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Development of a Precision Farming Model using Soil Temperature and Trees Growth of Azadirachta Indica for Randomized Tree Plantations and Maintaining Agro-Ecology

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A B S T R A C T

Dependence upon soil temperature just below the surface on the growth of trees has been established in this study. The trees studied serves as a raw data and are planted on a linear 2 feet high hedge of mud. These trees are planted randomly. Clusters were formed of nearby trees so that they were near enough to affect the growth of each other and the effect on soil temperature at different depths was evaluated. Two to five nearby trees were taken to develop a relation between growth of cluster and the soil temperature. Using tools of precision farming distance between trees in the agricultural field of Azadirachta Indica was known. Geographical Information Systems software was used to evaluate various parameters. Heatmap was generated for tree density. Interpolation map prepared for tree growth. Randomized plantation of Azadirachta Indica tree on a linear 2 feet high hedge of mud is a new approach to analysis where we may get to evaluate the advantages and disadvantages of such plantation and the economical use made by farmers of such plantation and how they have maintained an agro-ecological balance. Effect of climate change on soil temperature was considered by taking readings in winter season as well as spring season and thereby linked to tree growth.

Keywords: Precision farming · Soil temperature · Randomized tree plantation · Cluster of Trees · Cluster growth · Agro-ecological balance

1. Introduction

The way in which trees are planted can depend on the farmers working on the field and their overall thought process behind that. In this study we have explored such a method of planting trees. This can prove a boon to agricultural community of farmers. We have emphasized in this paper on overall field planning. A reduction of energy consumption can be achieved by an optimized field work pattern (Rodias et al., 2017). Scholand and Schmalz (2021) identified the cultivation direction for soil conservation measure. Automated vineyard detection and characteriza- tion was done by Rabatel et al. (2008). The headland includes all areas of the field polygon that intersect with tracks (Spekken & de Bruin, 2013) or includes all boundary areas (Sunoj et al., 2021). Trees planted on a linear hedge of mud at the boundary encompasses an idea of land use explored in this work and used by the farmers here.

For several decades soil spatial variability has been studied (Heuvelink & Webster, 2001). It has been found that within-field yield variability is a major source of variable yield across the field (Earl et al., 2003). Soil spatial variability affects soil health status (Adhikari et al., 2021; Zebarth et al., 2019) and soil microbial diversity (Juma, 1993; Naveed et al., 2016) resulting in differences in yield across a given field. Factors such as topography, soil, weather and management are also responsible for non-uniform yield across a field (Kravchenko et al., 2005). Management in the fields we have analysed is in the hand of farmers and they have used their own experience to plant trees. Soil temperature with depth, tree growth and climate has been our focus. Part of a field could produce more in one year but not the same amount in a different year (Cox & Gerard, 2007) thereby indicating we can plant trees in a random manner and later decide on the basis of growth pattern to identify new areas of plantation. Based on a 10 year analysis Porter et al. (1998) reported greater inter-annual variability than spatial variability.

During the analysis of suitable agricultural areas in mid-hills to plains in Darjeeling, India Pramanik (2016) used GIS, satellite imagery and a DEM to calculate the elevation, direction, slope, soil, water availability and distance from a road. Hamano et al. (2022) developed a method to measure the sloped areas of paddy field ridges with GIS software (QGIS 3.10). Agarwal et al. (2024) has worked on randomized tree plantation of Moringa Oleifera trees to identify clusters of trees and sparse area of trees and effect of this on the health of planted trees using QGIS software. Hamano et al. (2023) developed a method for creating planting and ridge area polygons on paddy fields using AI, GIS software and a precision DEM. A path planning algorithm was developed to identify the optimal cultivation direction by Donat et al. (2023). The on field approach by the farmers for planting trees in a random manner on a linear hedge shows a predetermined path planning the benefits of which have been discussed in this article.

Topographic character, climatic conditions and soil properties are taken into consideration and given weights based on expert judgement to discover possible solutions for land use (Jankowski, 1995; Joerin et al., 2001; Akinci et al., 2019). Geographical information systems (GIS) and remotely sensed data offer great opportunity for enhancing land suitability assessments as shown by several researches (Pereira & Duckstein, 1993; Kalogirou, 2002; El Baroudy, 2016). Data-driven agriculture technology and precision farming methods have been emphasized by Rozenstein et al. (2024). Digitization of agriculture has large potentialities to provide benefits for both producers and consumers (Bacco et al., 2019).

Challenges prior to and following precision agriculture can prevent many farmers from widely using it (Wang et al., 2023). Survey respondents from surveys carried out in Denmark and the Eastern corn belt, USA found soil maps to be more valuable than yield maps in management decisions (Fountas et al., 2005). In this article we have discussed how the farmers have used their expertise for planting trees occupying a minimum area and at the base of trees fodder for cattle are grown. A principal component analysis was conducted to analyse the influence of soil properties and elevation on the soil variability by Moral and Serrano (2019). We have analysed trees planted on a 2 feet high hedge of mud an elevated structure. Nine apple trees were captured photogrammetrically using a RGB camera of meadow orchards to automatically calculate tree models (Straub et al., 2022).

