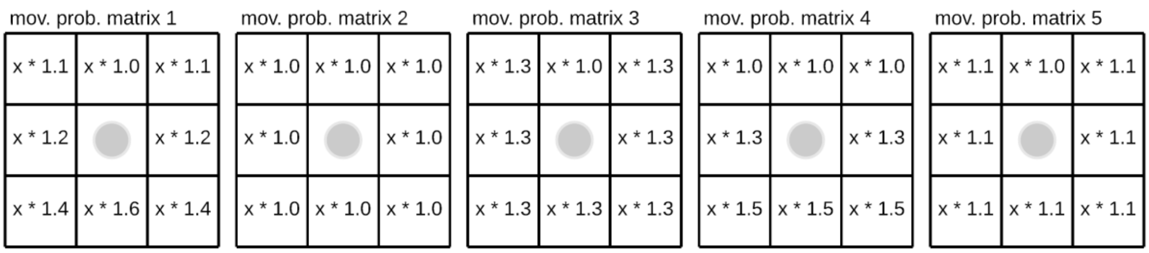

*Figure 20 Movement probability matrices for sensitivity analysis (grey circle – agent location, x * n – cost value multiplied by movement probability value)*

3.9. Landscape metrics

To assess forest connectivity, the study sites were investigated with respect to forest area. Additional to the three chosen approaches (Figure 13) common structural measures for connectivity and fragmentation are calculated. Metrics on landscape and patch level were chosen, because results from NN, LCP and ABM also were evaluated on both levels. Listed metrics are patch characteristics like minimum and maximum patch area, mean patch area, patch perimeter, ratio between patch area and perimeter as well as mean Euclidean nearest neighbour distance (edge to edge) (Bender et al., 2003; McGarigal et al., 2012). Mean Euclidean nearest neighbour distance takes only one single nearest patch into account and should be observed in contrast to the nearest neighbour metric described in chapter 3.5. Splitting index (Jaeger, 2000), which describes the patch number if patches are divided in even sized patches, is determined on landscape level. Contagion (McGarigal et al., 2012), which is based on cell adjacencies and describes landscape clumpiness, was also calculated for the whole survey area. Splitting Index and contagion are classified as aggregation metrics. Area distribution and total forest edge (McGarigal et al., 2012) also were included in the investigation. Table 14 gives an overview and information of the calculated landscape metrics. A binary landscape (forest/non-forest) (comparable Bender et al., 2003) and polygon vector data were used as base for the analysis. The calculations were made with help of R-package *landscapemetrics* (Hesselbarth, 2019), which is based on FRAGSTATS (McGarigal et al., 2012).

Table 14 Landscape metrics

metric	*formula*	*range/unit*	*comment*
patch area	area $=area_{patch}*(1/10\,000)$	area>0/hectares	patch level
perimeter	$perimeter_{patch}$	perimeter>0/meter	patch level
perimeter/area ratio	pa_ratio= $perimeter_{patch}/ area_{patch}$	pa_ratio>0/meters per hectares	patch level
Euclidean nearest neighbour distance	enn= edge-to-edge distance to nearest neighbouring patch	enn>0/meters	patch level, landscape level
Splitting Index	split= $area_{total}^2/ \Sigma area_{patch}$	0 <x < number of cells²/--	aggregation metric, landscape level
Contagion	see (McGarigal et al., 2012)	0 < x< 100/percent	aggregation metric, landscape level
forest percentage	f_perc=$(\Sigma area_{patch}/area_{total}) * 100$	0 < x< 100/percent	landscape level
total forest edge	$edge_{total}= \Sigma edge_{patch}$	$edge_{total}$>0/meter	landscape level

3.10. Summarizing and comparing results

Figures resulting from NN, LCP and ABM were lengths and cumulative costs for single connecting paths, these results were compared on landscape level and patch level after removing outliers. This removal of whole forest patches was necessary when only very few or none agents from ABM simulation reached their goal and the other two approaches gave outputs in a differing higher number. Single connecting paths from NN and LCP and single simulated paths from ABM are investigated statistically. Descriptive statistical measures (Table 15) are calculated for the connecting paths and distributions of lengths and cumulative costs are examined.

Subsequently a regression analysis considering the six metrics from NN, LCP and ABM as well as Euclidean nearest neighbour distances, patch area and patch perimeter were carried out with mean and median values for each patch separately for each survey area. To ensure the statistical difference between the survey areas, it is tested by a *Student's t-test*. The resulting landscape numbers are contrasted with landscape metrics mentioned before (chapter 3.9).

Table 15 Used descriptive statistical measures

statistical measure	*connectivity figure (NN, LCP, ABM)*	*level*
minimum	distance [m], cumulative costs[cost units]	landscape level
maximum	distance [m], cumulative costs[cost units]	landscape level
mean	distance [m], cumulative costs[cost units]	landscape level
median	distance [m], cumulative costs[cost units]	landscape level
standard deviation	distance [m], cumulative costs[cost units]	landscape level
mean	distance [m], cumulative costs[cost units]	patch level
means standard deviation	distance [m], cumulative costs[cost units]	patch level
median	distance [m], cumulative costs[cost units]	patch level
means standard deviation	distance [m], cumulative costs[cost units]	patch level
range	distance [m], cumulative costs[cost units]	patch level, landscape level

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