Environment and Ecology 42 (1A) :220—228, January—March 2024
Article DOI: https://doi.org/10.60151/envec/OTWB2845
ISSN 0970-0420

Study of the Impact of *Prosopis juliflora* on Soil Moisture and Humidity

Jayaparvathy R., Daphin Lilda S., Sheeba Angel A., Priyanka B. N.

Received 18 July 2023, Accepted 11 December 2023, Published on 6 March 2024

ABSTRACT

This paper aims to present the impact of invasive alien species on soil moisture over the other native species. *Prosopis juliflora* is a majestic, non-native species that grows abundantly over the arid and semi-arid regions especially over the southern part of Indian sub-continent. These non-native, invasive species are modifying the native bio diversity, natural irrigation and local ecosystem by alternating the soil fertility measures such as soil moisture and relative humidity of the soil. In this study, the impact of the non-native species and native species on soil moisture and atmospheric humidity are considered for the analysis of the effect of the *Prosopis juliflora* and the variation in the conditions are visualized using the k- means clustering technique. The soil moisture at a depth of 2 meters and 1 meter and the air humidity is compared for regions in the presence of the nonnative species and in the absence of nonnative species. The results indicate that the non-native species has a negative impact on the cultivating land, spoiling its fertility measures by reducing its soil moisture content. The study provides evidence for the need to take necessary actions to eradicate species such as *Prosopis juliflora* and in turn to protect the native vegetation and develop management strategies to control the spread of the species.

Keywords *Prosopis juliflora*, Soil moisture, Humidity, Clustering.

Jayaparvathy R.[1], Daphin Lilda S.[2]*, Sheeba Angel A.[3], Priyanka B. N.[4]

[1]Professor

[1,2,3,4]Dept of Electrical and Electronics Engineering
Sri Sivasubramaniya Nadar College of Engineering, Chennai 603110, Tamil Nadu, India

Email: daphinlilda@gmail.com

*Corresponding author

INTRODUCTION

Invasive alien species govern the native vegetation and are a persistent peril to the native ecosystem and its biodiversity. These non-native species seem to provide the benefits in the early stage and create a negative impact on the soil fertility measures later on (Hussain *et al.* 2020, Hussain *et al.* 2021). They alter the structure and flow of the native ecosystem by influencing the natural resources with high economic and other ecological values (Patnaik *et al.* 2017, Ukande *et al.* 2019, de Brito Damasceno *et al.* 2020). In India, *Prosopis juliflora* was introduced by the British to cultivate the seeds of the plant in arid tracts of South India in 1876. The seeds were delivered from Jamaica and cultivated in 1877. Later in the early 1960s, the species was considered as a savior to overcome the food shortage and supplied as a fuel wood for farmers, fodder and grazer for livestock and used as a fence for invading animals (Walter and Armstrong 2014). Today the species is dangerous to the native indigenous species as it depletes the underground water and soil moisture contents. This study aims to present the negative impact created by the *P. juliflora* when compared to the native species. Soil moisture is the ultimate factor for the plants root water absorption, seed germination and crop production. It plays a major role in influencing the soil nutrients and soil fertility. Adverse effects of *P. juliflora* on the soil moisture content and native ecosystem have been under investigation including the wetlands and flora. So, it is vital to study its ground water absorbing properties under the soil root zone. Machine learning techniques are the prominent and evolving method for soil moisture forecasting and smart irrigation applications (Togneri *et al.* 2022). ML is the data driven approach widely used in the accessible soil sensing and field communication technologies. So, it is more suitable to employ the ML techniques to classify and address this issue of soil moisture content on the root zone. In classifying the nature and properties of the two species, it would be more appropriate to use the collection of data such as soil moisture content, relative humidity and soil temperature.

Many machine learning algorithms have been used in the prediction of the environmental conditions for various agriculture purposes. Malik *et al.* (2021), predicted the crop yield from data which consists of factors such as temperature, humidity, pH, rainfall and crop name. The crop yield prediction has been done using k- Nearest Neighbor algorithm, Naïve Bayes algorithm and Decision Trees classifier. Junior *et al.* (2022) used the supervised learning classification methods to predict the class of data samples from these categories. The fog filter compresses the identified categories using two data compression techniques, run-length encoding (RLE) and the Huffman encoding, preserving the data time series nature. Abioye *et al.* (2022) discuss the integration of different machine learning models that can provide optimal irrigation decision management has been studied. Supervised learning algorithms for both classification and regression are integrated and appropriate model is selected for the data set in order to achieve high prediction accuracy. Sami *et al*. (2022) used the Smart Irrigation System (SIS) containing several physical sensors, which transmit temperature, humidity, and soil moisture data to calculate the transpiration in a particular field. The proposed deep learning-based neural sensor predicts the real-time values with high accuracy, especially the temperature values. The humidity and moisture values are also in an acceptable range.

