Satellite inventory of forest resources (*Righa Dahra* - Algeria): Intelligent modeling

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Abstract:*The southeastern region of Algeria (forest of Righa Dahra) is subject to natural and anthropogenic degradation factors, the squeals of which are visible in its floristic composition. This region is characterized by its temperate climate. The vegetation cover consists mainly of pines. In recent years and as a result of climate change and human action, changes in the ecosystem are noticed. A redistribution of the plant species covered by the region is noted. In this study, we try to identify and list these changes. Satellite mapping is being developed. This allowed us to identify the species of trees that inhabit the region and their distribution. We present the study area, its characteristics and environmental and its current evolution in a first part. In a second part, the characteristics of the satellite data are discussed by proposing symbolic fuzzy inference treatments. One of the main problems is that the plantation discrimination signals (a characteristic fall in the vegetation index) may be confused with indices. Viewing this uncertainty and imprecision we propose an analysis technique based on the principles of artificial intelligence. A fuzzy system is built. The input variables are exposure, altitude. A database is based on the recorded data satellite mapping results. The output variable will express the corresponding plant species. The result obtained is compared with the statistical data of the cadastres available and with the field surveys carried out by the author. This model will make it possible to predict the evolution of the forest cover from the climatic changes carried out.*

Key Words: *Satellite mapping, forestry, data analysis, fuzzy logic.*

1. INTRODUCTION:

In recent years there has been a significant and rapid development of the use of remote sensing which can be considered a valuable source in forest mapping and monitoring. This technique makes it possible to offer a fast and economical tool available to forest managers for the understanding and characterization of the forest in terms of area, location and even species even on individual tree levels. At the beginning, the analysis of the satellite data was interpreted manually, but nowadays new methods are used [1]. The importance of forests and the benefits they provide locally and globally have been widely documented [2]. In forestry, the data satellite mapping has been widely used for resource management, planning, monitoring, prediction...etc. However, the uses of the satellite image sometimes lack reliability when we are dealing with homogeneous species [3]. But there are several difficulties in assessing the level of diversity in plant communities from field data. Today, satellite remote sensing is one of the most cost-effective and widely used approaches to identifying biodiversity and predicting changes in species composition. This technique allows us to cover large areas and monitor it's temporally evolution [4]. Also, inventorying species over a large region is complicated by the fact that field biologists cannot inspect every individual organism in the region while accounting for changes in species composition over time [5]. Additionally, ground surveys are time consuming and costly. Moreover, in many biodiversity-rich locations, field survey can be risky due to challenging environmental and socio-political conditions [6]. In our study, we will try to define the trends of changes in the vegetation cover through the use of the satellite imaging. Also, evaluate the potential of data satellite mapping in order to detect forest cuts preceding a modification by species. The study area located at the southeastern region of Algeria (forest of Righa Dahra) Figure 1. Viewing the imprecise nature of the data and their complexity, we propose a fuzzy logic system in data analysis. Fuzzy logic deals with uncertainty and imprecision in a complex system by imitating human reasoning, its application in this area will be perfectly adequate. The fuzzy system constructed according to inputs, database and output. Each input or output variable is fuzzyfied by conversion the numerical data to the linguistic data. The established database refers to the real measured values on the basis of (If ... Then). Once the program has been done, it will be possible to randomly assign variables to the input of the system to instantly read the output result as the corresponding forest species. A comparison of the results obtained with the other data sources (statistics, Google Earth imagery, cadastral survey and field observation) will allow evaluating the contribution of this satellite imagery and the quality of the official data. The main interest will remain the prediction of the evolution of our forest system from the variables in question and therefore the prevention by the human intervention by acting on the controllable parameters.

