Fuzzy Decision Making in an Agent-Based Model of Non-Industrial Private Forest Owners

Robert Zupko
Department of Social Sciences
Michigan Technological University
Houghton, Michigan 49931-1295
Email: rzupko@mtu.edu

***Abstract*—This paper presents the development and application of a fuzzy inference system (FIS) to an agent-based model of non-industrial private forest owner (NIPFO) timber harvesting activity. The FIS inputs and rules are developed based upon survey and literature data on NIPFOs and agents are embedded into a forested landscape similar to real conditions. Model results indicate harvesting patterns similar to what is actually observed. I argue that these encouraging results indicate the technique merits further development.**

I. Introduction

In heavily forested regions bioenergy produced using woody biomass has the potential to be a significant part of a renewable energy portfolio. Globally it is estimated that by 2050 14 to 18% of the world's energy could be derived from woody biomass [1]. Despite this, it remains unclear who will provide the necessary feedstocks [2]. Non-industrial private forest owners (NIFPOs) are one possible source, but the current rate of timber harvesting by NIPFOs is low [3]. One potential solution to this is the use of policy interventions to encourage timber harvesting, such as those that are used to support traditional logging industries [4]. However, development of appropriate policies is dependent in part upon an understanding of NIPFO harvesting behavior. Given the timeframes associated with tree growth, computer models are useful in projecting timber harvests. Agent-based models (ABMs) allow NIFPOs to be implemented as agents and embedded in a virtual representation of a regional landscape to see how they harvest their land. However, development of the agent immediately begs the question, how should the agent decision making be implemented?

Fuzzy logic offers one possibility for agent decision making in the form of fuzzy inference systems (FIS) [5]. Since its introduction by Zadeh [6] fuzzy logic has continued to be formalized and is now a reasonable tool when vagueness is involved [7]. The vagueness of descriptive language by humans (e.g., "That tree is tall.") is the basis of an argument that humans may make use of fuzzy information in their reasoning [8]. If this same logic is applied to ABMs then a case can be made for the application of "computing with words" [9]. Effectively, the nature of fuzzy logic and FISs make them a good candidate for agent decision making when vagueness is involved with reasoning.

Despite the promise of fuzzy logic and extensive work on the decision making of agents in ABMs [10]–[13], the use of FISs or fuzzy logic has remained surprisingly limited. Early work, sometimes using the term "Fuzzy Agent-based Model" (FAM), was encouraging with fuzzy rules used to simulate agents on river trips [14], exploring spatial perception and behavior [15], and modeling aircraft evacuations [16]. However more recent work has been sparse with limited examples of FIS in agents representing organizations [17], conceptual work [18], and explorations of dialog models [19]. One explanation for this may be the ongoing debate over how simple or complicated ABMs should be [20], where an FIS may be viewed as a more complicated (or problematic) approach [21].

In the next section an FIS for NIFPO harvest decision making is developed. Section III describes a simulation framework which uses the FIS in an ABM. Section IV presents the model results followed by discussion in Section V where concerns from the literature are readdressed. The paper concludes with Section VI where potential future work is pointed out.

II. Fuzzy Inference System

Development of the FIS began with a literature search to identify NIPFO surveys or interviews. Surveys are a common means of eliciting information on why NIPFOs own their forested land and how they manage it. They also offer an good basis for fuzzy rules since a number of the questions are formatted as Likert items [22] with responses ranging from "Not Important" to "Very Important." How terms such as "Very Important" are defined can vary from person to person, implying a vague concept suitable for fuzzification.

The U.S. Forest Service's National Woodland Owner Survey (NWOS) [3], [23] was selected as the primary basis of the FIS. Interviews of NIPFOs [24], [25] along with a surveys of NIPFOs in and around the state of Michigan [26], [27] were also selected to support the development of the FIS. The NWOS is distributed to landowners in the United States that have at least one acre of forested land, although analysis is typically limited to ten acres or

TABLE I
DESCRIPTION OF FIS INPUT VARIABLES

Input	Description
parcel	The size of the NIPFOs parcel
CNC_CLIM	NIPFO's concern about climate change
CNC_FIRE	NIPFO's concern about wildfire
OBJ_BEA	How highly the NIPFO rates enjoyment of natural beauty as an objective
OBJ_NAT	How highly the NIPFO rates protection of nature or biological diversity as an objective
OBJ_WIL	How highly the NIPFO rates protection or improvement of wildlife habitats as an objective
OBJ_TIM	How highly the NIPFO rates timber production is an objective
CUT_LOG_SALE	Has the NIPFO previously harvested their parcel?
CERT	Does the NIPFO have a green certification?
MAN_PLAN	Does the NIPFO have a forest management plan?