This study is aimed at dependence of soil temperature on growth of Azadirachta indica trees planted randomly on a linear hedge of mud which is 2 feet above the ground level. The optimum land use is highlighted with the full use of Azadirachta indica tree leaves and berry falling on the ground. Mathematical models were developed in QGIS (QGIS, 2023) and on field readings of soil temperature for two seasons as well as circumference of tree trunks were taken. Line density interpolation map was prepared to verify the on field readings of circumferences of tree trunks. It is shown that a well-planned agro-ecological farming without the use of expensive equipment and intelligent land use has been made more valuable by the properties of Azadirachta indica tree leaves and berry.

2. Methodology

2.1 Study site and images

The site used in this study is the agricultural farms of Dairy Campus, Dayalbagh Educational Institute, Dayalbagh, Agra, India. Azadirachta indica trees are planted randomly in this field of study on a linear 2 feet high hedge of mud which is aligned with the northern edge of the field. This field is used for growing fodder for cattle at the base of the hedge used for planting trees. Images are taken from the front to cover the trunk of trees by a high resolution camera. A large field area with six clusters identified covering 20 trees in our analysis is clearly visible in the study site image for using advanced mathematical models (Fig. 1). Images of soil temperature were taken around each of the individual clusters for two subsequent seasons (Fig. 2 and Fig. 3). Images indicating circumference of trees were taken for 20 trees (Fig. 2).

2.2 Data flow and software

Figure 4 provides the main steps for image data processing and on field measurements and analysis of soil temperature and tree trunk circumferences.

2.3 Vector layer of points and heatmap

Total 6 clusters were formed with cluster 1 containing 2 trees, cluster 2 to 4 containing 3 trees each, cluster 5 containing 4 trees and cluster 6 containing 5 trees. Total 20 trees in these six clusters were marked in points vector layer as shown in figure 5. This figure shows a points vector layer placed over a raster layer of full image of the tree plantation. In figure 6 trees are numbered form 1 to 20 which is a single vector layer of points representing trees in clusters formed. Figure 6 shows each cluster with a unique colour. Figure 7 is the heatmap generated from vector layer of points using kernel density estimation. Heatmap allows easy identification of density of number of trees and spacing between the trees in clusters.

Fig.1 Study area of agricultural farm with Azadirachta indica trees Dairy Campus, Dayalbagh Educational Institute, Dayalbagh, Agra, India

Fig.2 1st image of each row shows a cluster of trees and six rows show six clusters of trees were formed for analysis. 2nd, 3rd and 4th image of each row were the on field readings of winter temperature taken on 10th of Jan 2024 at 8 AM at depths of 10, 15, 20 cm below the surface of soil around the cluster shown in that row. 5th and subsequent images of each row were the circumference readings of tree trunks of the cluster analysed in that row. Row 1 represents cluster 1, row 2 represents cluster 2 and so on up to row 6 which represents cluster 6.

Fig.3 1st image of rows 1, 2 and 3 shows a setup for temperature readings of the clusters 1, 3 and 5 respectively. 5th image of rows 1, 2 and 3 shows a setup for temperature readings of the clusters 2, 4 and 6 respectively. 2nd, 3rd and4th image as well as 6th , 7th and 8th image of each row were the on field readings of spring temperature taken on 20th of Feb 2024 at 8 AM at depths of 10, 15, 20 cm below the surface of soil around the clusters shown in that row. Every three sets of temperature reading images belong to a setup for temperature readings of the cluster shown preceding these images.