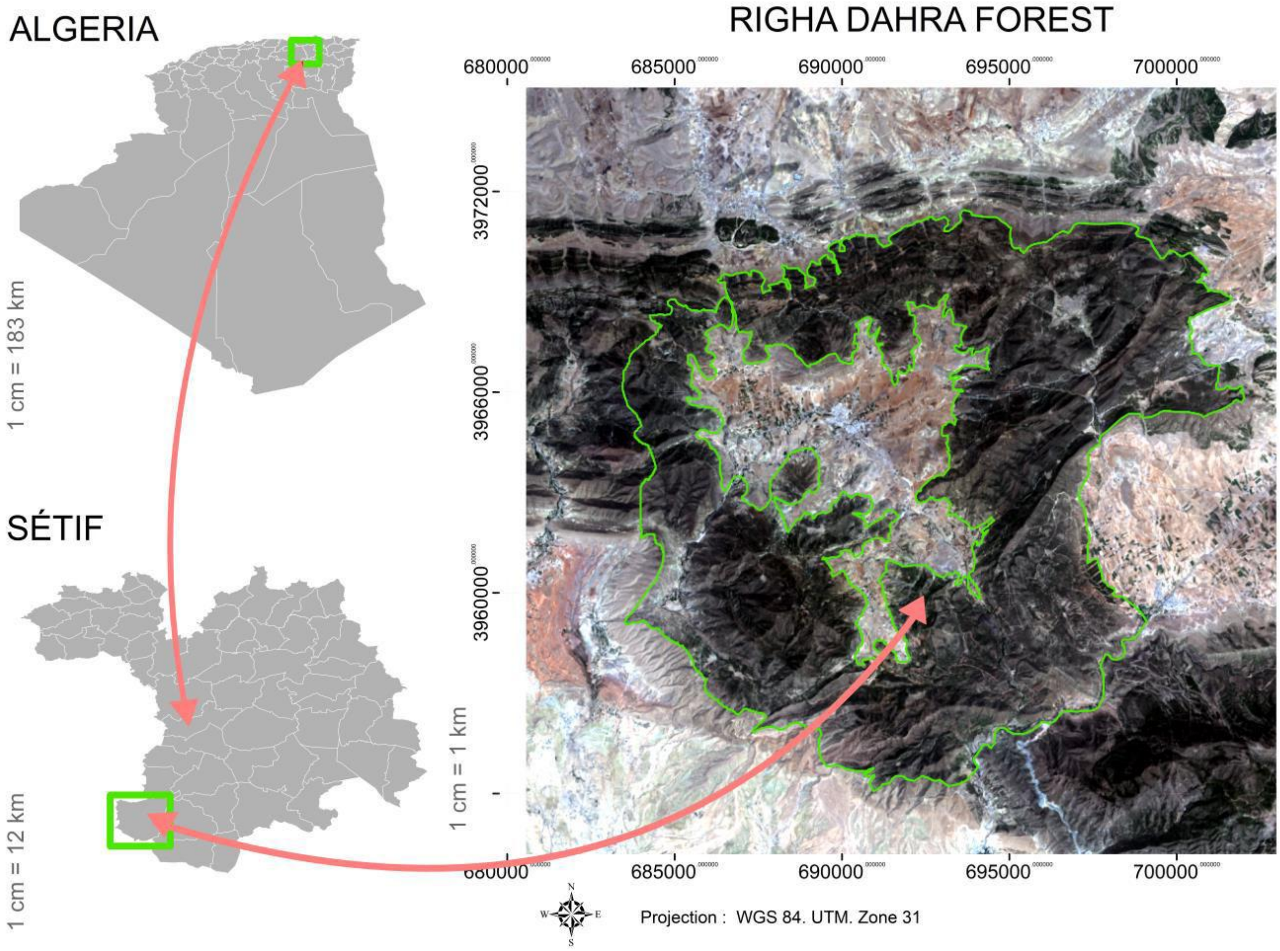

Figure 1. Study area location

2. METHOD

The establishment of a forest inventory is required in the acquisition of specific tree species information. The use of remote sensing data remains difficult, although some recent advances have been made [7]. The observations recorded during the sampling, in addition to a range of map data, these are: Vegetation from supervised classification, diachronic biomass map, valance subdivision maps provided by the Conservation of Setif Forests (CENATUS CONSULT), and altitudes maps produced the basis of the digital model of the land downloaded from the US site USGS. To facilitate the analysis the five maps of this area were introduced into the ARCGIS 10.1 GIS software and processed by the intersection tool to produce a single map containing all the information contained in the five input cards. The map obtained consists of 84338 polygons each of which contains a detailed description including: dominant species, biomass dynamics, altitudinal class, exposure and area (Table 1). It should be noted that it is very difficult to precisely present spatial distribution and redistributions. Available statistical data provide data at the regional level, but updates vary by region. Models for analyzing prediction data with high accuracy were used in particular in the classification and modeling of such as SVM and artificial neural networks (ANN) [8],[9]. In this context, our work attempts to present a predictive model with fuzzy logic. The built system consists of four input variables, a rule base and an output. What characterizes these variables is their vagueness and uncertainty. We consider them as fuzzy variables. For this, these variables must be fuzzyfied. The basis of the rules is based on the recorded values representing the 84338 polygons. First, we give a general overview of the basic principles of fuzzy inference that allow us to understand its application.

