A Literature Review: Forest Management with Neural Network and Artificial Intelligence

Akira Imada

Department of Intelligent Information Technology
Brest State Technical University
Moskowskaja 267, Brest 224017 Belarus
akira-i@brest-state-tech-univ.org

Abstract. The 8th International Conference on Neural Network and Artificial Intelligence invites a plenary talk whose topic is *Forest Resource Maintenance.* It's not specifically from the point of information technology but from a general point of view. Thinking of the title of this conference, *'neural networks and artificial intelligence,'* the talk follows this literature review on the topic of *forest management by neural network and/or artificial intelligence.* While focus is mainly put on *wildfire prediction*, also *preservation of biodiversity of forest ecosystems* and *forest resource management* are surveyed. Comparison of these methods with traditional statistical methods such as regression is mentioned too.

1 Introduction

As catastrophe usually comes all of a sudden unpredictably, people used to rely on fortune telling in our history to avoid such catastrophes, or to reduce calamities and tragedy caused by them. Hence, fortune telling also played an important role in theaters, such as Victor Herbert's operetta 'Fortune Teller,' 'Gypsy Baron' by Johan Strauss, or not to mention but also Bizet's 'Carmen.' Safi (2013) wrote, *"As predicting what might happen in the future has always been considered as a mysterious activity, scientists in modern era have tried to turn it into a scientific activity based on well-established theories and mathematical models."*

We now take a look at those approaches in the literature of how we predict what is going to happen in a forest such as wildfire, biodiversity, resources or something else, in which a well-established neural network model is exploited, or artificial intelligence is claimed to make it.

Selection of literature's is not optimized but rather spontaneous, expecting this article to be a set of initial pointers for readers' own survey.

2 Using Artificial Neural Network

Peng (1999) wrote, *"Data concerning forest environment are sometimes obscure and unpredictable, artificial neural network, which is good at processing such*

V. Golovko and A. Imada (Eds.): ICNNAI 2014, CCIS 440, pp. 9–21, 2014.

a non-linearity, has been extensively explored since late 1990's as an alternative approach to the classical method of modeling complex phenomena in forest (McRoberts et al. 1991; Gimblett et al. 1995; Lek et al. 1996; Atkinson et al. 1997)." We see such approaches in this section.

2.1 Forest Wildfire Prediction

Every year we hear quite a lot of news of wildfire somewhere in the globe, such as in US, Turkey, Greece, Spain, Lebanon and so on and on. Sometimes wildfire kills people or even firefighters. The article in New York times on 30 June 2013 reads:

> *Nineteen firefighters were killed on Sunday battling a fast-moving wildfire menacing a small town in central Arizona. The firefighters died fighting the Yarnell Hill Fire near the town of Yarnell, about 80 miles northwest of Phoenix. ... There were several fires still active in the Yarnell area. In a search of the scene, crews found the bodies of the firefighters.*

Let's see how frequently wildfires had happened in U.S. in 2013, as an example. Tres Lagunas fire, Thompson Ridge fire, Silver fire, Jaroso fire in New Mexico; Black Forest fire, Royal Gorge fire in Colorado; Yarnell Hill fire in Arizona (where 19 firefighters were killed as cited above); Quebec fire in Quebec; Mount Charleston fire, Bison fire in Nevada; Idaho Little Queens fire in Idaho; Silver fire, Beaver Creek fire, Rim fire, Morgan fire, Clover fire in California.[1]

Vasilakos et al. (2009) estimated, the percentage of the influence of lots of factors to fire ignition risk in Lesvos Island in Greece. Here let's see, at first, his well organized survey on wildfire prediction in detail, which would help us make a further survey in this topic.