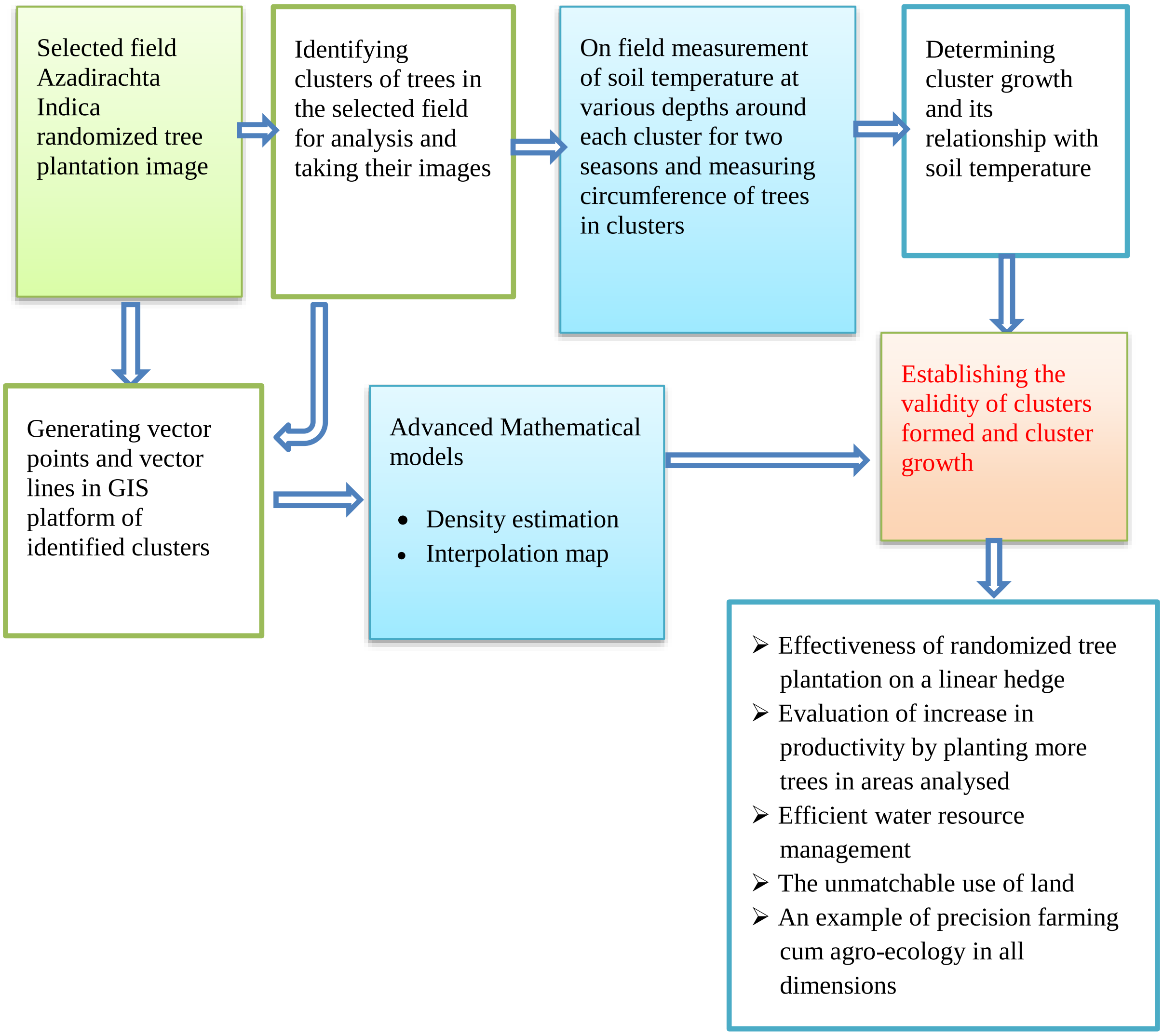

Fig.4 Flow chart of on field measurements, their analysis and image data processing. In the first step, field image was selected to continue our analysis. In the second step, tree clusters were formed and vector points layer as well as vector lines layer files were created. Next, on field measurements were done and mathematical model in GIS were created from vector layers. Then, relationship was developed from on field measurements. Then data generated was used to validate the clusters. Final evaluation was a probable decision based on the analysis to justify effectiveness of the randomized tree plantation, to optimize land use, for better resource management and to increase productivity by planting more trees.

Fig.5 Trees marked with vector points showing location of trees used in the analysis

Fig.6 Trees location vector points.

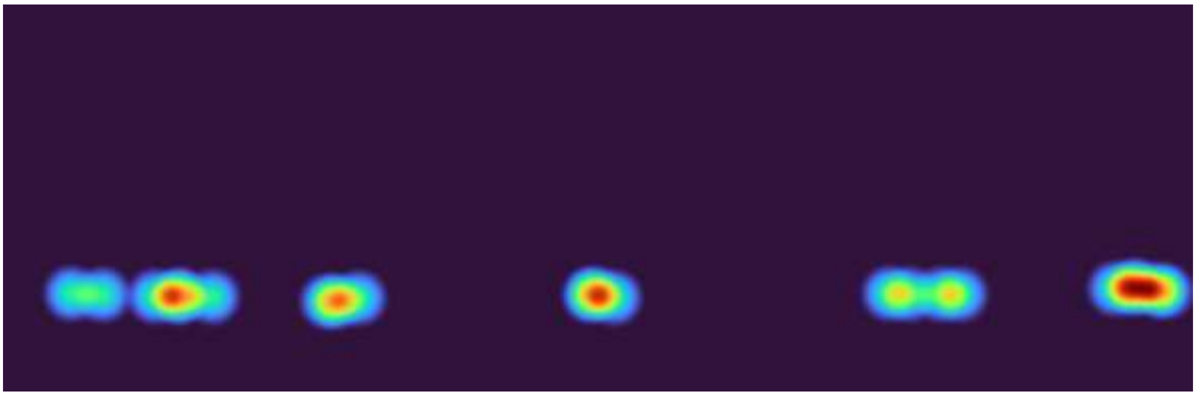

Fig.7 Heatmap representing tree density.