Note. It should be noted that the values presented in the table represent an image on the set of measurements carried out by satellite image and processed by ARCGIS 10.1 GIS software and which are of the order of 84338 polygons.

Table 1. Distribution of species on study area

Dominant species	Biomass	Altitude (m)	Exposure	Area (ha)
Cedar of Atlas	Black	1300-1400	North	0.0101
Cedar of Atlas	Green	1500-1600	North-East	0.0772
Cedar of Atlas	Yellow	1500-1600	North	0.1955
Cedar of Atlas	Red	1500-1600	North	0.1564
Cedar of Atlas	White	1500-1600	South	0.0530

Cedar of Atlas	Cyan	1300_1400	East	0.0469
Cedar of Atlas	Magenta	1200-1300	South-East	0.1787
Juniper	Black	1100-1200	North	0.0399
Juniper	Red	1300-1400	East	0.0532
Juniper	Green	1100-1200	North-West	0.1190
Aleppo pine	Green	1100-1200	East	0.0850
Aleppo pine	Cyan	1000-1100	West	0.1544
Aleppo pine	Yellow	1500-1600	South	0.1544
Aleppo pine	White	1500-1600	West	0.2304
Aleppo pine	Red	1100-1200	North-West	0.4359
Aleppo pine	Magenta	1100-1200	North-East	0.0772
Aleppo pine	Blue	1100-1200	North	0.0553
Aleppo pine	Black	1100-1200	South-West	0.2298
Holm oak	Red	1600-1700	North-East	0.1438
Holm oak	Green	1400-1500	North	0.2247
Holm oak	Yellow	1500-1600	North-West	0.5322
Holm oak	Cyan	1600-1700	North-East	0.2024
Holm oak	White	1400-1500	North	0.3969
Holm oak	Black	1100-1200	South-West	0.3325
Wasteland	Green	1200-1300	North-West	0.0216
Wasteland	Blue	1200-1300	West	0.0401
Wasteland	Black	1100-1200	North	0.1911
Wasteland	Cyan	1100-1200	North	0.0846
Wasteland	Red	1500-1600	West	0.0131
Wasteland	Yellow	1400-1500	East	0.0560

2.1. FUZZY INFERENCE SYSTEM

Fuzzy logic has developed greatly since the theory of Lotfi Zadeh (1965) [10]. The generalization of its application has concerned different areas. As a sub-domain of intelligent systems it is considered as an extension of set theory. Its principles imitate human reasoning and treat symbolic data in linguistic terms. This gives this technique the ability to solve many problems, especially in an environment where the data may be complex or insufficient. Fuzzy inference systems (FIS) are powerful tools for simulating nonlinear behaviors using fuzzy linguistic rules [11].

2.2. THE PROPOSED FUZZY INFERENCE SYSTEM

The proposed system has four inputs and one output (Figure 2). The Matlab 7.11.0 (R2010b) and the Mamdani's method mini-max software were used.

[System]
Name='Dominant Species'
Type='mamdani'
Version=2.0
NumInputs=4
NumOutputs=1
NumRules=0
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