TABLE II
FIS INPUT TERMS

Input	Terms
parcel	small, medium, large
CNC_CLIM CNC_FIRE	no_concern, of_little_concern, moderate_concern, concern, great_concern
OBJ_BEA OBJ_NAT OBJ_WIL OBJ_TIM	not_important, of_little_importance, moderately_important, important, very_important
CUT_LOG_SALE CERT MAN_PLAN	yes, no

more [23]. Since it is a national survey, the questions are of a general nature regarding landowner concerns (e.g., wildfires), objectives for owning the land (e.g., timber production), and how the forest is managed as opposed to regional concerns.

A. Inputs

From the NWOS data and the literature a total of ten inputs were identified, which are summarized in Table I with terms given in Table II. The *parcel* input corresponds to the number of forested acres in the NIPFO and is fuzzified using a trapezoidal membership function (Figure 1). The terms for *parcel* were selected due to the literature reflecting a clear bias towards harvesting by NIFPOs with more than 100 acres [3], [23], [26] with patterns shifting at about 50 acres. The objectives (i.e., *OBJ_BEA*, *OBJ_NAT*, *OBJ_WIL*, and *OBJ_TIM*), and concerns (i.e., *CNC_CLIM* and *CNC_FIRE*) are written as Likert items making them ideal for fuzzification using a triangular membership function (e.g., Figure 2). The remaining inputs, *CUT_LOG_SALE*, *CERT*, and *MAN_PLAN*, correspond to yes/no questions on the survey and were fuzzified using singletons (e.g., Figure 3).

B. Rules

Following identification and fuzzification of the inputs, the rules shown in Listing 1 were developed using expert analysis and correlation with the literature. Rules 1 through 3 are based upon the size of the NIFPOs forested land indicating that harvesting is likely as size increases. Rule 4 was developed on the basis that NIPFOs are not likely to harvest timber if they are concerned about climate change. While the primary concern of the FIS is timber harvesting, if NIPFOs are concerned about wildfire they may thin or harvest trees as, or in lieu of, fuel reduction treatments [28]. Rule 6 indicates that if enjoyment of nature is a major ownership objective, the owner is unlikely to harvest. The *OBJ_BEA* input and associated rule also makes a good proxy for other ownership objectives such as recreation and hunting, reducing the size of the rule set. Rules 7 and 8 both relate to conservation objectives which

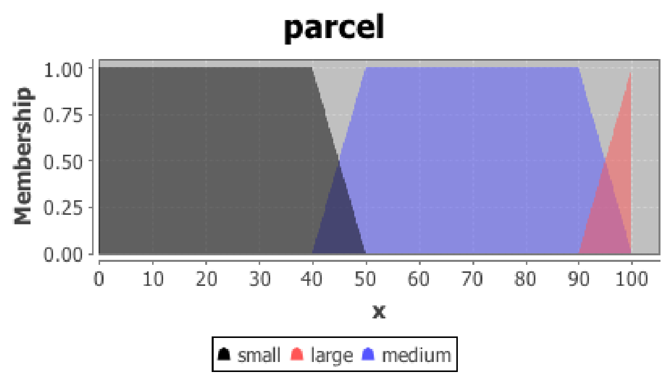

Fig. 1. Membership for parcel sizes, in acres. Note that the chart is truncated and values exceeding 100 are assigned the value *large*.

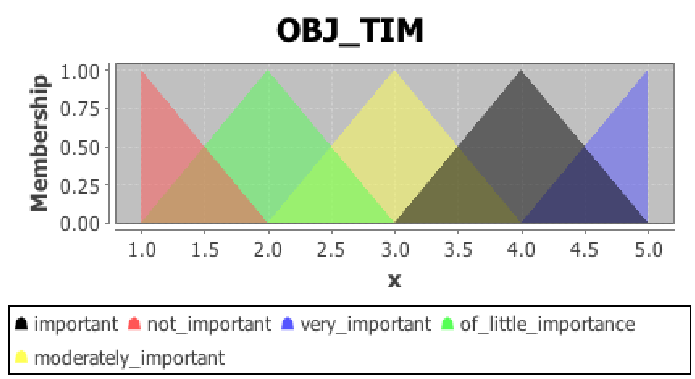

Fig. 2. Membership function for NIPFO objectives for ownership, shown here for the OBJ_TIM variable.

Listing 1
NIPFO agent rule set

```
RULE 1 : IF parcel IS small THEN result IS no;
RULE 2 : IF parcel IS medium THEN result IS maybe;
RULE 3 : IF parcel IS large THEN result IS yes;
RULE 4 : IF (CNC_CLIM IS concern) OR (CNC_CLIM IS great_concern) THEN result IS no;
RULE 5 : IF (CNC_FIRE IS concern) OR (CNC_FIRE IS great_concern) THEN result IS maybe;
RULE 6 : IF (OBJ_BEA IS important) OR (OBJ_BEA IS very_important) THEN result IS no;
RULE 7 : IF (OBJ_NAT IS important) OR (OBJ_NAT IS very_important) THEN result IS no;
RULE 8 : IF (OBJ_WIL IS important) OR (OBJ_WIL IS very_important) THEN result IS no;
RULE 9 : IF (OBJ_TIM IS important) OR (OBJ_TIM IS very_important) THEN result IS yes;
RULE 10 : IF CUT_LOG_SALE IS yes THEN result IS maybe;
RULE 11 : IF CERT IS yes THEN result IS yes;
RULE 12 : IF MAN_PLAN IS yes THEN result IS yes;
```

