An agent-based modelling approach to estimate dispersal potential of white-tailed deer: Implications for Chronic Wasting Disease

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Introduction & Background

Chronic wasting disease (CWD) is a fatal, neurodegenerative prion disease affecting cervid species across select regions of North America (Williams, 2005). The disease was first discovered in a Colorado captive cervid facility in 1967 (Williams and Young, 1980), and has since been detected in free-ranging cervid populations in at least twenty US states and two Canadian provinces (USGS, 2018). In locations where the disease is endemic, long-term population decline of white-tailed deer (*Odocoileus virginianus)* has been observed (Edmunds et al, 2016). This has raised concern among wildlife management agencies concern of the sustainability of current harvest rates among affected populations (Edmunds et al, 2016), and may pose a considerable threat to maintaining long term conservation funding.

At the landscape level, the geographic distribution of the disease is associated with the space use and movement patterns of white-tailed deer (Edmunds et al, 2017; Evans et al, 2015). Thus, factors influencing individual deer movement behavior are also likely to influence the spread of CWD. Juvenile dispersal events have important implications for disease management as they may facilitate long distance transport of infectious agents across the landscape. Dispersal potential is often related to landscape connectivity between resource patches and is therefore dependent upon individual-based perception of landscape permeability.

In Michigan, CWD was first detected in free-ranging white-tailed deer in May 2015 (MDNR, 2018). Since, at least 57 deer have tested positive for the disease (MDNR, 2018). These cases appear to be distributed between two distinct regions of the state (Figure 1), although their minimum degree of separation (~52 km) is not enough to be considered functionally isolated with respect to deer movement patterns and landscape connectivity. Our objective was to investigate the relative connectivity between the two regions where CWD has been detected in Michigan with respect to white-tailed deer movement patterns. To accomplish this, we have constructed and an agent-based model that simulates deer dispersals originating from each disease region and tracks the frequency at which these dispersals reach the opposite disease zone. These results will yield insight that will help wildlife managers understand how likely the disease areas are to be functionally isolated (indicating separate disease origins), thereby increasing their effectiveness in the application of limited disease surveillance resources.

Case Description

The study area was focused on the south-central portion of the Michigan lower peninsula surrounding the regions where CWD has been detected (Figure 1), although simulated dispersals were theoretically allowed to travel across the full extent of the lower peninsula. Disease detection data were obtained via personal communication with Michigan Department of Natural Resources staff. These data consisted of point shapefiles that represent the center of the section (Public Land Survey System) in which infected deer have been harvested. We defined disease zones (i.e., regions) by applying a convex hull minimum bounding geometry around points occurring in the Lansing (n = 7; Ingham and Clinton counties) and Montcalm (n = 41; Montcalm, Ionia, Kent, and Mecosta counties) areas. Each resulting polygon was then buffered by 1 km to account for error in data and the range of deer movements prior to harvest.

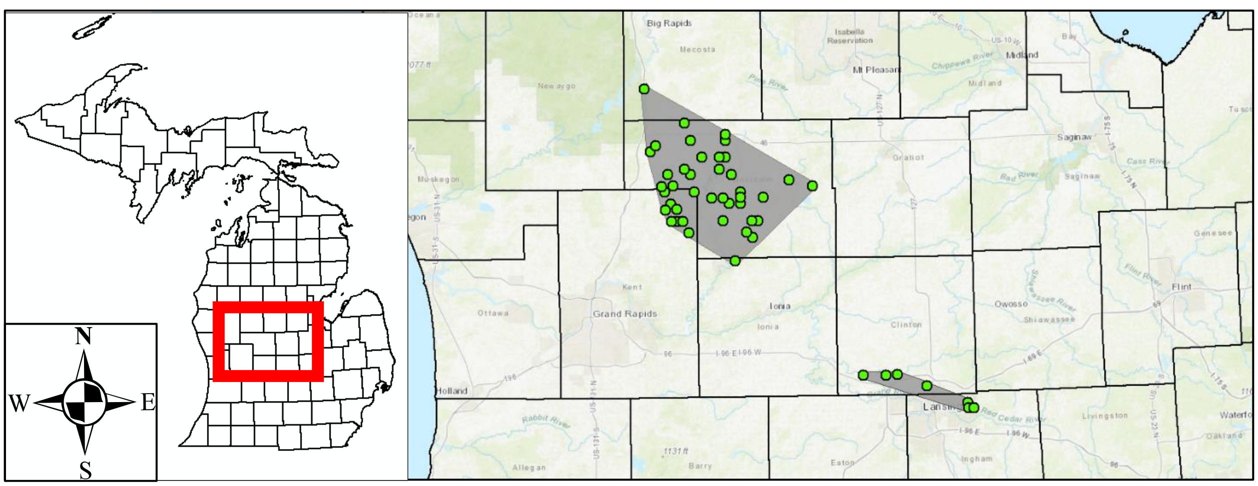

Figure 1 *Focus of study area centered around disease detection points (green dots). Disease zones represented in gray with Lansing occurring in the south-east and Montcalm in the north-west extents of the image.*