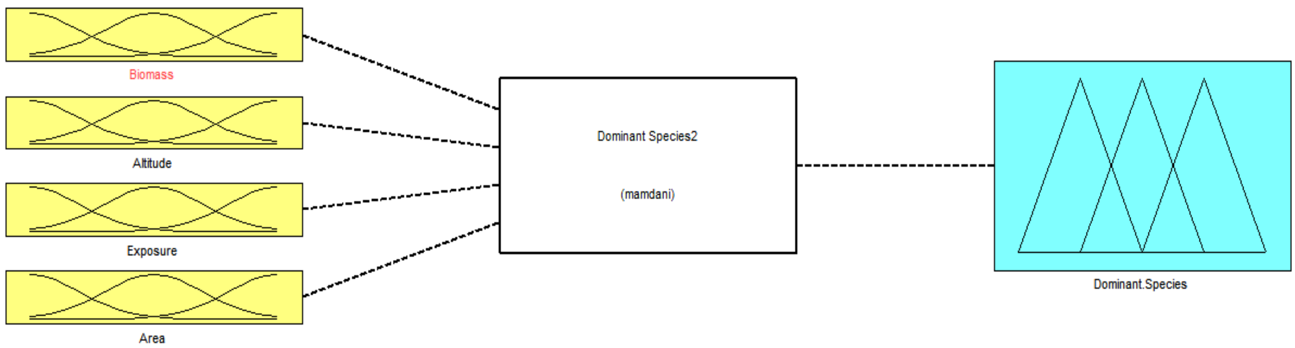

Figure 2. Structural scheme of the system

2.3. FUZZYFICATION OF INPUTS AND OUTPUT

The fuzzyfication operation consists of converting the recorded numeric variables to linguistic variables of type (low, medium or high). Each input or output variable must be expressed by a specific membership function and a degree of membership is assigned to the corresponding function. Human expertise is paramount at this level. *Fuzzyfication of 'Biomass variable'* What characterizes the "biomass" variable, the clear distinction between the different colors is far from clear. Between two neighboring colors there exist an infinity of levels of sub-colors. Then it is necessary to consider them as fuzzy variables. Each color is defined by a membership function and the degree of belonging to this set will express the degree of truth. Each color is located in an electromagnetic wavelength range (Figure 3). We assign an interval to each color with overlapping areas considered fuzzy areas.

- Black [0 nm]
- White [430-650 nm]
- Magenta [430-480 nm]
- Blue [450-500 nm]
- Green [475-550 nm]
- Yellow [525-600 nm]
- Red [590-650 nm]

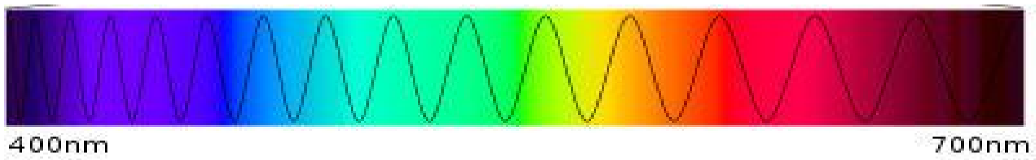

Figure 3. Electromagnetic spectrum

[Input1]
Name='Biomass'
Range=[400 700]
NumMFs=6
MF1='Green':'trimf',[475 513 550]
MF2='Blue':'trimf',[450 475 500]
MF3='Yellow':'trimf',[2 3 4]
MF4='Magenta':'trimf',[430 455 480]
MF5='White':'trimf',[430 540 650]
MF6='Red':'trimf',[580 615 650]

Fuzzyfication of 'Altitude class variable'

In our study area, the altitude varies from 1100 m to 1700 m. We take a scale that goes from 1000 m to 2000 m. This scale is fuzzyfied in three fuzzy intervals.

- Low altitude [1000-1400 m]
- Average altitude [1300-1700 m]
- High altitude [1600-2000 m]

[Input2]
Name='Altitude'
Range=[1000 2000]
NumMFs=3
MF1='LowAkttitude':'trimf',[1000 1200 1400]
MF2='Average.Altitude':'trimf',[1300 1500 1700]
MF3='High.Altitude':'trimf',[1600 1800 2000]

Fuzzyfication of 'Exposure variable'

The orientation towards the cardinal points is also characterized by their vagueness. Between the two neighboring senses there is no sharp limit. To deal with this uncertainty, we consider them as fuzzy variables. We assign numerical values to each direction of orientation.

- North [0 – 2]
- East [1 – 3]
- South [2 – 4]
- West [3 – 5]

The fuzzy representation will encompass values in terms of degree of belonging to each orientation (north-east, north-west, south-east or south-west) between [1 and 0].