Vasilakos wrote, *"Wildland fire danger evaluation is an integration of weather, topography, vegetative fuel, and socioeconomic input variables to produce numeric indices of fire potential outputs (Andrews et al. 2003; Pyne et al. 1996)."* He went on, *"Various quantitative methods have been explored for the correlation of the input variables in fire danger assessment; most of these methods include the input variables' importance as a direct or indirect output."* Traditionally, statistical methods were widely used for fire danger calculation. Vasilakos further wrote, *"More specifically, linear and logistic regression techniques were proposed, so the coefficients of the models reflect the influence of inputs on fire danger (Chou 1992; Chou et al. 1993; Kalabokidis et al. 2007; Vasconcelos et al. 2001).*

"Artificial neural networks have been also used in fire ignition risk estimation (Chuvieco et al. 1999; Vasconcelos et al. 2001; Vasilakos et al. 2007; Vega-Garcia et al. 1996). ... In our previously published research (Vasilakos et al., 2007), three different neural networks were developed and trained to calculate three intermediate outcomes of Fire Ignition Index, i.e., the Fire Weather Index, the Fire Hazard Index, and the Fire Risk Index."

[1] Extracted from `http://en.wikipedia.org/wiki/List_of_wildfires`.

Multilayer Perceptron is an architecture of the neural network that most such reports exploit. Fig. 1 is the one of those multilayer perceptorns Vasilakos used. And the backpropagation algorithm[2] is used for training of these neural networks in most of such approaches.

Vasilakos (2009) analyzed wildfire data in the history of Lesvos Island, and then designed a neural network that was trained with using such previous data. The neural network receives a set of inputs that may influence the output that shows us a probability of the risk of occurrence of the wildfire. One important question is, how can we know the degree of importance of those factors given as the inputs.

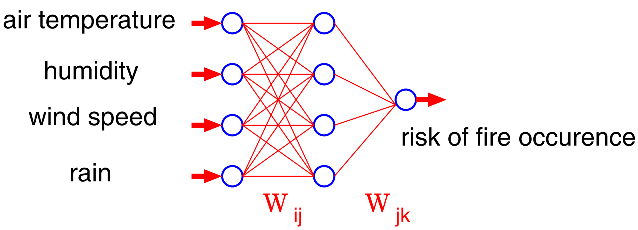

Fig. 1. One example of Multilatyer perceptron from those used by Vasilakos (2009) to know which input is the most influential factor for the output of ignition of fire occurrence

Logistic Regression is a well established method to estimate the probability of a binary independent variable from a set of independent continuous variables. It can be used to know the degree to how important the influences of dependent continuous variables $x_1, x_2, \cdots$ to the binary independent variable y.

To imagine how it works, let's now consider a simple situation where provability y depends only on one variable x. Then sample data of (x, y) could be assumed to fulfill the equation

$$y = \frac{1}{1 + exp\{-(a_0 + a_1 x)\}} \tag{1}$$

where two parameters a_0 and a_1 could be estimated so that these sample points are best fit to the graph of this equation. For the purpose, we can use, for example, maximum likelihood estimation. Then we can infer the probability y of any x given.

Now we have n independent variables $x_1, x_2, \cdots, x_n$. Then dependent variable y is expressed as n-dimensional logistic function

$$y = \frac{1}{1 + exp\{-(a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_n x_n)\}} \tag{2}$$

[2] In this paper, assuming all the readers are familiar with the basic idea of neural network, allow us not to refer to who firstly proposed or where we can obtain a detailed idea for the well known methodology such as *backpropagation*.

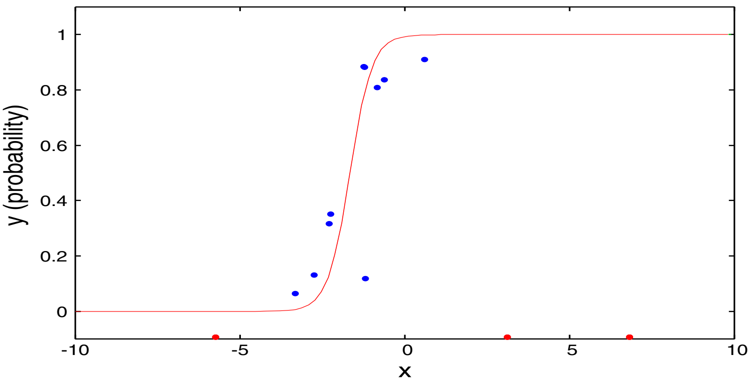

Fig. 2. A fictitious example of logistic regression from nine different values of x, after adjusting two parameters a_0, and a_1 by the maximum likelihood estimation

where a_i $(i = 0, 1, \cdots, n)$ are parameters. After adjusting these $(n+1)$ parameters such that the points in n-D space corresponding to the sample data given fit this hyper surface with maximum likelihood, we can interpret a_i as the degree of influence of x_i to y.