We modified Coastal Change Analysis Program 2016 Regional Land Cover data to represent the environment of the study area (Office for Coastal Management, 2018). These data originally contained 22 classes of land use/ land cover (LULC) represented at 30m x 30m resolution, although we reclassified and the dataset to include 6 cover types relevant to deer movement behavior (Table 1) and resampled to 90m x 90m resolution to increase computational efficiency. We also used these data to create a raster that represents the Euclidean distance to the nearest forested cell at each location within the study area.

Aggregated Class	Original Classes
Forest	Deciduous Forest; Evergreen Forest; Mixed Forest; Scrub/ Shrub; Palustrine Forested Wetland; Palustrine Scrub/ Shrub; Estuarine Forested Wetland; Estuarine Scrub/ Shrub
Agriculture/ Range	Cultivated Crops; Pasture/ Hay; Grassland Herbaceous
Emergent Wetland	Palustrine Emergent Wetland; Estuarine Emergent Wetland
Low Intensity Urban Development	Developed, Low Intensity; Developed, Open Space; Bare Land
High Intensity Urban Development	Developed, High Intensity; Developed, Low Intensity
Open Water	Open Water; Palustrine Aquatic Bed; Unconsolidated Shore

Table 1 *Reclassifications of C-CAP 2016 LULC dataset. Aggregated class represents classes included in modified dataset, while original classes represents the classes present in the original dataset that were attributed to each aggregated class.*

Methods and Modelling Approach

Agent-based modeling (ABM, alternatively termed "'individual-based model") is a well-established simulation tool to analyze complex systems involving dynamic and nonlinear linkages between heterogeneous agents (Axelrod et al. 1997, Ligmann-Zielinska 2010). While ABMs are increasingly used in wildlife management and conservation research (McLane et al. 2011), there are currently no publications that describe their application to CWD management. Agent-based models are particularly useful because they can incorporate species responses to dynamic environments. Along with their adaptable structure, this makes them useful for incorporating human-wildlife interactions and testing future scenarios and management actions (McLane et al. 2011). This ability to consider complex stochastic systems has made agent-based models a useful tool for assessing population connectivity (Kool et al. 2013) and tracing the movement of wildlife species (Togar 2018). Ultimately, we believe that ABMs represent a potentially invaluable tool in the management of CWD, particularly in cases where the disease is emergent.

In this model, agents are represented as juvenile male white-tailed deer that exist in a 90m x 90m raster environment representing the lower peninsula of Michigan. Agents have attributes including: unique ID; location in space; preferred direction of movement; and memory of past 11 steps (movements). Each agent is initialized with a random location chosen within a 1 sq. km area surrounding a disease detection point to account for inaccuracies in reporting of point locations and variability in range of deer prior to harvest (i.e., the point at which the deer was harvested does not represent the entire range it occupied while infected and alive). The preferred direction of each agent describes the general direction in which it would prefer to disperse across the landscape and represents the pattern for deer to move in a general direction away from their natal range during a dispersal event. As this model is raster based, preferred direction can be any of 8 options: N; NE; E; SE; S; SW; W; or NW. Preferred direction is initialized randomly for each agent and maintained as constant for the first 11 time steps. After this point, preferred direction is defined by the mode of the directions moved in the last 11 steps (i.e., preferred direction of each agent is updated based on its past movements).