[Input3]
Name='Exposure'
Range=[0 5]
NumMFs=4
MF1='North':'trimf',[0 1 2]
MF2='East':'trimf',[1 2 3]
MF3='South':'trimf',[2 3 4]
MF4='West':'trimf',[3 4 5]

Fuzzyfication of 'Area variable'

The studied surfaces vary from 0.0101 to 0.4359 ha. It is not possible to decide on the exact evaluation of the surface. From what value can we say that it is a large or a small area? To solve them, we consider them as fuzzy variables. We assign linguistic values to each surface value from 0.01 to 0.45 ha.

- Small area [0.01 - 0.2 ha]
- Average surface area [0.15 - 0. 35 ha]
- Large surface area [0.3 - 0.5 ha]

[Input4]
Name='Area'
Range=[0.01 0.5]
NumMFs=3
MF1='Large':'trimf',[0.3 0.4 0.5]
MF2='Small.Area':'trimf',[0.01 0.1 0.2]
MF3='Average':'trimf',[0.15 0.25 0.35]

Fuzzyfication of 'Dominant species variable'as output

Each surface is populated by a dominant species of trees. However, this does not exclude coexistence between different species but with different degrees. The specification of each zone in an exact way is very difficult if not impossible. The distribution of species on an area is therefore considered fuzzy. A numerical value is assigned to each dominant species. The representation of the other species is expressed by a degree of belonging on the membership function.

- Wasteland [0 – 2]
- Cedar of Atlas [1 – 3]
- Juniper [2 – 4]
- Aleppo pine [3 – 5]
- Holm oak [4 – 6]

Each value obtained at the output of the system will reflect the degree of settlement by the corresponding species of the area in question (Figure 4).

[Output1]
Name='Dominant.Species'
Range=[0 6]
NumMFs=5
MF1='Wasteland':'trimf',[0 1 2]
MF2='Cedar':'trimf',[1 2 3]
MF3='Juniper':'trimf',[2 3 4]
MF4='Pine':'trimf',[3 4 5]
MF5='Holm.Oak':'trimf',[4 5 6]

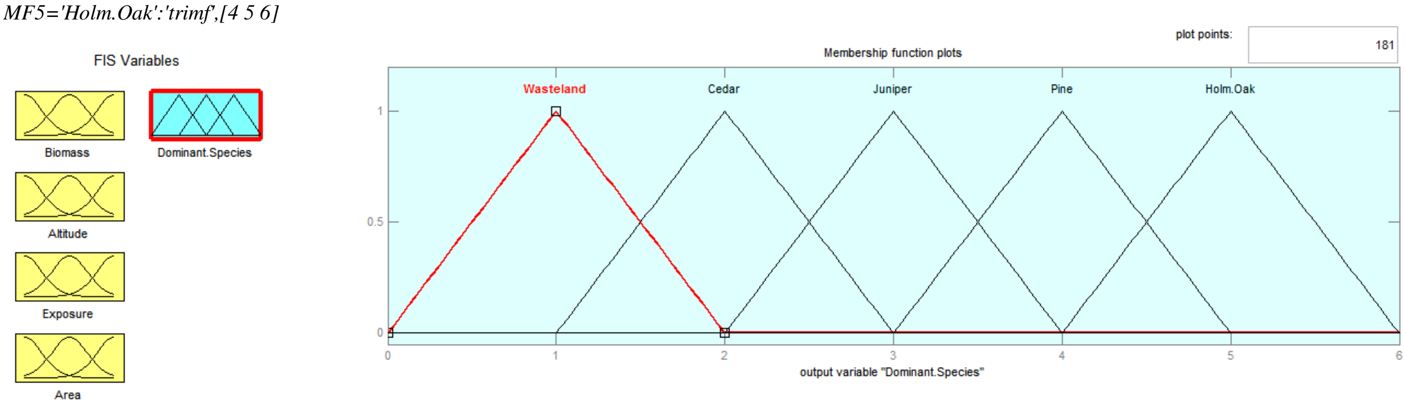

Figure 4. Output fuzzyfication

3. BASIS OF RULES:

The result at the system output is determined by fuzzy membership functions that are defined for each input and output variable. Fuzzy sets describe the nature of each variable. For input variables they express (biomass, altitude class, exposure and area). The output variable expresses the corresponding dominant species). The general rule of the system in linguistic terms after fuzzyfication is of the form:

IF X_1 is X_1 (1) AND X_2 is X_2 (2) AND ... Xn is Xn (n) THAN Y_1 is Y_1 (1)

At this stage, it is a matter of matching the two input and output spaces. The establishment of this base refers to the values recorded.