Garson's Method is an algorithm to measure the relative importance of input variables of an already successfully trained neural network based on its connection weights (Garson 1991). Assuming now w_{ij}'s are the connection weights between N input neurons and L hidden neurons, and u_{jk}'s are the connection weights between L hidden neurons and M output neurons, the percentage of influence Q_{ik} of input x_i on the output y_k is estimated by

$$Q_{ik} = \frac{\displaystyle\sum_{j=1}^{L} \left(\frac{w_{ij}}{W_j} u_{jk} \right)}{\displaystyle\sum_{i=1}^{N} \left(\sum_{j=1}^{L} \left(\frac{w_{ij}}{W_j} \right) \right)} \tag{3}$$

where

$$W_j = \sum_{r=1}^{N} w_{rj} \tag{4}$$

for normalization.

Using logistic-regression, Garson's equation and some other methods, Vasilakos et al. (2008) estimated, the percentage of the influence of lots of factors to fire ignition risk in Lesvos Island. Here let's see the result by Garson's equation, among others. The degree of importance of air temperature, wind speed, humidity and amount of rainfall to the risk of fire occurrence were found to be 28.7%, 20.9%, 14.5% and 35.9%, respectively, where in this example, the neural network was feedforward one with four input neurons, four hidden neurons and one output neuron trained by the backpropagation. The other factors chosen by the authors were altitude, distance to urban areas, day of the week, month of the year, etc. Thus, the authors determined influential ones out of 17 factors, with dependent variable being binary expressing presence or absence of fire ignition possibility. Training and validation samples were created from the total fire history database.

Support Vector Machine is, to simply put, a method to classify objects in a multi-dimensional space with hopefully by hyperplane, or otherwise a hyper surface. Sakr et al. (2010) proposed a forest fire risk prediction algorithm based on Support Vector Machines. The algorithm predicts the fire hazard level of the day from previous weather condition. The algorithm used the data from a forest in Lebanon for training.

Safi et al. (2013) used similar approach with forest fire data from the wild area of 700 square kilometers of ancient oak forests in the Portuguese Montesinho Natural Park with the output signal representing the total surface in hectare of the corresponding burned area.

2.2 Preservation of Biodiversity of Forest Ecosystems

Gil-Tena et al. (2010) modeled bird species richness in Catalonia, Spain. The authors wrote, *"Forest characteristics that determine forest bird distribution may also be influencing other forest living organisms since birds play a key functional role in forest ecosystems and are often considered good biodiversity indicators (Sekercioglu 2006)."*

Then authors exploited a three layer feedforward neural network with training being based on adaptive gradient learning, a variant of backpropagation. After optimizing the structure of neural network, estimated bird richness values by each neural network model are compared with the observed values in the real forest, and evaluated using linear correlation. Forest bird species richness was obtained using presence/absence data of 53 forest bird species as well as 11 data concerning forest (such as tree-species-diversity and past-burnt-area), five data on climate (such as temperature and precipitation) and 5 data on human pressure (such as road density and human population). Those bird data were collected by the volunteers from the Catalan Breeding Bird Atlas (Estrada et al. 2004). The other data are obtained from various sources, such as Spanish Forest Map, Forest Canopy Cover, Catalan Department Environment and Housing, Spanish Digital Elevation Model, National Center of Geographical Information, etc. (See references cited therein.) Data were divided into two groups. One was used for training and the other was for validation.

Also from this aspect, using neural networks, Peng et al. (1999) studied which of the forest features correlate with biodiversity, and then modeled forest bird species richness as a function of environment and forest structure. The authors wrote, *"Much progress has been made in this area since the initial use of artificial neural network to model individual tree mortality in 1991 (Guan and Gertner*

1991a). In the same year, Guan and Gertner (1991b) successfully developed a model, based on an artificial neural network, that predicts red pine tree survival."

To know this topic more in detail, The Ph.D dissertation by Fernandez (2008) might be good to be read.