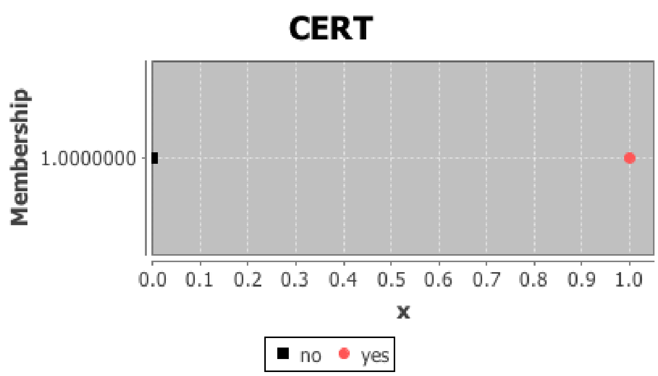

Fig. 3. Singleton membership function for yes/no survey responses, shown here for the CERT variable

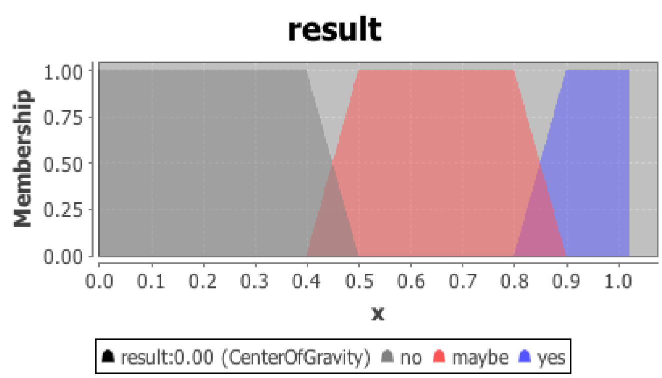

Fig. 4. Membership function for the output variable indicating the NIPFOs likeliness to harvest

typically indicate the NIPFO is not willing to harvest. Rule 9 weights the NIPFO saying that they are concerned about timber production as indicating they are intending to harvest. Since previous harvesting activity is a good, but not definitive, indicator of future intent, rule 10 biases towards harvesting. Finally, rules 11 and 12 are both based upon yes/no responses indicating has a green certification or forest management plan. Since these typically indicate timber production, they are a good indicator that the NIFPO will harvest in the future.

C. Output

The rules of the FIS only has one output variable, *result* which has the terms 'yes', 'no', and 'maybe' (Figure 4). When activated, rules are accumulated as a union using the formula $max(\mu_A(x), \mu_B(x))$ where μ_A and μ_B are membership functions for the sets A and B respectively. To defuzzify the result into a crisp value, the standard center of gravity defuzzifier is used.

D. Preparation of FIS Input Data

Since the basis of the FIS is the NWOS survey, it is necessary to ensure that the simulation uses the survey results as the basis of agent attributes. Algorithm 1 was developed to process the original NWOS response data. The algorithm works by eliminating irrelevant and invalid data before binning data on the basis of the fuzzified parcel term and survey response. A data clean-up step is needed to ensure that an accurate frequency of responses can be found. Likewise, some values such as 'NA' are relabeled to ensure consistency between the Likert scales used in the questions. After data clean-up, the frequency of responses are turned into a cumulative sum of the percentiles. These can then be used probabilistically to determine the the value assigned to an NFIPO agent during initialization (see Section III-B). Thus allowing the actual survey response distributions to be used by the NIPFO agents during model execution.

III. Simulation Framework

The simulation[1] is built upon the ForestSim[2] ABM framework which is briefly described in [29]. The framework is intended to be used in models of NIPFO interactions with forested landscapes. As such is ideal for this

[1] Source code available at https://github.com/rjzupkoii/FuzzyNIPFO
[2] Available at https://github.com/forestsim-mtu/forestsim

Algorithm 1 NWOS data processing algorithm

```
Input: Aggregate survey responses as matrix, data
Output: Matrix with processed results
  Initial load and processing
  Discard rows from data where frequency = 0
  Discard rows from data where acreage ≤ 10
  Survey response processing
  Discard rows from data with invalid or missing survey responses
  Rescore 'NA' responses as 'no concern'
  Fuzzification of acreage
  Add a parcel column to data with value 'medium'
  if acreage ≤ 40 then
    parcel is 'small'
  else if acreage ≥ 100 then
    parcel is 'large'
  end if
  Delete acreage column from data
  Calculate response distributions as a continuous sum
  Delete irrelevant columns from data
  Sort data rows by response in ascending order
  Aggregate frequency on other unique row values in data
  for size in ['small', 'medium', 'large'] do
    total = sum of frequency where parcel = size
    for each row where parcel = size do
      frequency = frequency/total
      frequency = frequency plus previous frequency
    end for
  end for
  return data
```

simulation. ForestSim is written in Java and provides customization though interfaces or abstract methods that are invoked during model execution. Due to the use of Java, jFuzzyLogic [30] was used to implement the FIS defined in Section II using Fuzzy Control Language. In order to use the ForestSim framework, the forested environment needs to be defined along with agent (i.e., NIPFO) decision making which we now describe.