2.4 Soil temperature and cluster growth

On field soil temperature measurements were done at depths of 10, 15, and 20 cm below the surface of soil around each of the clusters. Tree trunks circumferences were measured for 20 trees in 6 clusters. Soil winter season temperature readings were used to prepare table 1 and soil spring season temperature readings were used to prepare table 2 for evaluating average soil temperature during the winter season as well as the spring season respectively. Table 3 was used for evaluating total cross-sectional area of all trees in each of the individual cluster thereby indicating the proportionality to cluster growth or growth of trees in a cluster.

Table 1 Unique tree ID given to each tree and cluster number allotted to trees. Average winter season soil temperature was determined by taking average of three soil temperatures at depths of 10cm, 15cm and 20cm for each cluster. Readings were taken on 10th of Jan 2024 at 8 AM.

Tree ID	Cluster No.	Soil temperature at 10cm T1 °C	Soil temperature at 15cm T2 °C	Soil temperature at 20cm T3 °C	Average winter soil temperature TW_{avg}°C
1	1	12.6	12.8	13.0	12.8
2	1	12.6	12.8	13.0	12.8
3	2	10.9	11.1	11.2	11.07
4	2	10.9	11.1	11.2	11.07
5	2	10.9	11.1	11.2	11.07
6	3	10.3	11.0	11.6	10.97
7	3	10.3	11.0	11.6	10.97
8	3	10.3	11.0	11.6	10.97
9	4	10.7	11.0	13.1	11.6
10	4	10.7	11.0	13.1	11.6
11	4	10.7	11.0	13.1	11.6
12	5	10.9	12.0	12.1	11.67
13	5	10.9	12.0	12.1	11.67
14	5	10.9	12.0	12.1	11.67
15	5	10.9	12.0	12.1	11.67
16	6	12.2	12.2	13.0	12.47
17	6	12.2	12.2	13.0	12.47
18	6	12.2	12.2	13.0	12.47
19	6	12.2	12.2	13.0	12.47
20	6	12.2	12.2	13.0	12.47

Table 2 Average spring season soil temperature was determined by taking average of three soil temperatures at depths of 10cm, 15cm and 20cm for each cluster. Readings were taken on 20th of Feb 2024 at 8 AM.

Tree ID	Cluster No.	Soil temperature at 10cm T1 °C	Soil temperature at 15cm T2 °C	Soil temperature at 20cm T3 °C	Average spring soil temperature TS_{avg}°C
1	1	18.8	18.9	19.4	19.03
2	1	18.8	18.9	19.4	19.03
3	2	16.8	17.6	17.8	17.4
4	2	16.8	17.6	17.8	17.4
5	2	16.8	17.6	17.8	17.4
6	3	16.9	17.2	17.4	17.17

7	3	16.9	17.2	17.4	17.17
8	3	16.9	17.2	17.4	17.17
9	4	17.9	18	18.4	18.1
10	4	17.9	18	18.4	18.1
11	4	17.9	18	18.4	18.1
12	5	17.6	18	18.5	18.03
13	5	17.6	18	18.5	18.03
14	5	17.6	18	18.5	18.03
15	5	17.6	18	18.5	18.03
16	6	18.3	18.9	19.5	18.9
17	6	18.3	18.9	19.5	18.9
18	6	18.3	18.9	19.5	18.9
19	6	18.3	18.9	19.5	18.9
20	6	18.3	18.9	19.5	18.9

Table 3 Tree trunk cross-sectional area was determined for 20 trees from on field measured circumferences of tree trunks. Cluster cross-sectional area was determined after summing up the cross-sectional areas of all trees in a cluster.

Tree ID	Measured circumference cm	Cluster No.	Tree cross-sectional area cm^2	Cluster cross-sectional area cm^2
1	168.9	1	2270.078	3785.499
2	138	1	1515.421	3785.499
3	51	2	206.986	1817.674
4	57.8	2	265.847	1817.674
5	130	2	1344.841	1817.674
6	59.9	3	285.502	1183.89
7	52.1	3	216.007	1183.89
8	92.6	3	682.381	1183.89
9	92.2	4	676.467	2730.059
10	73	4	424.046	2730.059
11	143.1	4	1629.546	2730.059

12	25	5	49.739	2740.905
13	114	5	1034.227	2740.905
14	137.2	5	1497.946	2740.905
15	44.7	5	158.993	2740.905
16	95	6	718.213	3388.381
17	100.8	6	808.576	3388.381
18	88.5	6	623.252	3388.381
19	123	6	1203.92	3388.381
20	20.8	6	34.42	3388.381

2.5 Vector layer of lines and line density interpolation

Lines indicating diameter of tree trunks were drawn over the tree trunks as vector lines (Fig.8). Field image of trees as a raster layer when separated from lines vector layer gives figure 9 where only the vector layer of lines is shown and each cluster is given a distinct colour. A line density interpolation map takes the vector layer of lines as input applied and calculates a density measure of linear features. Figure 10 illustrates line density interpolation map with cluster growth categorized with colours and is indicative that on field cross sectional area measurements of tree trunks and thereby clusters as appropriate and verifiable.