2.3 Forest Cover Type Prediction

Forest cover type is a classification system based on trees that predominate in a particular area, as defined by Steve Nix.[3] Figure 3 suggests an image that shows the distribution of 25 classes of general forest cover such as (Eastern Oak_Pine forests) as well as water and non-forest land, in the United States and Puerto Rico.[4] When we concern a management of land, a 'Natural Resource Inventory' is a vital information. 'Forest cover type' is one of the most basic items in such inventories (Blackard et al. 1999). Blackard et al. (1999) predicted forest cover

Fig. 3. An example of forest cover maps (taken from the web page by NationalAtras.gov)

types in the four wilderness areas of the Roosevelt National Forest in northern Colorado – Rawah, Comanche Peak, Neota, and Cache la Poudre. A feedforward neural network model was used. After looking for an optimal architecture by trial and error experiment, the neural network was made up of 54 input neurons, 120 hidden neurons, and 7 output neurons. Training was by backpropagation. Then they compared the results with the results by a traditional statistical model based on Gaussian discriminant analysis, and found a more accurate prediction by neural network.

In addition to the accuracy, Blackard et al. (1999) wrote, *"Recording the data by human is prohibitively time consuming and/or costly. ... Furthermore, an agency may find it useful to have inventory information for adjoining lands that are not directly under its control, where it is often economically or legally impossible to collect inventory data. Predictive models provide an alternative method for obtaining such data."*

[3] `http://forestry.about.com/cs/glossary/g/for_cov_type.htm`.
[4] `http://nationalatlas.gov/mld/foresti.html`.

Meyer (2001), then student of Wisconsin University, made a similar study in his term project.[5] He used a Support Vector Machine, with input being 54 variables, of which 10 were quantitative measures such as altitude, distance to water, while the remaining 44 were Boolean values representing soil conditions such as soil-type and wilderness-type. He classified these data into 7 classes, and the outputs showed one of these 7 classes. Almost 600,000 samples were used for training and testing. The data he used were forest cover type data set from the University of California-Irvine Knowledge Discovery in Databases Archive[6] compiled initially by Blackard (1998). Thus the Support Vector Machine classified the input data to one of the seven forest cover type with a success rate of 70%.

Peng et al. (1999) cited (Campbell et al. 1989) and (Downey et al. 1992) as studies in which neural network classifies land cover using data from Landsat satellite. Bennediktsson et al. (1990) used Landsat multispectral scanner network imagery and three topographic data sets (elevation, slope and aspect) to classify land cover. Peddle et al. (1994) applied the neural network approach to classify land cover in Alpine regions from multi-source remotely sensed data. Gong et al. (1996) have tested the feasibility of applying feedforward neural network and backpropagation to land system. Pattie et al. (1996) compared neural network model with regression model on forecasting wilderness.

2.4 Forest Resource Management

Peng et al. (1999) cited Coulson et al. (1987) as a study that had started to apply 'expert system' to forest resources management. The authors also cited (Gimblett et al. 1995; Lek et al. 1996) as an emergence of artificial neural network model as an alternative approach for modeling nonlinear and complex phenomena in forest resources management. Let's see such studies now.

Growth Model. Castro (2013) proposed a model of the growth of eucalyptus in northern Brazil, to predict tree height, diameter and mortality probability by neural network. Lots of architectures of neural network were trained using real data from the forest with the purpose being looking for the optimized architecture. Then, the author concluded that neural network may work as an alternative to the traditional procedure such as regression analysis with linear or nonlinear functions, to model an individual tree. Furthermore, an artificial neural network may help identify the most critical input variables to predict diameter and height growth as well as mortality probability, and provide a better understanding of the dynamic of models at the individual tree level, becoming a valuable tool for eucalyptus forest management.

Castro also cited (Merkl et al. 1998), (Weingartner et al. 2000) and (Hasenauer et al. 2001) as a study of mortality prediction by neural network, (Diamantopoulou 2005) as a study of tree volume estimation also by neural network,

[5] `http://homepages.cae.wisc.edu/~ece539/project/f01/meyer.pdf`.
[6] `http://kdd.ics.uci.edu`.

(Paruelo et al. 1997), (Gevrey 2003) and (Leite et al. 2011) as a report of estimation of forest resources by regression.