A. Environment

The Western Upper Peninsula (WUP) of Michigan, USA (see Figure 5), was selected as the basis for the model's environment. This region is ideal since it is heavily forested [31] with approximately one third of forested land owned by NIPFOs [32]. Parcel maps in the form of GIS shapefiles were collected for the WUP counties of Baraga, Gogebic, Houghton, Iron, Keweenaw, and Ontonagon. The parcel maps were processed to ensure that plats had private ownership and at least ten acres of forested land. Forested land was identified based upon landcover data from the 2011 National Land Cover Database (NLCD) [33]. During model execution an agent will be assigned to each of 23,362 plats in the final shapefile by ForestSim ensuring results are spatially relevant and have distributions consistent with the real world.

Algorithm 2 NIPFO Agent Decision Method

```
Input: Matrix of labels and values, attitudes; reference to FIS, fis
  Load attitudes into fis
  score = fis.evaluate()
  if isNo(score) then
    return
  end if
  if isMaybe(score) and random() ≤ score then
    return
  end if
  Get a list of harvestable stands
  if area of stands ≥ MINIMUM then
    Request a harvest of stands
  end if
```

The forest model is based upon a whole-stand even-aged growth model [34]. With this approach, each NLCD pixel that is coded as forest or woody wetlands represents a stand of trees of the same species, age, and size. Upon model initialization, forest stands are randomly distributed using Perlin noise [35] and NLCD data. NLCD pixel codes are used to identify the species of the stand with Red Maple (*Acre rubrum*) and White Pine (*Pinus strobus*) being selected due to their dominance in the region [31]. The Perlin noise at the pixel is then used as the basis of tree stand parameters (i.e., age, diameter at breast height, and tree count) which are scaled based upon the species and actual forests in the region [31]. The annual growth of the stands then occurs based the mean growth of the species with a 10% variance. In the event the stand becomes over crowded, up to 10% of the trees present may be removed simulating natural thinning.

B. Agent Decision Making

Implementation of the NIFPO agent in the simulation requires the agent initialization and agent decision making code be defined. Upon model initialization, agents are sequentially created and assigned to each of the plats defined in the shapefile (see Section III-A). Agents are assigned *attitudes*, which correspond to the inputs of the FIS, based upon the processed NWOS survey results (see Section II-D). A uniformly distributed random number is used to select the value based upon the bins defined for the input. Agent decision making takes place when the *doHarvestOperation* method is called by ForestSim each time step of the simulation. When the method is called, the agent executes Algorithm 2. Since the result of the FIS is a crisp value, additional methods were written to fuzzify the value. In the event of a 'maybe' response, the crisp value is used to stochastically determine if the agent will harvest. This is typical of ABMs and reflects natural uncertainty. When the agent does harvest, a minimum of