Fig.8 Trees marked with vector lines showing diameter of tree trunks used in the analysis

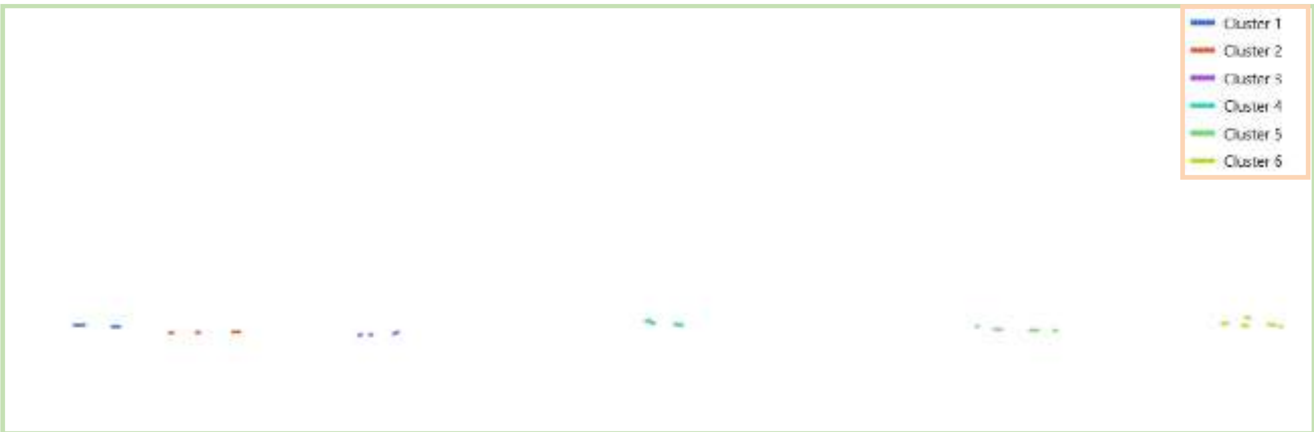

Fig.9 Vector lines representing tree trunk diameters

Fig.10 Line density interpolation map of lines vector layer. Cluster 1 and 6 can be seen with dark blue colour nucleus signifying very high cluster area. Cluster 4 and 5 can be seen in light blue or blue green colour nucleus signifying high cluster area. Cluster 2 and 3 can be seen in light yellow colour nucleus signifying medium or low cluster area. These results match with the cluster area calculated from on field readings thereby verifying the readings.

2.6 Scientific process of development of study

While taking images of temperature readings precautions were taken that fodder grown at base of field was not given water during last one day to get an actual estimate of temperature. Since trees are grown on the hedge which is 2 feet above the ground the level at which the readings were taken was kept the same for all clusters and depths were measured up to the accuracy of 2mm. The thermometers were calibrated before taking the readings with the help of water at atmospheric temperature. Study site is a long hedge of trees grown intentionally by farmers here keeping in mind the advantages of such plantation. For the images of circumference readings close-up were taken to get an accurate measure in maximum significant figures possible. The part of tree trunks selected for circumference measurements were within five feet from the ground and cylindrical area of tree trunks selected were uniform for at least two feet to give a best measure of tree growth.

After selecting the full image of study site the six clusters were selected within this site. The trees in clusters were near enough to affect the growth of whole cluster. This was done keeping in mind the spread of roots inside the soil so that they intermix with the roots of surrounding trees sufficiently to affect the soil temperature. The whole cluster considered as one was within 4 feet radius from the centre. Readings at 10 cm, 15 cm and 20 cm depths were taken and recorded for soil temperature measurements and temperatures at surface of soil and 5 cm below the surface of soil were measured but discarded as these readings were not affected by growth of roots owing to the nearness to the surface of soil where atmosphere temperature was present as constant.

It was borne in mind that once the cluster cross-sectional areas had been determined they were to be validated by QGIS software. Points vector layer has shown the density of trees validating the clusters formed through kernel density estimation heatmap. Lines vector layer has shown the diameter of tree trunks validating the cross-sectional area of clusters through line density interpolation map. Line density interpolation map takes into account the circular radius thereby categorizing the clusters proportionate to their growth. The size of clusters as seen in this map is indicative that spread of clusters is within range necessary for analysis. On seeing the data of trees trunk diameters and soil temperatures and observing the relation between the two it was inspirational to plot the graph of cluster cross-sectional area versus average soil temperature, to study the nature of graph, to develop an equation and finally to further the studies in this area by discussing various aspects of randomized tree plantations.