The PR2 Profile Probe (Delta-T Devices) is a multi-sensor frequency domain reflectometry probe designed to measure the Volumetric Water Content (VWC) at a particular place up to a depth of 1 meter. In order to provide accurate performance without the influence of salinity or temperature the PR2 probe is built around patented sensing technology. The PR2 probe has been used in various works. Di Matteo *et al.* (2018) estimated the VWC is for the evaluation of shallow landslides. Using the PR2 probe the testing was carried out in two sandy soils in Italy. The use of PR2 probe in the early monitoring system provided a more reliable forecast thereby enhancing the warning alarm system. Dhakal *et al.* (2019) carried out an experiment in the Pullman Clay-Loam Soil of Southern High Plains. In this work new calibration coefficient was introduced and in order to achieve better precision and accuracy and reduce the overall root mean square error (RMSE). Ortenzi *et al.* (2022), proposed the specific calibration equation for the proper use of PR2 probe on different soil types. Work was to understand the different EM responses carried out on the Tiber River basin sands. It was observed that as the iron oxide increased, the calibration line slope increased. Kaman and Ozbek (2021) proposed the indirect measurement of the soil water content was carried out using the PR2 probe. The coefficient of determination (R^2) value is the important parameter in determining the linear relationship between the indirect and other direct measurement techniques. It was observed by this method the R^2 values varied between 0.7947 and 0.9305 and accurate measurement of soil water content was concluded in this work. The humidity and the soil temperature along with the soil moisture content also make a great impact in the crop yield.

This study provides an analysis of the impact of *P. juliflora* and the native species on soil moisture, relative humidity and air temperature. These parameters were collected on the root zone of *P. juliflora* and native species using the soil moisture sensor (PR2) probe, the humidity sensor (RHT2nl-02) and other required apparatus . The data is collected under various climatic conditions such as sunny, partially sunny or cloudy and rainy. The influence of these parameters was studied using the K-mean algorithm. The method comprises of, data normalization, dimensionality reduction (principal component analysis), data augmentation using SMOTE technique, evaluation of the performance using the various machine learning technique. The paper is organized as follows: Section 2 describes the materials and methods used for the data collection and classification. Section 4 briefs about the results and discussions based on the comparison of the soil moisture measures of non- native species followed by its comparison with the native species. Finally, the conclusion and future work are provided in Section 4.

MATERIALS AND METHODS

Soil parameters in the presence and absence of non-native species (*P. juliflora*) are collected. After collecting and processing the data, parameters as a quantitative measure, then, k-means clustering technique is applied to the data for a prescribed number of groups.

Site selection

For this study, data were taken at Chennai and Coimbatore, Tamil Nadu. The setup used for the data collection is given in Fig.1. In Chennai data were collected at six different places, three area fully covered by the other non-native species (*P. juliflora*), one region under a Neem tree (*Azadirachta indica)*, one common region between the *P. juliflora* and *A. indica* and one open ground between two *P. juliflora.* The data collection sites location at Chennai are shown in Fig. 2. The latitude and longitude of the data collected regions in Chennai are as follows.

12.749698, 80.198410 *P. juliflora* 1
12.750556, 80.197348 Common ground

Fig. 1. Setup for Data Collection.