Prediction of Tree Mortality. In order to predict individual tree mortality, Weingartener et al. (2000) compared multi layer perceptron, Learning Vector Quantization, and Cascade Correlation Networks with the conventional model using logit function (i.e., inverse of the sigmoidal logistic function). Training these three networks with the data from the Austrian National Forest Inventory, they compared the performance of each networks of mortality prediction using dataset from the Litschau Forest, and concluded Learning Vector Quantization slightly outperformed the others.

Common Pool Resource is a resource that benefits a group of people, but which provides diminished benefits to everyone if each individual pursues his or her own self interest, such as forest river.

Ulrich (2013) wondered why some communities succeed in managing common pool resources, while others fail. By restricting his analysis only to traditional commons of land use, forest management, irrigation and fisheries, he tried to look for essential factors to explain why. He cited (Hess 2008) as a more comprehensive overview of common pool problems. He wrote, *"We don't have universal such success factors that can explain any system concerning common pool resource (Meinzen-Dick 2007). ... Some comprehensive set of such success factors have already reported (See, e.g., (Pagdee et al. 2006)) which comprises more than 100 factors. Or there are consensus on a set of 20 to 30 success factors."*

Ulrich (2013) sought to find a set including less factors but a result as comprehensive as possible, starting with such reports as (Ostrom 2009) and (Agrawal 2001). Ulrich briefly exemplified the methodology using data on Nepal irrigation systems collected in the 'Nepal Irrigation Institutions and Systems' database.[7] It contains 263 cases with 478 variables per case. The cases were coded during 1982 and 1997. He continued, *"For further information see (Tang 1989)."*

3 Using Artificial Intelligence

It's not difficult to search for papers that claim artificial intelligence. There exist lots of such papers that propose a new method for predicting a future. Let's take a look at those already published papers, for example, on wildfire prediction, the title of which includes the term *'artificial intelligence.'*

In their paper, Peng et al. (1999) wrote, *"The application of artificial intelligence in forest and natural resources management started with the development of expert systems (Coulson et al. 1987)."*

[7] NIIS research team (1993) "Nepal irrigation institutions and systems' database coding sheets and forms." Indiana University, Workshop in political theory and policy analysis.

Since then, indeed, not a few approach have claimed that they use the artificial intelligent methodology. Let's name a few. Kourtz (1990) studied forest management in all aspects of Canadian forestry by expert system in his paper entitled *'Artificial intelligence: a new tool for forest management.'* Arrue et al. (2000) proposed a system to detect forest fires by using computer vision, neural networks and expert fuzzy rules, in their paper entitled *'An intelligent system for false alarm reduction in infrared forest-fire detection.'* Actually, the late 1990's was a dawn of artificial intelligence and they dreamed a bright future of establishing a *human-like artificial intelligence*. But nowadays, we don't think the state of the art then had such a bright future.

Now let's see more recent ones. Angayarkkani et al. (2010) proposed a system of detecting forest fires in their paper *'An intelligent system for effective forest fire detection using spatial data.'* The digital image in the forest area were converted from RGB to XYZ color space, and then segmented by employing anisotropic diffusion to identify fire region. Radial basis function neural networks was employed.

The title of already mentioned paper by Sakr et al. (2010) was *'Artificial intelligence for forest fire prediction.'*

But Are Those Intelligence Really Intelligent? In his paper, Castro (2013) wrote, *"Artificial neural networks are a type of artificial intelligence system similar to human brain, having a computational capability which is acquired through learning."*

In fact, many claim their proposed machine to be intelligent. However, are these machines really intelligent like human intelligence as they claim? We cannot be so sure. For example, the paper by Sakr et al. (2010) reads, *"The methods are based on artificial intelligence"* in the abstract, while the term *'artificial intelligence'* never appeared afterwords in the whole text. Instead, he concluded, just *"advanced information communication technologies could be used to improve wildfire prevention and protection."* That's all there is to it.

Yet another such example is the paper by Wendt et al. (2011) entitled *'Input parameter calibration in forest fire spread prediction: Taking the intelligent way.'* The appearance of the term *'intelligent'* is only once, i.e., *"Evolutionary Intelligent System"* without mentioning what is that.