3. Results and Discussions

As a result of data generated in methodology average soil temperature was plotted against cluster cross-sectional area for winter season (Fig.11). Average winter season soil temperatures TW_{avg}°C were taken from table 1 which is specific for every cluster. Cluster cross-sectional areas were taken from table 3.

$CCSA$ = *Cluster cross-sectional area in cm²*

TW_{avg} = *Average winter season soil temperature in °C for cluster*

$$CCSA = (-(TW_{avg})^2 + 26 \times (TW_{avg}) - 160) \times K_1$$

where K_1 is a constant and its value comes out to be 622 and the above second order polynomial equation plotted in figure 11 is valid for temperature range of 10.8 to 13.0 °C.

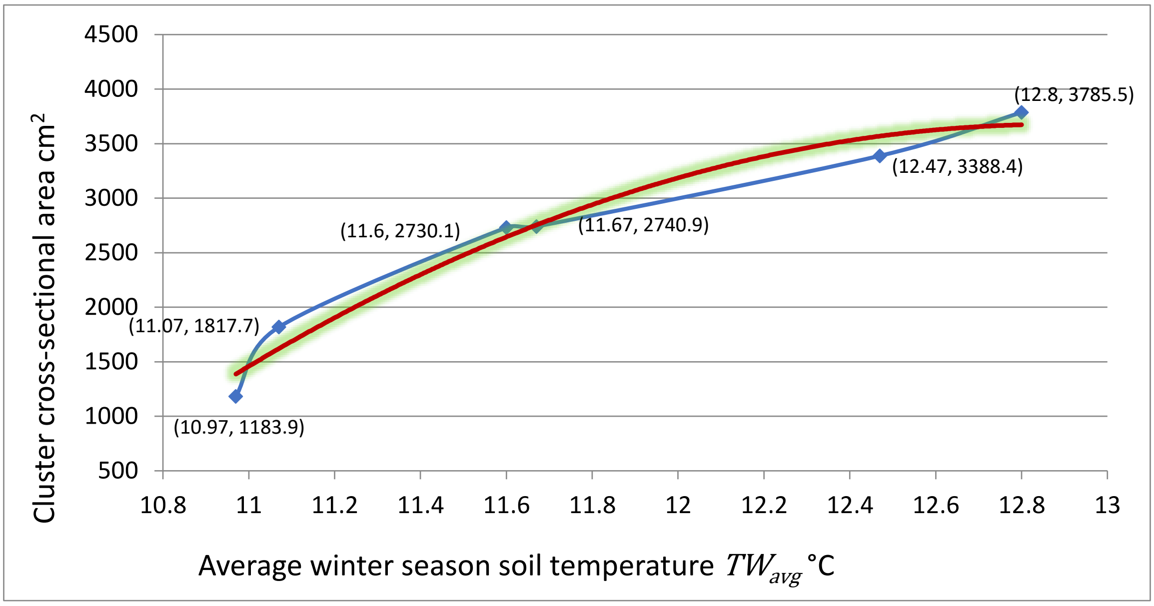

Fig.11 Blue line is the plot with coordinates for winter season representing clusters in increasing order of cluster cross-sectional area. Red line is a second order polynomial fitted over the coordinates.

A saturation of *CCSA* and thereby cluster growth is reaching as temperature exceeds 13 °C for winter readings implying that in the areas where the tree growth is higher the growth increases very slowly for a considerable rise in temperature and this indicates that further growth is not possible in this area whereas more trees can be planted in the areas of lesser growth. Temperature rise also indicates that soil temperature is being governed by spread of roots and as the roots become denser the soil temperature comes nearer to the temperature of roots and further scope of rise in temperature is not possible where atmospheric temperature is constant for the winter season.

Average soil temperature was plotted against cluster cross-sectional area for spring season (Fig.12). Average spring season soil temperatures TS_{avg}°C were taken from table 2 which is specific for every cluster. Cross-sectional areas were taken from table 3.

TS_{avg} = *Average winter season soil temperature in* °C *for cluster*

$$CCSA = (-(TS_{avg})^2 + 39.5 \times (TS_{avg}) - 380) \times K_2$$

where K_2 is a constant and its value comes out to be 381 and the above second order polynomial equation plotted in figure 12 is valid for temperature range of 17 to 19.5 °C.