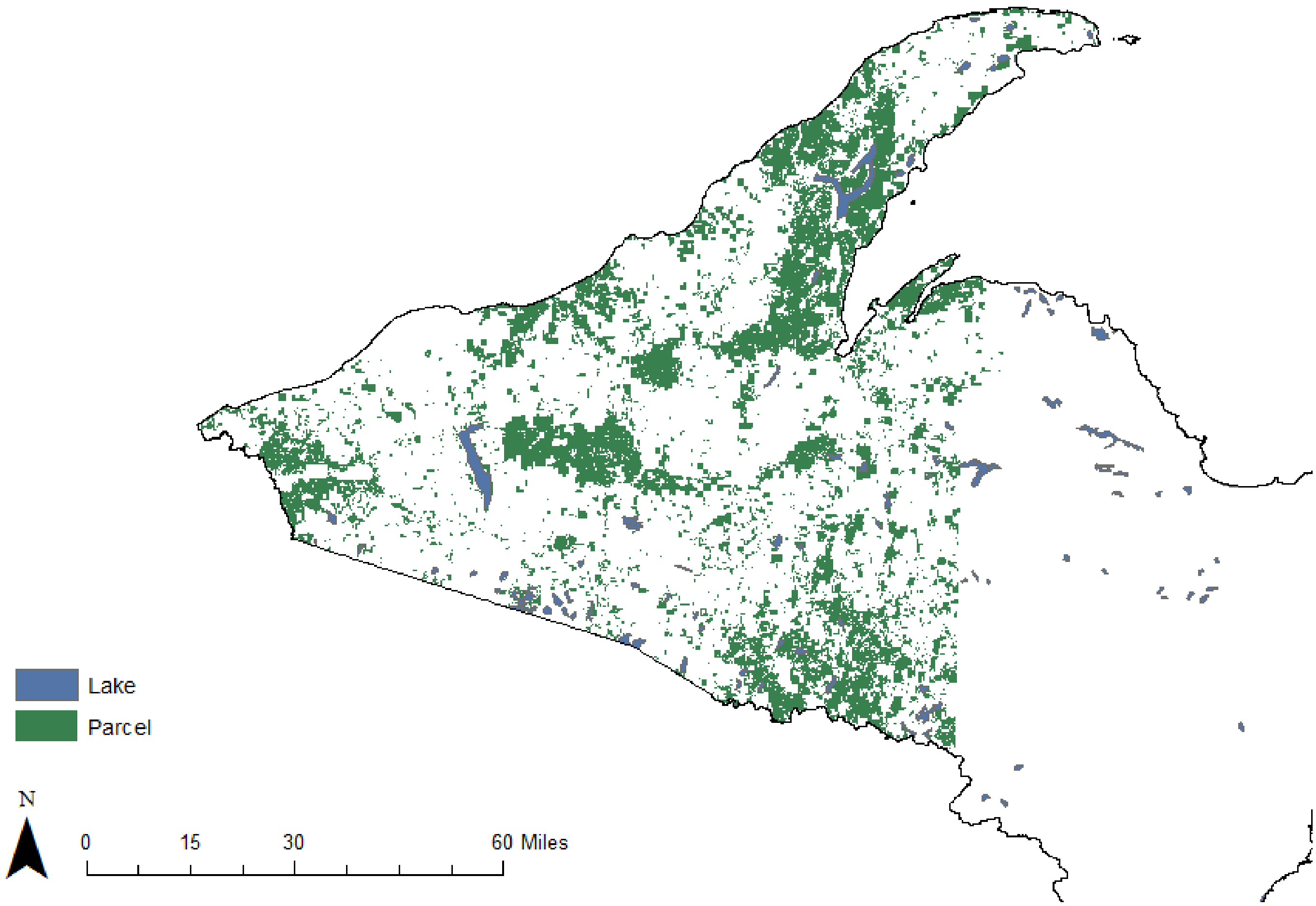

Fig. 5. WUP region of Michigan, USA showing the parcels that were featured in the model.

ten acres of forests are required, the same as the minimum forested plat size.

IV. Results

As shown by Figure 6 the number of harvested parcels per time step (i.e., year) was quite low. Across the entire simulation timespan, approximately 51.9% of the agents conducted at least one harvest. Overall this compares quite favorably to actual NWOS survey results since in any given year a small minority of NIPFOs may harvest, while overall about 46% of them will at some point [23]. The overall trend of the plot is consistent with how ForestSim gradually introduces agents into the model (approximately 450 per time step) to simulate changes in land tenure which accounts for the gradual increase in harvesting over time. Furthermore, the sawtooth pattern exhibited is also characteristic of the cycle of tree growth and harvesting.

V. Discussion

Izquierdo et al. [21] argued that "the use of [fuzzy logic] in Social Simulation should not be taken lightly." This statement bears consideration. As this paper demonstrates, an FIS of NIPFO harvest decision making can prove effective. However, the concerns of Izquierdo et al. appear to be two fold: first, fuzzy sets apply precise definitions to vague concepts; second, rule interpolation is not a method of logical deductive inference. Both of these concerns appear to be resolvable with proper development and application of the fuzzy logic. With regards to the first point, the FIS developed in this paper ultimately defers to individual interpretations by making input set terms the same as the Likert item labels where appropriate. This allows the model to base agent *attitude* assignment (see Section III-B) on patterns observed in the survey data, thus preserving the vagueness of the individual interpretations. The second point is more nuanced since it effectively depends upon what are the objectives of a model. When the goal is replicating observed behavior of a large population, interpolation of fuzzy rules may be the best approach. One reason for this is that the full extent of individualized decision making may be impossible to fully capture. However, fuzzy rules may allow the dominant,