Intelligent Robot Might do Human Dangerous Jobs. Firefighters' jobs are crucially dangerous. The same goes, more or less, for other jobs such as policemen, soldiers, astronauts etc. It will be nice if we can replace them with intelligent robots. As a human-like intelligence is sometimes required for such robots, this could be one of our strong motivations to develop machine intelligence.

A recent article in the New York times[8] reads:

[8] From the article with the headline "Border's new sentinels are robots, penetrating deepest drug routes," in the New York Times on-line on 22 February 2014.

> *Tom Pittman has made a career as a Border Patrol agent here guarding this city's underground drainage system, where the tunnels that carry sewage and storm runoff between the United States and Mexico are also busy drug-smuggling routes. Over the years, he has crawled and slithered past putrid puddles, makeshift latrines and discarded needles left behind by drug users, relying on instincts, mostly, to gauge the risks ahead. It is a dirty and dangerous business, but these days, there is a robot for that.*

As the article went on *"The robots can serve as the first eyes on places considered too risky for humans to explore,"* the aim is not a creation of intelligent robot agent, at least up to this moment. However, there would be a evolutionary race between the smugglers and robots. Which will become more intelligent next time?

Toward More Human-Like Intelligence. Stipanicev (2011) proposed what he calls the 'Intelligent Forest Fire Monitoring System - iForestFire' in his paper whose title is, *'Intelligent forest fire monitoring system - from idea to realization.'* The goal is *"to achieve early wildfire detection, which is traditionally based on human wildfire surveillance, realized by 24 hours observation by human located on selected monitoring spots in Dalmatian forest in Croatia which belongs to countries with high wildfire risk,"* he wrote. *"With its ultimate aim being replacing human with intelligent machine, operators could be located on any location with broadband Internet connection and its user interface to the standard Web browser.*

"The system is an example of 'Future Generation Communication Environment' where all applications and services are focused on users, and 'user' in our case is the natural environment, having the main task – wildfire protection. For such environment behavior the term 'environmental intelligence' was introduced (Stipanicev et al. 2007; Seric et al. 2009)."

Thus, the author claims *"iForestFire is intelligent because it is based on artificial intelligence, computational intelligence and distributed intelligence technologies such as multi-agent based architecture where all agents share the same ontology and speak the same agent communication language."*

4 Concluding Remarks

To cover the plenary talk on 'forest resource maintenance' in general, a literature survey on the topics specifically from IT point of view has made, with focus being *wildfire prediction, preservation of biodiversity in ecosystems, forest cover type prediction, forest resource maintenance* such as *common pool resource.*

In Belarus, we have a huge forest called *'Belovezhskaya Pushcha National Park'* where it is said to be *"the home to 900 plants and 250 animals and birds, including several rare species."* Hence, contributions to a maintenance of this ecological environment is a duty to us IT scientists in Belarus. Further, this issue is going to be worldwide now in this era of global warming. The author wish this small survey paper to play a role of useful pointers for this field.

References

Agrawal, A., et al.: Explaining success on the commons: community forest governance in the Indian Himalaya. World Development 34(1), 149–166 (2006)

Andrews, P.L., et al.: BehavePlus fire modeling system user's guide, v. 2.0. General technical report RMRS-GTR-106WWW, USDA, Forest Service, Rocky Mountain Research Station (2003)

Angayarkkani, K., et al.: An intelligent system for effective forest fire detection using spatial data. International Journal of Computer Science and Information Security 7(1) (2010)

Arrue, B.C.: An intelligent system for false alarm reduction in infrared forest-fire detection. IEEE Intelligent Systems and their Applications 15(3), 64–73 (2000)

Atkinson, P.M., et al.: Introduction: Neural networks in remote sensing. International Journal of Remote Sensing 18, 699–709 (1997)

Benediktsson, J.A., et al.: Neural network approaches versus statistical methods in classification of multisource remote sensing data. IEEE Transaction on Geoscience and Remote Sensing 28, 540–552 (1990)

Blackard, J.A.: Comparison of neural networks and discriminant analysis in predicting forest cover types. Ph.D. dissertation, Department of Forest Sciences, Colorado State University (1998)