12.750861, 80.198065 *P. julifora* 2
12.750787, 80.197164 Neem tree
12.749935, 80.198525 *P. juliflora* 3
12.748954, 80.195623 Open ground

In Coimbatore, data were collected at four places including two under *P. juliflora* trees, one under a tamarind (*Tamarindus indica*) tree, and one in open space. There were less than 500 meters between each tree. The data collection sites location at Coimbatore are shown in Fig.3. The latitude and longitude of the data collected regions in Coimbatore are as follows

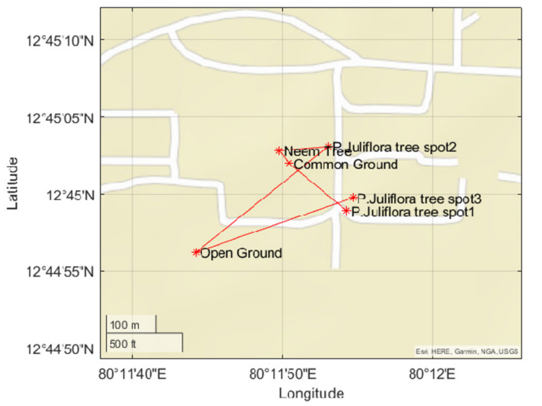

Fig. 2. Latitude and longitude of the data collected regions at Chennai.

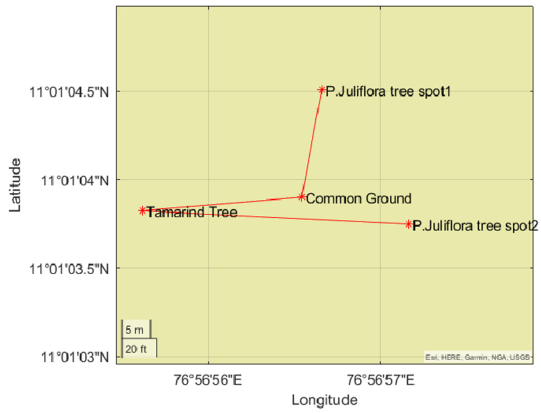

Fig. 3. Latitude and longitude of the data collected regions at Coimbatore.

11.017919,76.949072 *P.juliflora* tree spot1
11.017750, 76.949040 Common ground
11.017729, 76.948783 Tamarind tree
11.017708, 76.949212 *P.juliflora* tree spot 2

Data collection

Experimental setup

The experimental setup for the work carried out is given in Fig. 4. The major components of the experiment are as follows : i) Data logger (GP2), ii) Profile Probe (PR2), iii) HH2 Moisture meter, iv) Access tubes, v) Relative humidity/ Air temperature sensor (RHT2nl-02).

Data logger (GP2)

The data logger used in this experiment is GP2. The GP2 is a 12-channel data logger which is easy to use, rugged and versatile. Most sensor inputs such as voltage, current, resistance, frequency and digital state inputs can be logged using the GP2 logger. The user control over the readings is given by the Delta *LINK* software. Users can add their customized sensor types form the sensor library. 4 MB of FLASH memory enable storage of 2.5 million readings (typical). Data can be collected in a laptop locally via USB/RS232 or remotely using the cellular modem options. The GP2 has 6 alkaline AA internal batteries.

PR2 profile probe

The PR2 probe is a flexible device to measure the soil moisture content up to a depth of 1 meter. The PR2 probes are portable and can be easily inserted and removed using the access tube. In order to provide best performance, the PR2 probe is built around patented sensing technology. The PR2 profile probe is available in two sizes, to measure to a depth of 40 cm or 100 cm. The PR2/4 measures the WVC up to a

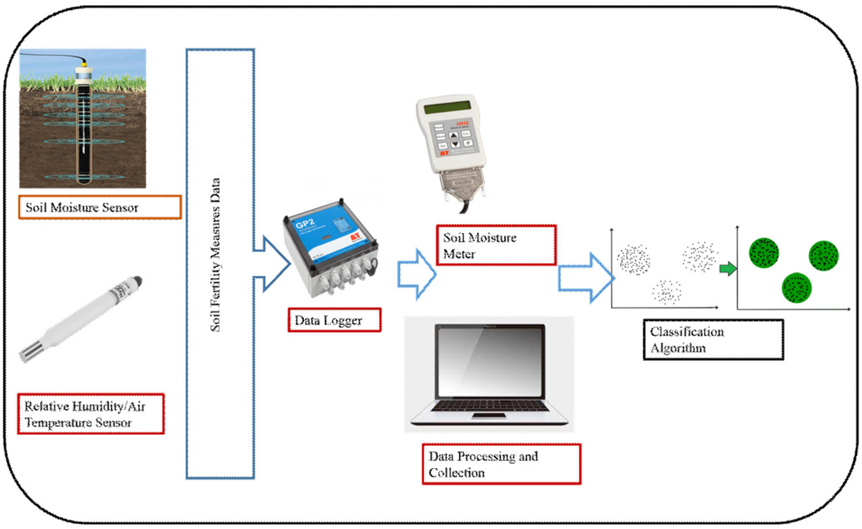

Fig. 4. Experimental setup.

depth of 40 cm, using the sensing elements present at 10, 20, 30 and 40 cm. The PR2/6 measures the WVC up to a depth of 100 cm, using the sensing elements present at 10, 20, 30, 40, 60 and 100 cm.