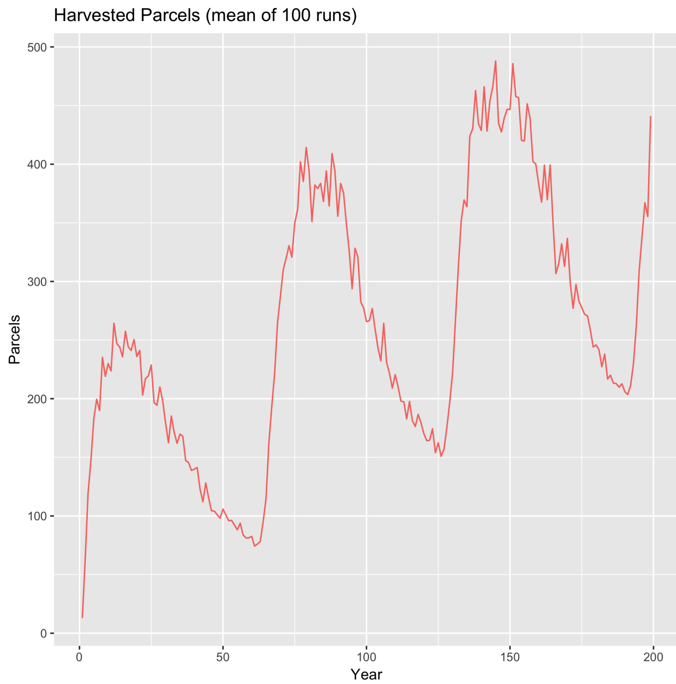

Fig. 6. NIPFO harvest rates per year, mean over 100 runs.

generalizable, IF-THEN patterns to be used.

One issue with the development of the FIS that Izquierdo et al. did not address is the availability of data. Since NIFPOs are well studied, a sufficient amount of data could be found to develop the FIS. In other cases modelers may not be so fortunate. One possible way to address the problem is to develop a survey to capture the needed data. This presents its own challenges due to the development, distribution, and collection of the survey must take place before FIS development can take place. Developing a survey, knowing it will be used for an FIS, presents opportunities as well. One possibility is to modify the survey questions to support responses as a best estimate and associated uncertainty [36] leading to the development of membership functions based upon the responses.

Another intriguing aspect of an FIS based ABM, which could also address scholarly concerns, is the use of the participatory approach in developing the rules [37]. The participatory approach engages with members of the application domain (e.g., NIPFOs) to develop an appropriate rule set. While this may present a higher barrier to the development of the FIS, the resulting product could also be of higher quality since rules not apparent from the survey data may be developed. One potential issue with this approach is that care needs to be used to ensure that focus groups are properly balanced. For example, in the case of NIPFOs, a robust selection of individuals that harvest as well as those that do not would be needed.

Despite these issues, the results of the FIS developed in this paper are encouraging. The techniques used open agent decision making up for inspection and criticism helping to address one of may reasons ABMs are accused of being "black boxes" [38]. Furthermore, the availability of tools such as jFuzzyLogic help to reduce programmatic burden on modelers allowing them to focus on the model itself as opposed to the underlying code. While there remain issues such as data availability, these problems are endemic to ABMs and should not be a barrier to the use of fuzzy logic in agent decision making.

VI. Conclusions and Future Work

This paper presented the development of an FIS of NIPFO harvest decision making for use in an ABM. When agents using the FIS for decision making were embedded into a virtual landscape, harvesting behavior consistent with the real-world was observed. These results are encouraging for the further use of FIS in ABMs.

This technique offers rich opportunities for future work, starting with the refinement of the FIS using survey data from NIPFOs in the WUP. Increasing application of FIS to ABMs also offers chances for methodological development in the areas of participatory research and surveys as well. A robust comparison of the use of FIS-based decision making compared to common approaches in ABMs (ex., logistic regression) is warranted. Ultimately, members of the social simulation community may also find that the development FIS based ABMs offers rich opportunities for novel research.

Acknowledgment

The author would like to thank Brett Butler (U.S. Forest Service) for providing the NWOS data used in this paper. I would also like to thank Timothy Havens (Michigan Technological University) and the four anonymous reviewers for their feedback.

References

[1] P. Lauri, P. Havlíŋk, G. Kindermann, N. Forsell, H. Böttcher, and M. Obersteiner, "Woody biomass energy potential in 2050," *Energy Policy*, vol. 66, pp. 19–31, Mar. 2014. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0301421513011403

[2] M. J. Groom, E. M. Gray, and P. A. Townsend, "Biofuels and Biodiversity: Principles for Creating Better Policies for Biofuel Production," *Conservation Biology*, vol. 22, no. 3, pp. 602–609, Jun. 2008. [Online]. Available: http://dx.doi.org/10.1111/j.1523-1739.2007.00879.x

[3] B. J. Butler, "Family Forest Owners of the United States, 2006," U.S. Department of Agriculture, Forest Service, Northern Research Station, Newtown Square, PA, Tech. Rep. NRS-GTR-27, 2008, dOI: 10.2737/NRS-GTR-27. [Online]. Available: http://www.treesearch.fs.fed.us/pubs/15758

[4] A. L. Mayer and P. M. Tikka, "Biodiversity conservation incentive programs for privately owned forests," *Environmental Science & Policy*, vol. 9, no. 7-8, pp. 614–625, Nov. 2006. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1462901106001018

[5] G. J. Klir and B. Yuan, *Fuzzy Sets and Fuzzy Logic: Theory and Applications*. Upper Saddle River, NJ: Prentice Hall PTR, 1995.