Agents disperse across the digital landscape by moving from their current cell (location in the raster) to one in their immediate neighborhood (adjacent cell; Figure 2). From the eight available options for movement within the neighborhood, agents will iterate across cells, evaluate their suitability (defined below), and move to the first which is evaluated as suitable for movement (Figure 3). The order in which agents evaluate cells is determined by their preferred direction. Preferred cells include the five that are within 90 degrees of the preferred direction of the agent on the two-dimensional plane (Figure 2). Secondary cells are the 3 remaining that fall outside of 90 degrees of the preferred direction. Agents

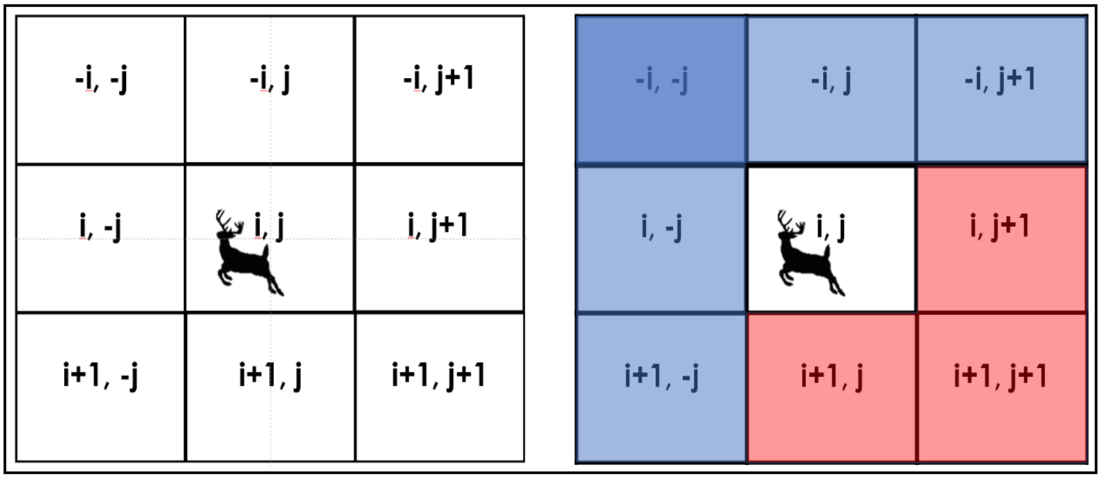

Figure 2 *Movement of agents across digital landscape. Agents can move to any adjacent cells, although they evaluate cells in their preferred direction (blue; NW) prior to cells in the opposite direction (red; SE). Agents randomly select from cells in preferred direction until suitable cell is identified. If no cells in the preferred direction are suitable, they randomly choose from cells in opposite direction. Cells are randomly chosen without replacement.*

randomly select without replacement from the preferred cells until a suitable cell is located. If no cells in the preferred direction are evaluated as suitable, the agent will repeat the process for the secondary cells. In the case that no cells are evaluated as suitable within a particular time step, the agent does not move during the respective time step and will reevaluate the same neighborhood during the next time step. As suitability is probabilistic (see below), the agent is unlikely to remain "stuck" in this location across the entire dispersal.

The suitability of a cell for deer movement are defined by the land cover present at the cell and the distance of the cell from the nearest forested patch. Each land cover type has a discrete probability of being suitable in any evaluation (Table 2). If a cell is within 130m of a forested patch (e.g., cell is forested or is adjacent to forested cell) the cell is evaluated as suitable with respect to the distance to forest parameter, although beyond this distance the probability of a cell being suitable decreases with its distance away from the nearest forested patch (Equation 1; Williams, 2010). At any given cell, agents must determine that a cell is suitable with respect to both parameters for the cell to be suitable for movement, and therefor agents consider utility as multiplicative.

Land Cover Class	**Probability of Evaluating as Suitable**
Forest	**1.0**
Agriculture/ Range	**0.8**
Emergent Wetland	**0.8**
Low Intensity Urban Development	**0.5**
High Intensity Urban Development	**0.15**
Open Water	**0.05**

Table 2 *Probabilities of land cover classes being suitable for movement. Each cover class has a discrete probability related to habitat suitability and movement patterns of white-tailed deer.*

$$y = 1.038x^{-0.008}$$

Equation 1 *Defines the probability of cells being suitable for deer movement (y) based on the Euclidean distance of the cell from the nearest forested patch (x).*

To apply to our model to the Michigan landscape, we initiated 100 agents at each disease detection point and allowed dispersals to occur for 5000 time steps. Agents disperse across the landscape as defined above and in the behavioral algorithm below (Figure 3). Dispersal success occurred if an agent reached the opposite disease zone from which it originated. A rate of dispersal success was determined at both the level of individual detection points and disease zones. The paths travelled by agents during simulated dispersals was also recorded and may be useful in identifying movement corridors between the two disease zones.