HH2 moisture meter

The HH2 meter is an impressive functionality unit designed for field use to offer measurement in a compact and hand-held unit. The readings are initially displayed on the LCD screen which can also be stored to a memory and can be later downloaded to a PC. HH2 is mostly used to display and store readings from profile probes in an easy and convenient way. The HH2 meter along with profile probes can be moved from one access tube to another with much ease enabling multiple soil moisture content readings from various sites.

Access tube

Profile probes are inserted within access tubes which are inserted into augured holes in the soil. For accurate measurement of soil moisture profiles, it is important that the correct installation of profile probes is done. It is important that there is an optimal contact between the soil and the wall of the access tube. The augured holes should be straight, smooth sided and the correct diameter.

Relative humidity/ Air temperature sensor (RHT-2nl-02)

The RHT2nl-02 comprises an RH and air temperature transducer housed in the solar radiation shield. It uses a 2k thermistor for temperature measurement. Data is collected from various sensors at various sites and the analysis is done using various machine learning (ML) techniques. The various ML techniques used are discussed below.

Principal component analysis (PCA)

Principal component analysis is an unsupervised learning algorithm that is used for the dimensionality reduction in machine learning. It is a statistical process that converts the observations of correlated features into a set of linearly uncorrelated features with the help of orthogonal transformation. These new transformed features are called the principal components (Stephen Marsland 2015).

Synthetic minority oversampling technique (SMOTE)

Data augmentation is required for the balance of data, as with imbalanced data there will be very few samples in the minority class making it difficult to learn the decision boundary. This can be solved by oversampling the samples in the minority class by duplicating the data in the training set before fitting the model. This will balance the data distribution but does not provide any additional information to the model. This is done by using the SMOTE technique which works by drawing a line between the samples in the feature space and extracting a new data at a point along that line. This is a type of data augmentation for tabular data and is found to be very effective (Chawla *et al.* 2002).

K-means clustering

K- means algorithm is an unsupervised learning algorithm which performs classification in an iterative manner. It divides the dataset which are unlabeled into k different clusters. The dataset is grouped into clusters based on the similarity in the properties. The value of k denotes the number of clusters. Each cluster is associated with the centroid. The clusters are grouped in a way that the sum of distances between the data points and their corresponding clusters are minimum. The optimal number of clusters are decided by the ‘elbow method’. The elbow method depends on the Within Cluster Sum of Squares (WCSS) value.

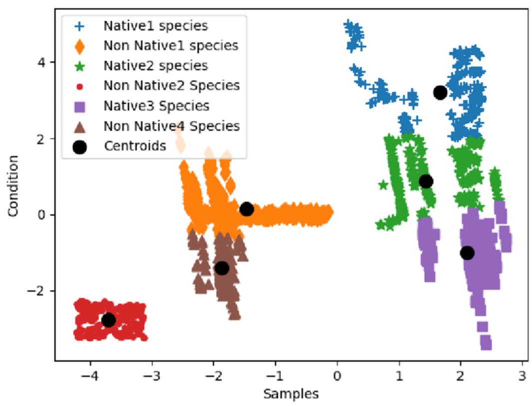

Fig. 5. K-means clustering of the data set in region of the native and non-native species.

Table 1. Averaged experimental data collected at Chennai.