Blackard, J.A.: Comparative accuracies of artificial neural networks and discriminant analysis in predicting forest cover types from cartographic variables. Computers and Electronics in Agriculture 24, 131–151 (1999)

Braitenberg, V., et al.: Cortex: statistics and geometry of neuronal connectivity. Springer (1997)

Campbell, W.J., et al.: Automatic labeling and characterization of objects using artificial neural networks. Telematic and Informatics 6, 259–271 (1989)

Castro, R.V.O.: Individual growth model for eucalyptus stands in Brazil using artificial neural network. In: International Scholarly Research Network, ISRN Forestry Volume. Hindawi Publishing Corporation (2013)

Chou, Y.H.: Spatial autocorrelation and weighting functions in the distribution of wildland fires. International Journal Wildland Fire 2(4), 169–176 (1992)

Chou, Y.H., et al.: Mapping probability of fire occurrence in San Jacinto Mountains, California, USA. Environment Management 17(1), 129–140 (1993)

Coulson, R.N., et al.: Artificial intelligence and natural resource management. Science 237, 26–67 (1987)

Chuvieco, E., et al.: Integrated fire risk mapping. In: Remote Sensing of Large Wildfires in the European Mediterranean Basin. Springer (1999)

Diamantopoulou, M.J.: Artificial neural networks as an alternative tool in pine bark volume estimation. Computers and Electronics in Agriculture 48(3), 235–244 (2005)

Downey, I.D., et al.: A performance comparison of Landsat thematic mapper land cover classification based on neural network techniques and traditional maximum likelihood algorithms and minimum distance algorithms. In: Proceedings of the Annual Conference of the Remote Sensing Society, pp. 518–528 (1992)

Estrada, J., et al.: Atles dels ocells nidificants de Catalunya 1999–2002. In: Institut Catal d'Ornitologia (ICO)/Lynx Edicions, Barcelona, España (2004)

Fernandez, C.A.: Towards greater accuracy in individual-tree mortality regression. Ph.D dissertation, Michigan Technological University (2008)

Frey, U.J., et al.: Using artificial neural networks for the analysis of social-ecological systems. Ecology and Society 18(2) (2013)

Garson, G.D.: Interpreting neural-network connection weights. AI Expert Archive 6(4), 46–51 (1991)
Gevrey, M., et al.: Review and comparison of methods to study the contribution of variables in artificial neural network models. Ecological Modelling 160(3), 249–264 (2003)
Gil-Tena, A., et al.: Modeling bird species richness with neural networks for forest landscape management in NE Spain. Forest Systems 19(SI), 113–125 (2010)
Gimblett, R.H., et al.: Neural network architectures for monitoring and simulating changes in forest resources management. AI Applications 9, 103–123 (1995)
Gong, P., et al.: Mapping ecological land systems and classification uncertainties from digital elevation and forest-cover data using neural network. Photogrammetric Engineering and Remote Sensing 62, 1249–1260 (1996)
Guan, B.T., et al.: Using a parallel distributed processing system to model individual tree mortality. Forest Science 37, 871–885 (1991a)
Guan, B.T., et al.: Modeling red pine tree survival with an artificial neural network. Forest Science 37, 1429–1440 (1991b)
Hasenauer, H., et al.: Estimating tree mortality of Norway spruce stands with neural networks. Advances in Environmental Research 5(4), 405–414 (2001)
Hess, C.: Mapping the new commons. Governing shared resources: connecting local experience to global challenges. In: Proceedings of the Twelfth Biennial Conference of the International Association for the Study of Commons (2008)[9]
Kalabokidis, K.D., et al.: Geographic multivariate analysis of spatial fire occurrence. Geotechnical Scientific Issues 11(1), 37–47 (2000) (in Greek language)
Kalabokidis, K.D., et al.: Multivariate analysis of landscape wildfire dynamics in a Mediterranean ecosystem of Greece. Area 39(3), 392–402 (2007)
Kourtz, P.: Artificial intelligence: A new tool for forest management. Canadian Journal Forest Research 20, 428–437 (1990)
Leite, H.G.: Estimation of inside-bark diameter and heartwood diameter for Tectona Grandis Linn trees using artificial neural networks. European Journal of Forest Research 130(2), 263–269 (2011)
Lek, S., et al.: Application of neural networks to Modeling nonlinear relation-ships in ecology. Ecological Model. 90, 39–52 (1996)
McRoberts, R.E., et al.: Enhancing the Scientific process with artificial intelligence: Forest science applications. AI Applications 5, 5–26 (1991)
Meinzen-Dick, R.: Beyond panaceas in water institutions. Proceedings of the National Academy of Sciences of the United States of America 104(39), 15200–15205 (2007)
Merkl, D., et al.: Using neural networks to predict individual tree mortality. In: Proceedings of International Conference on Engineering Applications of Neural Networks, pp. 10–12 (1999)
Meyer, B.: Forest cover type prediction. Course ECE 539 Term Project, Wisconsin University (2001)
Ostrom, E.: A general framework for analyzing sustainability of social-ecological systems. Science 325, 419–422 (2009)
Paruelo, J.M.: Prediction of functional characteristics of ecosystems: A comparison of artificial neural networks and regression models. Ecological Modeling 98(2-3), 173–186 (1997)