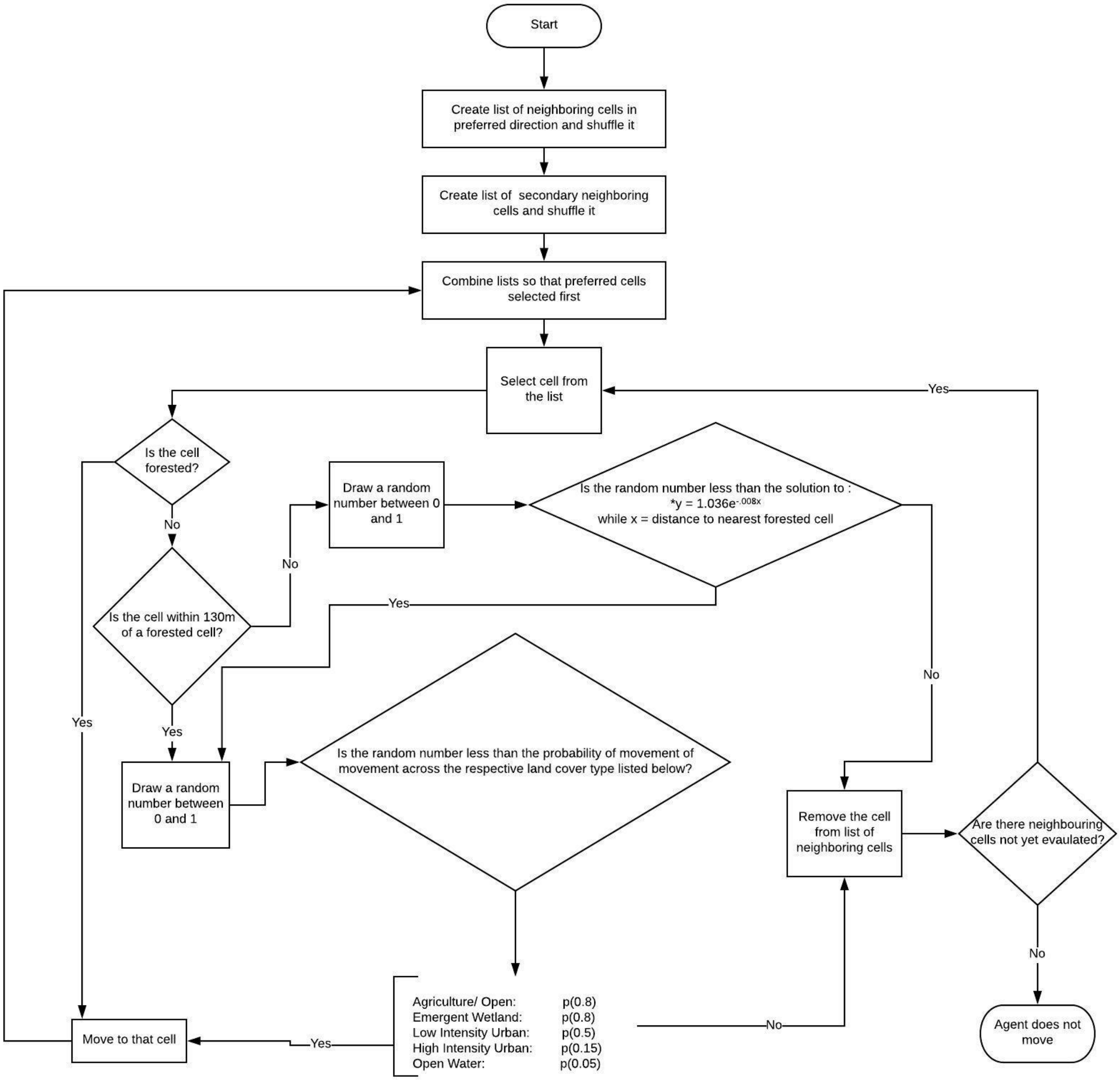

Figure 3 *Behavioral algorithm for white-tailed deer agents. Agents are initiated in area immediately surrounding disease detection point and progress across the landscape following above rules. Agents are terminated at 5000 time steps.*

Results

Out of all simulations for both the Lansing and Montcalm areas, only two dispersals were successful. Both successes originated in the Lansing CWD area, yielding a success rate of roughly 0.3% (2/700) in Lansing and 0% (0/4100) in Montcalm, indicating low connectivity between the two CWD areas. This also illustrated in Figure 4, which maps the locations across which dispersing deer travelled on the landscape.