	Day	1	2	3	4	5	6	7	8	9	10	11	12
	NS 1	34.1625	33.6	33.2	35.258	34.3	32.6	33.8	32.8	36.32	32.1	33.2	32.6
	NS 2	34.15	33.4735	34.1270	34.2763	33.725	39.2	35.48	36.220	33.702	34.416	34.4	33.6
Averaged	NS 3	32.5	34.5	33.83	34.88	32.39	32.87	32.36	34.04	32.4	33.5	34.1	33.17
data at 1	NNS1	23.86	22.21	23.28	28.65	23.6	22.09	22.69	22.78	27.312	22.41	22.45	23.08
meter	NNS2	24.85	26.86	24.9	27	24.78	26.35	23.21	29.65	24.3	26.11	26.31	24.51
depth	NNS3	25.9518	25.8	23.175	30.12	24.99	25.2	24.5969	27.1	26.915	26.8	29.34	26.102
	NS 1	37.26	35.38	33.3	37.33	32.47	37.11	36.39	38.52	35.65	33.68	36.5	37.4
	NS 2	32.55	31.25	30.65	30.87	31.56	32.58	31.25	30.69	30.87	33.58	33.98	32.98
Averaged	NS 3	35.6	34.8529	34.1	34.5647	35.2866	35.2586	34.2939	33.22	34.589	35.894	34.224	36.589
data at 2	NNS1	6.56666	6.82647	6.481081	7.397368	6.8	6.4	6.5	5.8	6.89	7.5	7.5	5.9786
meter	NNS2	8.61	8.47	9.89	8.47	9.14	10.74	11.33	9.95	11.36	8.29	8.03	8.87
depth	NNS3	7.52	4.82	4.94	6.15	6.64	7.57	6.02	5.81	7.44	5.29	5.87	8.56
	NS 1	64.5333	62.8264	64.8756	58.9394	61.738	63.25	56.62	55.606	57.99	64.89	64.16	62.35
	NS 2	61.4481	69.4647	67.589	68.0147	64.528	62.4517	61.259	68.589	67.98	66.89	66.48	65.32
Averaged	NS 3	65.63	65.12	65.34	66.13	66.3	65	65.25	64.92	64.9	66.66	64.97	65.98
humidity	NNS1	50.598	48.658	47.698	47.523	46.987	45.987	42.123	45.658	46.98	47.85	48.95	49.23
data	NNS2	43.99	45.88	48.63	47.64	47.22	43.23	48.09	43.64	43	45.75	48.41	43.15
	NNS3	48.96	49.68	50.14	49.76	50.1	49.58	50.54	48.67	49.39	48.75	50.77	49.42

*NS- Data collected in the presence if native species, * NNS- Data collected in the presence of non-native species.

WCSS defines the total variations within a cluster (Stephen Marsland 2015).

RESULTS AND DISCUSSION

Variations of moisture and humidity

For this study, data were taken at three different places, one area fully covered by the other non-native species (*P. juliflora*) and the other two areas covered by the native species. In order to make the features used in the data less sensitive during the model training in ML data normalization is done. Normalization refers to rescaling real-valued numeric attributes into a 0 to 1 range. It is observed that the rescaling of the data to a value between 0 and 1 shows a general and even distribution.

PCA is applied in order to represent a multivariate data set as smaller set of variables in order

Table 2. Averaged experimental data collected at Coimbatore.

	Averaged data at 1 meter depth				Averaged data at 2-meter depth			
Day	Juliflora1	Tamarind	Common	Juliflora 2	Juliflora 1	Tamarind	Common	Juliflora 2
1	3.345588	12.25507	11.44487	5.6098	2.819118	24.90435	24.08205	12.6725
2	2.98042	12.23125	11.89097	5.61736	2.778322	24.9	24.07917	12.7514
3	2.963194	12.17778	12.15	5.53472	2.882639	24.93819	24.06458	12.8611
4	3.053793	12.05556	11.96319	5.44306	2.906207	25.05972	24.06875	12.9493
5	3.071429	11.94437	11.95069	5.43333	2.959028	25.1993	24.14167	13.0431
6	3.109302	11.86944	11.59097	5.45069	2.948611	25.24028	24.14306	13.0868
7	3.079365	11.82292	11.19444	5.475	2.954167	25.29792	24.17361	13.1604
8	3.178676	11.79514	12.09236	5.44931	3.03125	25.39722	24.16597	13.2056
9	3.1375	11.74722	12.0875	5.44653	3.049306	25.39583	24.16944	13.2306
10	3.019014	11.72361	11.93056	5.45556	3.095139	25.43958	24.15833	13.2604
11	3.001389	11.73958	11.47361	5.44653	3.088889	25.53333	24.22569	13.2306
12	2.926087	11.74514	11.86667	5.449306	3.071528	25.57222	24.30208	13.20556
13	2.801149	11.77014	11.68889	5.446528	2.982759	25.64653	24.27222	13.23056
14	3.125	11.79861	11.597	5.509375	3.0251	25.73056	24.987	13.4
15	2.987	11.82014	12.087	5.87	2.987	25.75903	24.152	13.87
16	3.3253	11.76044	11.548	5.445	2.987	25.72747	24.98	12.98

Table 2. Continued.