[6] L. Zadeh, "Fuzzy sets," *Information and Control*, vol. 8, no. 3, pp. 338–353, Jun. 1965. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S001999586590241X

[7] V. Novák, "Are fuzzy sets a reasonable tool for modeling vague phenomena?" *40th Anniversary of Fuzzy Sets*, vol. 156, no. 3, pp. 341–348, Dec. 2005. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0165011405002794

[8] L. A. Zadeh, "Toward a theory of fuzzy information granulation and its centrality in human reasoning and fuzzy logic," *Fuzzy Sets: Where Do We Stand? Where Do We Go?*, vol. 90, no. 2, pp. 111–127, Sep. 1997. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0165011497000778

[9] ——, "Fuzzy logic = computing with words," *IEEE Transactions on Fuzzy Systems*, vol. 4, no. 2, pp. 103–111, May 1996.

[10] R. Sun, Ed., *Cognition and Multi-Agent Interaction: From Cognitive Modeling to Social Simulation.* Cambridge, United Kingdom: Cambridge University Press, May 2008.

[11] M. D. A. Rounsevell, D. T. Robinson, and D. Murray-Rust, "From actors to agents in socio-ecological systems models," *Philosophical Transactions of the Royal Society B: Biological Sciences*, vol. 367, no. 1586, p. 259, Dec. 2011. [Online]. Available: http://rstb.royalsocietypublishing.org/content/367/1586/259.abstract

[12] L. An, "Modeling human decisions in coupled human and natural systems: Review of agent-based models," *Ecological Modelling*, vol. 229, pp. 25–36, Mar. 2012. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0304380011003802

[13] J. M. Epstein, *Agent_Zero: Toward Neurocognitive Foundations for Generative Social Science.* Princeton, New Jersey: Princeton University Press, 2013.

[14] H. R. Gimblett, C. A. Roberts, T. C. Daniel, M. Ratliff, M. J. Meitner, S. Cherry, D. Stallman, R. Bogle, R. Allred, D. Kilbourne, and J. Bieri, "An Intelligent Agent-Based Model for Simulating and Evaluating River Trip Scenarios along the Colorado River in Grand Canyon National Park," in *Integrating Geographic Information Systems and Agent-Based Modeling Techniques for Simulating Social and Ecological Processes*, ser. Santa Fe Institute Studies in the Sciences of Complexity. New York: Oxford University Press, 2002, pp. 245–275.

[15] R. M. Sperb and R. B. Cabral, "Fuzzy Agent-based Model: A hybrid tool for exploring spatial perception and behavior," in *Fuzzy Information, 2004. Processing NAFIPS '04. IEEE Annual Meeting of the*, vol. 1, Jun. 2004, pp. 120–125 Vol.1.

[16] S. Sharma, H. Singh, and A. Prakash, "Multi-agent modeling and simulation of human behavior in aircraft evacuations," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 44, no. 4, pp. 1477–1488, Oct. 2008.

[17] R. E. Streit and D. Borenstein, "Design and development of a fuzzy agent-based model to measure interest rate expectations," *Expert Systems with Applications*, vol. 39, no. 8, pp. 7391–7402, Jun. 2012. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0957417412000802

[18] M. Raoufi and A. R. Fayek, "Integrating Fuzzy Logic and agent-based modeling for assessing construction crew behavior," in *2015 Annual Conference of the North American Fuzzy Information Processing Society (NAFIPS) held jointly with 2015 5th World Conference on Soft Computing (WConSC)*, Aug. 2015, pp. 1–6.

[19] P. Dykstra, W. Jager, C. Elsenbroich, R. Verbrugge, and G. Renardel de Lavalette, "An Agent-Based Dialogical Model with Fuzzy Attitudes," *Journal of Artificial Societies and Social Simulation*, vol. 18, no. 3, p. 3, Jun. 2015. [Online]. Available: http://jasss.soc.surrey.ac.uk/18/3/3.html

[20] Z. Sun, I. Lorscheid, J. D. Millington, S. Lauf, N. R. Magliocca, J. Groeneveld, S. Balbi, H. Nolzen, B. Müller, J. Schulze, and C. M. Buchmann, "Simple or complicated agent-based models? A complicated issue," *Environmental Modelling & Software*, vol. 86, pp. 56–67, Dec. 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1364815216306041

[21] L. R. Izquierdo, D. Olaru, S. S. Izquierdo, S. Purchase, and G. N. Soutar, "Fuzzy Logic for Social Simulation Using NetLogo," *Journal of Artificial Societies and Social Simulation*, vol. 18, no. 4, p. 1, Oct. 2015. [Online]. Available: http://jasss.soc.surrey.ac.uk/18/4/1.html

[22] R. Likert, "A technique for the measurement of attitudes." *Archives of psychology*, vol. 22, no. 140, pp. 5–55, 1932.