Overall, dispersal paths tended to favor movement away from the opposite CWD area and their dominant direction of travel was influenced by the preferred cardinal direction chosen at initialization. A distinct pattern of high path densities along cardinal directions emerged (Figure 4); indicating that the influence of raster based movement rules manifests at large scales. Further, this may indicate that agents in our model display path dependence in the sense that their dominant direction of travel is dependent primarily upon their initial preferred direction.

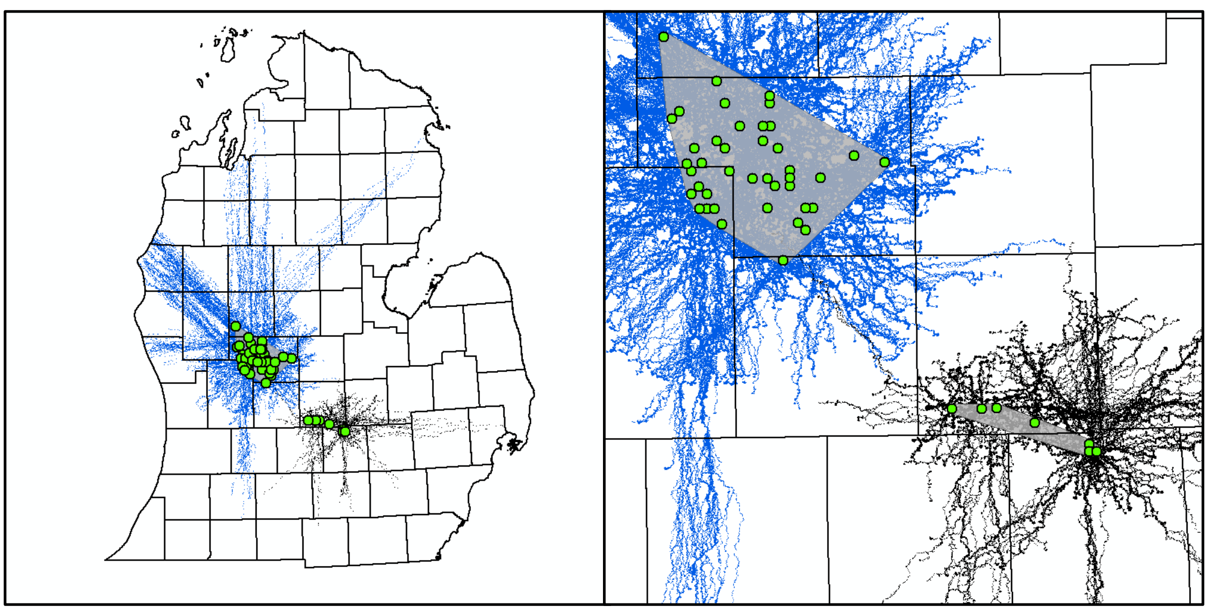

Figure 4 *Depicts cells encountered by agents during dispersal events. Connectivity appears to be low between Lansing (black) and Montcalm (blue) disease zones, relative to the rest of the landscape. Raster based movement rules produce emergent branching pattern at large scales.*

Discussion

With respect to our research objective, it appears that landscape connectivity between the two CWD zones in the Michigan Lower Peninsula is low relative to the rest of the landscape. This may indicate that the sources of these two disease zones may be independent, and that increased disease surveillance resources should be allocated along the enveloping edge of these zones rather than between them. Further, the only successful dispersal paths between the zones (n = 2) travelled along the Grand River Corridor, suggesting that functional connectivity between these two zones is highly dependent upon this landscape feature. Therefor, disease surveillance between CWD zones should be focused along this corridor to maximize interception.

Further development of the model will likely produce more ecologically realistic patters and thus more accurate estimates of connectivity. The inclusion of variability in deer movement is critical. Deer movement is known to vary by sex, age, as well as season. Human factors, such as road density, are also known to inhibit deer movement and could be easily incorporated into the model. Transmission of CWD can also be accounted for by allowing infection to spread from one agent to another. While an individual agent may not be able to disperse from one CWD area to another it could transmit it to individual deer inhabiting the intermediate regions. CWD can also saturate the environment, thus modelling of transmission may not require actual contact between deer, only overlap of dispersal movements. Finally, the use of continuous based movement rules may help in reducing the distinct, emergent patterns we observed in this simulation (Figure 4).

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