	Averaged data of humidity			
Day	Juliflora 1	Tamarind	Common	Juliflora 2
1	36.90882353	83.81449275	54.72564103	70.96666667
2	51.70909091	82.9875	61.50694444	68.59166667
3	68.96736111	75.08194444	63.58541667	68.2
4	68.94689655	68.22569444	56.87430556	72.44236111
5	55.21666667	68.40492958	59.67083333	66.07152778
6	47.31736111	66.91388889	60.15694444	65.63333333
7	46.66944444	64.11597222	54.81875	68.50972222
8	47.82638889	61.68819444	55.36111111	58.77430556
9	50.21597222	62.41180556	59.30694444	62.77222222
10	45.90138889	62.15486111	63.31736111	67.20347222
11	39.98611111	64.16527778	57.90138889	62.77222222
12	40.78472222	62.05347222	68.08055556	58.77430556
13	48.22988506	59.37222222	71.24305556	62.77222222
14	47.698	64.02638889	60.23	68.7734375
15	45.987	64.07083333	62.847	68.32
16	46.669	67.28791209	70.354	70.96

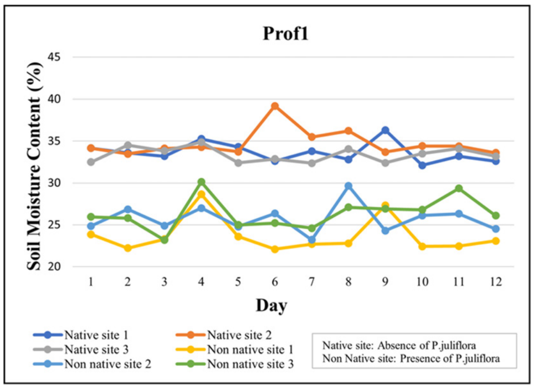

Fig. 6. Soil moisture comparison of native and non-native species region in Chennai at 1 meter depth.

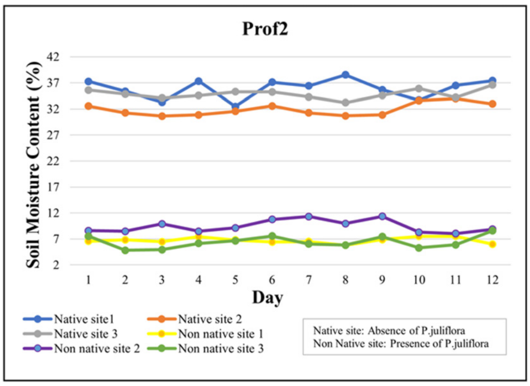

Fig. 7. Soil moisture comparison of native and non-native species region in Chennai at 2 meters depth.

to observe the clusters and outliers. By applying the SMOTE technique, the data is balanced in each class of the samples collected. The dimensionally reduced data is given as input to the K-means clustering algorithm to view the scatter between different clusters and the similarity between them. It is found from Fig. 5 which depicts the clusters of the data containing the native and the non-native species, that the data for the region which contains the native species are closely bound thereby denoting a similar condition existing for the regions in the absence of the non-native species (*P. juliflora*).

The non-native species (*P. juliflora*) has a direct impact on the soil moisture contains of the surrounding soil. It is stated that this non-native species has a

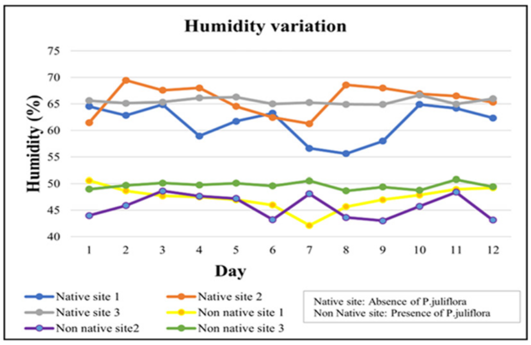

Fig. 8. Humidity comparison of native and non-native species region in Chennai.