[9] It was difficult to find the book of this volume any more, if not at all. So information of 'pp' cannot be shown here. The paper is available at `http://works.bepress.com/charlotte_hess/6`.

Pattie, D.C., et al.: Forecasting wilderness recreation use: Neural network versus regression. AI Application 10(1), 67–74 (1996)

Peddle, D.R., et al.: Multisource image classification II: An empirical comparison of evidential reasoning, linear discriminant analysis, and maximum likelihood algorithms for alpine land cover classification. Canadian Journal Remote Sensing 20, 397–408 (1994)

Peng, C., et al.: Recent applications of artificial neural networks in forest resource management: An overview. In: Environmental Decision Support Systems and Artificial Intelligence, pp. 15–22 (1999)

Pyne, S.J., et al.: Introduction to wildland fire, 2nd edn. Wiley (1996)

Safi, Y., et al.: Prediction of forest fires using artificial neural networks. Applied Mathematical Sciences 7(6), 271–286 (2013)

Sakr, G.E., et al.: Artificial intelligence for forest fire prediction. In: Proceeding of International Conference on Advanced Intelligent Mechatronics, pp. 1311–1316 (2010)

Sekercioglu, C.H.: Increasing awareness of avian ecological function. Trends of Ecological Evolution 21, 464–471 (2006)

Seric, L., et al.: Observer network and forest fire detection. Information Fusion 12, 160–175 (2011)

Stipanicev, D.: Intelligent forest fire monitoring system - from idea to realization. In: Annual 2010/2011 of the Croatian Academy of Engineering (2011)

Tang, S.Y.: Institutions and collective action in irrigation systems. Dissertation. Indiana University (1989)

Ulrich, J.F., et al.: Using artificial neural networks for the analysis of social-ecological systems. Ecology and Society 18(2), 42–52 (2013)

Vasconcelos, M.J.P., et al.: Spatial prediction of fire ignition probabilities: Comparing logistic regression and neural networks. Photogramm Engineering Remote Sensors 67(1), 73–81 (2001)

Vasilakosi, C., et al.: Integrating new methods and tools in fire danger rating. International Journal of Wildland Fire 16(3), 306–316 (2007)

Vasilakosi, C., et al.: Identifying wildland fire ignition factors through sensitivity analysis of a neural network. Natural Hazards 50(1), 12–43 (2009)

Vega-Garcia, C., et al.: Applying neural network technology to human caused wildfire occurrence prediction. Artificial Intelligence Application 10(3), 9–18 (1996)

Weingartner, M., et al.: Improving tree mortality predictions of Norway Spruce Stands with neural networks. In: Proceedings of Symposium on Integration in Environmental Information Systems (2000)

Wendt, K., et al.: Input parameter calibration in forest fire spread prediction: Taking the intelligent way. In: Proceedings of the International Joint Conference on Artificial Intelligence, pp. 2862–2863 (2011)

Yoon, S.-H.: An intelligent automatic early detection system of forest fire smoke signatures using Gaussian mixture model. Journal Information Process System 9(4), 621–632 (2013)