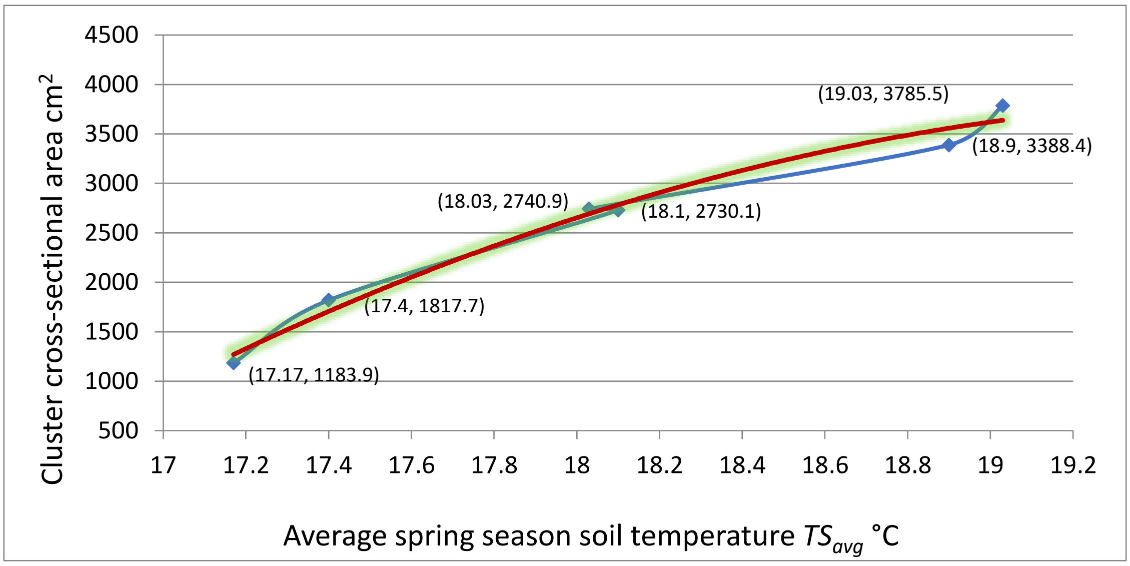

Fig.12 Blue line is the plot with coordinates for spring season representing clusters in increasing order of cluster cross-sectional area. A second order polynomial fitted over the coordinates is indicated by red line.

A saturation of *CCSA* is reaching as temperature exceeds 19.5 °C for spring readings implying that in the areas where the tree growth is higher the growth increases very slowly for a considerable rise in temperature. Temperature rise also indicates that as the roots become denser the soil temperature comes nearer to the temperature of roots and further scope of rise in temperature is not possible where atmospheric temperature is constant for the spring season. So both the things that in winter as well as spring seasons above certain temperature growth of more trees is not possible and temperature rise is also not possible and this helps in identifying areas where more trees can be planted.

3.1 Formulation of a law on agro-ecology

If there are m clusters and we arrange the clusters in increasing order of their cross-sectional area then for n^{th} cluster where $n \leq m$ increase in soil temperature is denoted as $T_n - T_{n-1}$, for *(n-1)th* cluster increase in soil temperature is denoted as $T_{n-1} - T_{n-2}$ and so on. Similarly the increase in *CCSA* is denoted as $CCSA_n - CCSA_{n-1}$ for n^{th} cluster, $CCSA_{n-1} - CCSA_{n-2}$ for *(n-1)th* cluster and so on.

A_T = *Increase in cluster cross-sectional area per* °C

Then increase in *CCSA* per °C is given by the following equation :

$$A_T = \frac{CCSA_n - CCSA_{n-1}}{T_n - T_{n-1}} \qquad (1)$$

where both the areas $CCSA_n$ and $CCSA_{n-1}$ are sufficiently spaced apart at least 600 cm^2 from our analysis and soil temperature $T \leq 19.5$ °C up to a depth of 20 cm below the surface of soil. The above equation derived by the first author of this paper can be used as "Prashant's law of agro-ecology" in context of randomized tree plantation.

Prashant's law of agro-ecology states that, " the higher the value of increase in cluster cross-sectional area per °C (A_T) for the two seasons that is winter and spring the more likely are the chances of planting new trees with maximum soil temperature recorded at and not exceeding 19.5 °C below the surface of soil and that A_T will vary depending on seasons as soil temperature changes but will remain more or less same during the same time of the year every year provided seasons do not shift their timings".

Equation (1) can be generalized as follows:

$$A_T = \frac{\Delta CCSA}{\Delta T} \qquad (2)$$

3.2 Predicted percentage increase in growth of agricultural field

Clusters of Azadirachta Indica trees are arranged in increasing order of their *CCSA* (table 4) and given a number *n* as per equation (1) for A_T with $m = 6$, where m is the maximum number of clusters analysed. Clusters 1 and 6 have shown very good growth near saturation. Clusters 4 and 5 have shown good growth. Cluster 2 has shown average growth and cluster 3 has shown poor growth with 3 trees each. Here one more tree can be grown in cluster 2 and two more in cluster 3. Rise in temperature possible for cluster 2 from winter season data is 1.73 °C. Cluster 2 and 3 have been set to achieve a cluster growth of 2730.1 cm^2 of cluster number 4. A_T for winter season from equation 2 for cluster number 4 and 2 is 1721.5 cm^2 per °C and for cluster number 4 and 1 is 879.5 cm^2 per °C. A higher value of A_T is found, approximately double, for cluster number 4 and 2 as compared to 4 and 1. Similarly, A_T for winter season from equation 2 for cluster number 4 and 3 is 2454.3 cm^2 per °C. A higher value of A_T is found, approximately 2.8 times, for cluster number 4 and 3 as compared to 4 and 1. Thereby considering 2730.1 cm^2 as good growth and easily achievable as verified.