4. DISCUSSION:

Similar samples tend to have similar spectral values, which may influence the outcome of supervised classification and the establishment of accurate maps [12-15]. We estimate that these results provide a basis for mapping forest tree species over a wide spatial range. The spatial and temporal variability of the phenology of tree species on a regional or national scale should also be considered. These results are in line with those already obtained in other studies [16]. In our review of the literature, we noted that a land cover map can be used to assess trends in land cover, study managed and natural ecosystems, and facilitate regional and global sustainability and climate change modeling [17]. What has also been noted is that mosaics of cultivated land and natural vegetation were the less reliable ground cover classes in the assessment of land cover maps [18]. The satellite mapping of the study area identified (84338 polygons) at different altitudes, exposure and dynamics. The heaviness, complexity and inadequacies of the statistical models used to date have led us to propose this model based on the principles of artificial intelligence including the principles of fuzzy inference. These shortcomings are largely offset by our model. The proposed model remains extensible to other variables that may have an effect and are not taken into account in our study. An example of an application is shown in figure 5. It is enough to randomly assign variables to the input of the system (Biomass, altitude, exposure and the surface concerned) to instantly read the result at the exit (the species of Tree that populates this area with its degree of settlement).

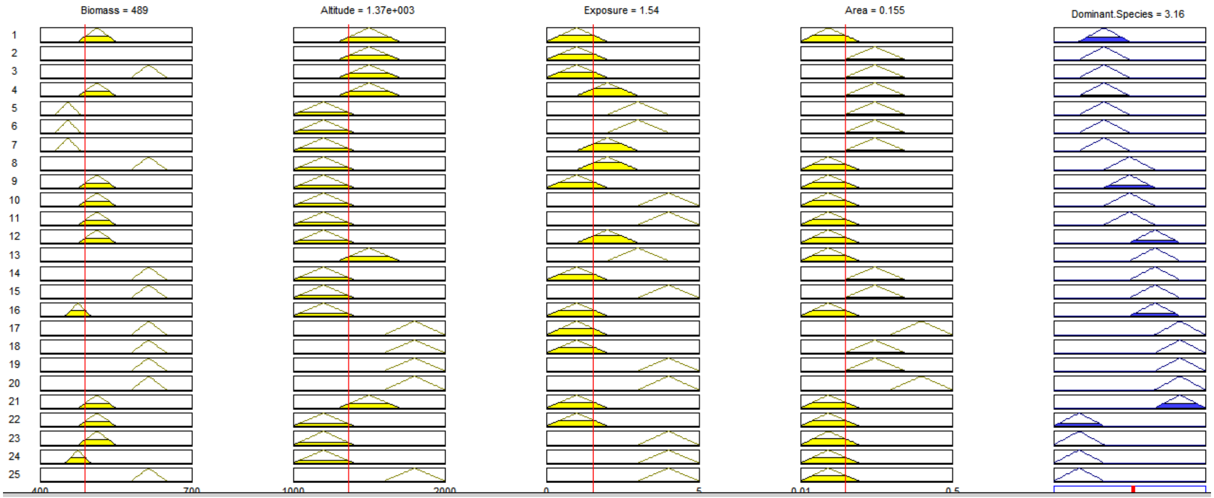

Figure 5. Application example

5. CONCLUSION:

The observed difficulty of a native plantation based solely on the low spatial resolution vegetation index is compensated for by the fuzzy reasoning that takes into account these uncertainties. Of the results obtained, the use of satellite imagery is particularly indicated for forest dynamics studies covering large areas and lacking accurate or updated mapping. From our results, it is clear that remote sensing has the capacity to cover wide areas with precise species differentiation. The proposed data analysis model is designed to address data inadequacies and inaccuracies. The fuzzy model makes it possible to take these uncertainties into account. This model adapted to the remote sensing of forest species opens the way to a more precise mapping. This study can be considered as a first step towards detailed and accurate species maps for forest managers. These results will also be of great help to environmentalists. The development of this model, once refined with field observations, will allow a spatial estimation of the temporal evolution of the stand of the study area with the different tree species. The results of this study allow the use of this approach to reduce the cost of forest inventories, which is a useful tool for mapping forest variables.

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