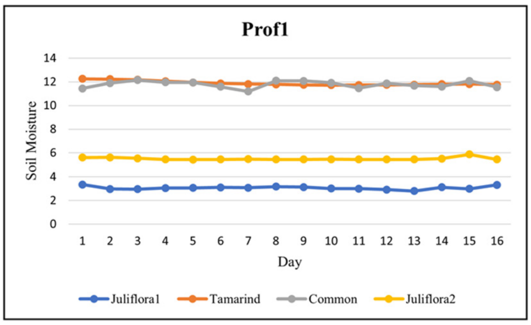

Fig. 9. Soil moisture comparison of native and non-native species region in Coimbatore at 1 meter depth.

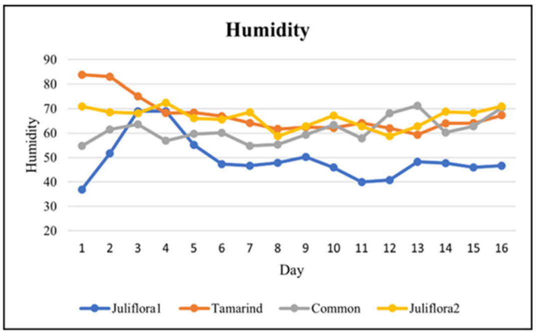

Fig. 11. Humidity comparison of native and non-native species region in Coimbatore.

penetrating capacity up to 52 meters. Data is collected for a period of 2 months each is the above mentioned six different regions. The average of the data for a duration of five days each is calculated and the graph is plotted to observe the variation at different regions.

The averaged values of the data collected at various sites in Chennai and Coimbatore are given in Tables 1– 2. Figs. 6–8 shows the soil moisture percentage content at a depth of 1 meter, 2 meters and the air humidity in the presence and absence of the species for the data collected in Chennai. Figs. 9–11 shows the soil moisture percentage content at a depth of 1 meter, 2 meters and the air humidity in the presence and absence of the species for the data collected in Coimbatore. It is visible that the moisture content in the region of the presence of the non-native species is relatively less when compared to the region where the non-native species is absent.

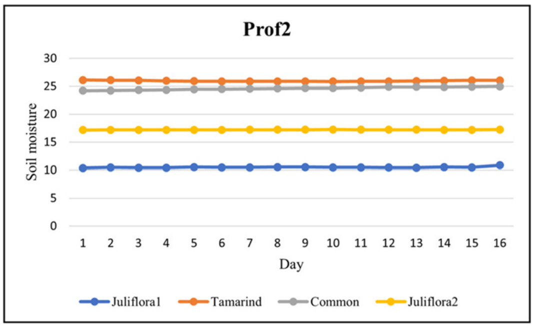

Fig. 10. Soil moisture comparison of native and non-native species region in Coimbatore at 2 meter depth.

This comparison signifies the harmful effects of the *Prosopis.juliflora* on the environmental factors. This effects on the environment may affect the vegetations and crops nearby making the land very dry and inappropriate for the crop growth. Thus, these harmful non-native species have to be eradicated to make the environment more fertile for the vegetation.

CONCLUSION

Prosopis juliflora is one of the top invasive plants, which has created negative biodiversity in many parts of the world. By having roots that reach deep into the ground, it draws too much groundwater out and also taints the water and therefore no other shrub or plant can grow nearby these species. It has the ability to regenerate from the roots, and those roots can spread out like tentacles. It also releases relatively little oxygen into the environment. Data was collected in regions with the absence and presence of the *P. juliflora* and machine learning algorithms were used to study the impact of these species on the soil moisture and the humidity of the atmosphere. The obtained results from this study justify these effects of the *P. juliflora* on the environmental conditions therefore making the environment unfit for the growth other crops. These species should be totally deteriorated from regions where the natural vegetation is of importance. In Tamil Nadu, due to the prevailing drought conditions there is a court order issue to completely uproot these species.

ACKNOWLEDGMENT

We would like to extend our sincere gratitude to Dr. Rajasekaran A., Scientist-E and Mr. K. Senthil, Technical Officer, Forest Ecology and Climate Change division, Institute of Forest Genetics and Tree Breeding (IFGTB) (Indian Council of Forestry Research & Education-ICFRE), Coimbatore-641002, Tamil Nadu for their support in carrying out this research

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