Cluster No.	Cluster cross-sectional area cm^2	Average winter soil temperature TW_{avg}°C	Average spring soil temperature TS_{avg}°C	Cluster no in increasing order of *CCSA* *n*
3	1183.9	10.97	17.17	1
2	1817.7	11.07	17.4	2
4	2730.1	11.6	18.1	3
5	2740.9	11.67	18.03	4
6	3388.4	12.47	18.9	5
1	3785.5	12.8	19.03	6

Table 4 Cluster number in increasing order of *CCSA*

Total number of trees that can be planted are 3 in number. There are total 20 trees in 6 clusters. Then predicted percentage increase in growth achievable by planting 3 more trees by ratio of new trees planted to the total number of trees is 15% (3×100/20).

Now considering 2730.1 cm^2 as growth which will be achieved by cluster number 2 and 3, by planting more trees there, the increase in *CCSA* of cluster 2 and 3 is 2458.6 cm^2 (912.4 + 1546.2). Total cross-sectional area of all 20 trees is 15646.5 cm^2. By this method predicted percentage increase in growth is 15.7% (2458.6 cm^2×100/15646.5 cm^2). This result is nearly the same as 15% calculated from ratios of number of trees justifying our analysis from A_T and this is more dependable as growing more trees and calculating ratio of trees for increase in growth is a linear process while the growth is not linear as it depends on *CCSA* and soil temperature below the surface of soil.

3.3 Effectiveness of randomized tree plantation on a linear hedge

Trees of Azadirachta indica planted on a linear hedge of mud are having the benefit of minimum land use. The hedge is aligned with northern side of one field and southern side of the other field. This way using the hedge between the two agricultural fields means saving of land. Trees are aligned with a field in which the fodder for cattle is grown. This way the fodder and the soil of the field is enriched with the beneficial properties of Azadirachta indica tree leaves and berry keeping the fodder of cattle and soil of the field as healthier. Trees also serve as a shade in summer for grazing of cattle.

Randomized tree plantation is proving more effective for Azadirachta indica trees as initially it is not known which trees will grow better and later areas with lesser growth can be used to plant more trees using precision farming tools.

4. Conclusion

Increase in average soil temperature with increase in tree growth during winter and spring season can be accounted for by the densely populated roots when trees growth in clusters increases considerably. The roots are at higher temperature and they affect the temperature of soil surrounding them. As the temperature of soil reaches nearer to the temperature of roots then further increase in temperature is not possible and this also indicates that soil is densely populated with roots which is enough not to support any further growth of new trees.

Growing trees on a linear hedge of mud provides greater area of soil near the roots of trees exposed to atmosphere. Thereby tree roots getting more water and oxygen naturally. All this has led to better maintenance of trees as well as keeping soil healthy as per agro-ecological principals.

There is a tremendous scope of further research in this area as this is going to be a new era plantations where the brain of farmers has worked on many fronts to produce an ecological balance where optimum land use, beneficial properties of tree leaves and berry of Azadirachta indica tree for enriching fodder and soil, using shade of trees for grazing of cattle, maintaining soil moisture of trees only by watering the fodder that is efficient water use all have been brought under one folder and now precision farming tools have been applied to further enhance the growth and how trees grown randomly and in clusters can be more beneficial for Azadirachta indica tree plantations has been concluded.

Same study can be applied to other randomized tree plantations and increase in growth by planting more trees can be established.

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Author Contributions

Conceptualization: [PKA], [AA], [HA]; Data collection: [PKA], [DKV], [DS]; methodology on Agricultural land use, soil temperature and tree growth analysis/GIS: [PKA], [AA], [PA]; formal analysis on Agricultural land use, soil temperature and tree growth analysis/GIS: [PKA], [AA]; writing─original draft preparartion on Agricultural land use, soil temperature and tree growth analysis/GIS: [PA], [HA], [DKV], [DS]; writing─ review and editing on Agricultural land use, soil temperature and tree growth analysis/GIS: [PKA], [PA], [AA], [HA], [DKV], [DS]; supervision: [PA], [HA].

Data availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

1. Declarations

Competing interest

The authors declare that they have no conflict of interest.

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