[23] B. J. Butler, J. H. Hewes, B. J. Dickinson, K. Andrejczyk, S. M. Butler, and M. Markowski-Lindsay, "Family Forest Ownerships of the United States, 2013: Findings from the USDA Forest Service's National Woodland Owner Survey," *Journal of Forestry*, vol. 114, no. 6, pp. 638–647, Nov. 2016. [Online]. Available: http://www.ingentaconnect.com/content/saf/jof/2016/00000114/00000006/art00006

[24] J. R. Schubert and A. L. Mayer, "Peer Influence of Non-Industrial Private Forest Owners in the Western Upper Peninsula of Michigan," *Open Journal of Forestry*, vol. 2, no. 3, pp. 150–158, 2012.

[25] J. Lind-Riehl, S. Jeltema, M. Morrison, G. Shirkey, A. L. Mayer, M. Rouleau, and R. Winkler, "Family legacies and community networks shape private forest management in the western Upper Peninsula of Michigan (USA)," *Land Use Policy*, vol. 45, pp. 95–102, May 2015. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0264837715000083

[26] F. X. Aguilar, Z. Cai, and A. W. D'Amato, "Non-industrial private forest owner's willingness-to-harvest: How higher timber prices influence woody biomass supply," *Biomass and Bioenergy*, vol. 71, pp. 202–215, Dec. 2014. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0961953414004589

[27] A. Brunner, W. S. Currie, and S. Miller, "Cellulosic ethanol production: Landscape scale net carbon strongly affected by forest decision making," *Biomass and Bioenergy*, vol. 83, pp. 32–41, Dec. 2015. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0961953415300726

[28] J. K. Agee and C. N. Skinner, "Basic principles of forest fuel reduction treatments," *Forest Ecology and Management*, vol. 211, no. 1, pp. 83–96, Jun. 2005. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0378112705000411

[29] R. Zupko, H. Ghimre, P. Nouhan, and M. Rouleau, "An Agent-based Model of Voluntary Incentive Programs for Sustainable Biofuel Development," in *Social Simulation Conference 2016*, Rome, Italy, Sep. 2016, pp. 1–4.

[30] P. Cingolani and J. Alcala-Fdez, "jFuzzyLogic: a robust and flexible Fuzzy-Logic inference system language implementation," in *Fuzzy Systems (FUZZ-IEEE), 2012 IEEE International Conference on.* IEEE, 2012, pp. 1–8.

[31] S. A. Pugh, L. D. Pedersen, D. C. Heym, R. J. Piva, C. W. Woodall, C. J. Barnett, C. M. Kurtz, and W. K. Moser, "Michigan's Forests 2009," U.S. Department of Agriculture, Forest Service, Northern Research Station, Newtown Square, PA, Tech. Rep. NRS-66, 2012. [Online]. Available: http://www.treesearch.fs.fed.us/pubs/40471

[32] A. L. Mayer and M. D. Rouleau, "ForestSim Model of Impacts of Smallholder Dynamics: Forested Landscapes of the Upper Peninsula of Michigan," *International Journal of Forestry Research*, vol. 2013, p. 13, 2013. [Online]. Available: http://dx.doi.org/10.1155/2013/520207

[33] C. G. Homer, J. A. Dewitz, L. Yang, S. Jin, P. Danielson, G. Xian, J. Coulston, N. D. Herold, J. D. Wickham, and K. Megown, "Completion of the 2011 National Land Cover Database for the conterminous United States-Representing a decade of land cover change information," *Photogrammetric Engineering and Remote Sensing*, vol. 81, no. 5, pp. 345–354, 2015.

[34] H. E. Burkhart and M. TomÃĪ, *Modeling Forest Trees and Stands.* Dordrecht: Springer, 2012.

[35] K. Perlin, "An image synthesizer," *SIGGRAPH Comput. Graph.*, vol. 19, no. 3, pp. 287–296, 1985.

[36] M. J. Smith, C. Wagner, K. J. Wallace, A. Pourabdollah, and L. Lewis, "The contribution of nature to people: Applying concepts of values and properties to rate the management importance of natural elements," *Journal of Environmental Management*, vol. 175, pp. 76–86, Jun. 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0301479716300482

[37] C. Wagner, M. Smith, K. Wallace, and A. Pourabdollah, "Generating Uncertain Fuzzy Logic Rules from Surveys: Capturing Subjective Relationships between Variables from Human Experts," in *2015 IEEE International Conference on Systems, Man, and Cybernetics*, Oct. 2015, pp. 2033–2038.

[38] C. J. Topping, T. T. H∅ye, and C. R. Olesen, "Opening the black box-Development, testing and documentation of a mechanistically rich agent-based model," *Ecological Modelling*, vol. 221, no. 2, pp. 245–255, Jan. 2010. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0304380009006346