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Effect of Moringa Oleifera Tree Clusters and Sparsity on Health of Trees and Development of a Precision Farming Method for Farm Growth

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A B S T R A C T

Growth of trees is found dependent on the adjacent trees size and distancing with each other. Moving across a field if trees are grown randomly, then this can be studied for random analysis pertaining to tree health and size. Thickness of tree trunks, cross-sectional area of tree trunks and distancing between trees in an agricultural field are studied using different analytical models. Generating heatmaps and interpolation techniques can be used to find meaningful results. Geographical Information Systems software has been used to evaluate various parameters and to derive randomized tree plantations conclusive results. Both vectors and raster layers are used for processing in multiple dimensions. Raw data from a field of Moringa Oleifera trees with randomized plantation of trees is a new approach to analysis. Most of the time the analysis is based on well planned agricultural fields but there we may not get to evaluate the advantages and disadvantages of randomized planted trees. Cost effectiveness can be attained by identifying the sparse tree areas where they can be converted to areas with cluster of trees keeping in view the optimum tree health and ease of irrigation for Moringa Oleifera tree plantations.

Keywords: Geographical Information Systems · Randomized tree plantation · Tree clusters · Tree sparsity · Tree growth · Points vector layer · Lines vector layer

1. Introduction

The direction of cultivation is many a times a result of experience of farmers (Oksanen & Visala, 2009) and so is the randomized plantation of trees and has been passed from one generation to the next. Satellite imagery was used by Wang et al. (2016) to identify the sowing direction which was visually inspected by them and manually mapped as lines in a geographical information system (GIS). To generate analytical view of our randomized tree plantation and to make valid agrotechnological decision GIS is used by us for handling the data.

Investigations on the appropriateness of land for a particular crop and land conservation strategies and land use development were conducted separately (Nyeko, 2012; Schwilch et al., 2011). Factors such as environmental and social costs must be considered of a piece of land in conjunction with intrinsic features (Duc, 2006; Bandyopadhyay et al., 2009). For identifying changes in land use and land cover mapping the modern techniques are remote sensing and GIS (Kumar, 2022). For optimized farming advanced GIS field mapping and precision crop planning has been emphasized (Kotam et al., 2024). Integrating trees into agricultural landscapes through agroforestry enhances biodiversity and improves soil fertility (Ali et al., 2024).

Distribution of parks was assessed using GIS by Kyushik Oh and Seunghyun Jeong (2007). The soil erosion is estimated using remote sensing techniques and GIS by Machiwal et al. (2015). In analysing and measuring land use land cover changes, remote sensing and GIS have shown high efficiency (Ragini et al., 2023). GIS and remotely sensed data offer great potential for enhancing land suitability as shown by several researches (Akinci et al., 2013; Pereira & Duckstein, 1993; Kalogirou, 2002; El Baroudy, 2016).

Non-productive machinery movement can be reduced by efficient in-field operations (Filip et al., 2020). Simple field structures were used by dividing complex field polygons into subfields and calculating the optimal path within these subfields (Hofstee et al., 2009; Bochtis & Oksanen, 2009; Jin & Tang, 2010). Spatial modelling of crop/weed images was done by Jones et al. (2009).

Precision agriculture may be site-specific to optimize environmental benefits, yield and sustainability (Bongiovanni & Lowenberg-Deboer, 2004; Oliver et al., 2013). Precision agriculture principles application is more pronounced when farm profitability and optimization in conservation practices are desired (McConnell & Burger, 2011; Capmourteres et al., 2018). Effects of application of conservation practices at field-scale has been reported (Her et al., 2016).

Oyoshi et al. (2016) developed an algorithm to measure the growth status of crops with data from GIS, remote sensing and SAR imagery. Hamano et al. (2022) developed a method to measure the sloped areas with GIS software. Rizzo et al. (2022) carried out an analysis to increase the productivity of crops, to quantify different factors and agronomic management holds an overall contribution of 38% for the total yield gains. A study was conducted in nine corn fields located near Reisel, Texas by Adhikari et al. (2023) for farm-level economic benefits.

Crookston (2006) identified Precision Agriculture will play a vital role in agricultural modernization. Identification of groundwater potential is important for the preparation of management plan of groundwater resource was given by Nigam et al. (2020). Water use efficiency can be a factor to be considered in random plantation of trees.

This study is aimed at small field area randomised tree plantation of Moringa Oleifera trees. The aim is to identify clusters of trees and sparse area of trees on a small size field and effect of this on the health of planted trees in that area. To determine whether this affects our produce positively. Marking of trees is done in QGIS (QGIS, 2023) geographic information system software. Tree trunk width is determined in to see the growth patterns. Analysing through mathematical models in QGIS software to determine where to plant more trees has been done keeping in view the ease of irrigation, cost effectiveness and overall health of all trees in the field

used in analysis. Heatmap and line density interpolation mathematical models have been used. From relative diameter of tree trunks to cross-sectional area of all tree trunks in a cluster of trees has been determined to reach at results.

2. Methodology

2.1 Study site and images

Data of the field used is collected from agricultural farms of Dairy Campus, Dayalbagh Educational Institute, Dayalbagh, Agra, India. Moringa Oleifera trees are planted in this field of study. Images are taken by a high resolution mobile camera. High resolution near image covering a large field area and large number of trees is selected with 27 trees and the trunks of these trees clearly visible for using advanced mathematical models (Fig. 1).

2.2 Data flow and software

The main steps for image data processing are provided in figure 2. Vector layers of points and lines are created. Kernel density estimation heatmap is applied to vector layer of points. Line density interpolation map is generated for vector layer of lines. Data storage, image analysis and mathematical models applied are done using geographical information systems software.

2.3 Vector layer model for determination of tree density

Total 27 trees have been marked in points vector layer created in GIS software as shown in figure 3. The figure represents a vector layer of points placed over a raster layer. Moringa Oleifera trees are shown planted in randomized manner in the field depicted by raster layer.

Fig.1 Study area of agricultural field Dairy Campus, Dayalbagh Educational Institute, Dayalbagh, Agra, India

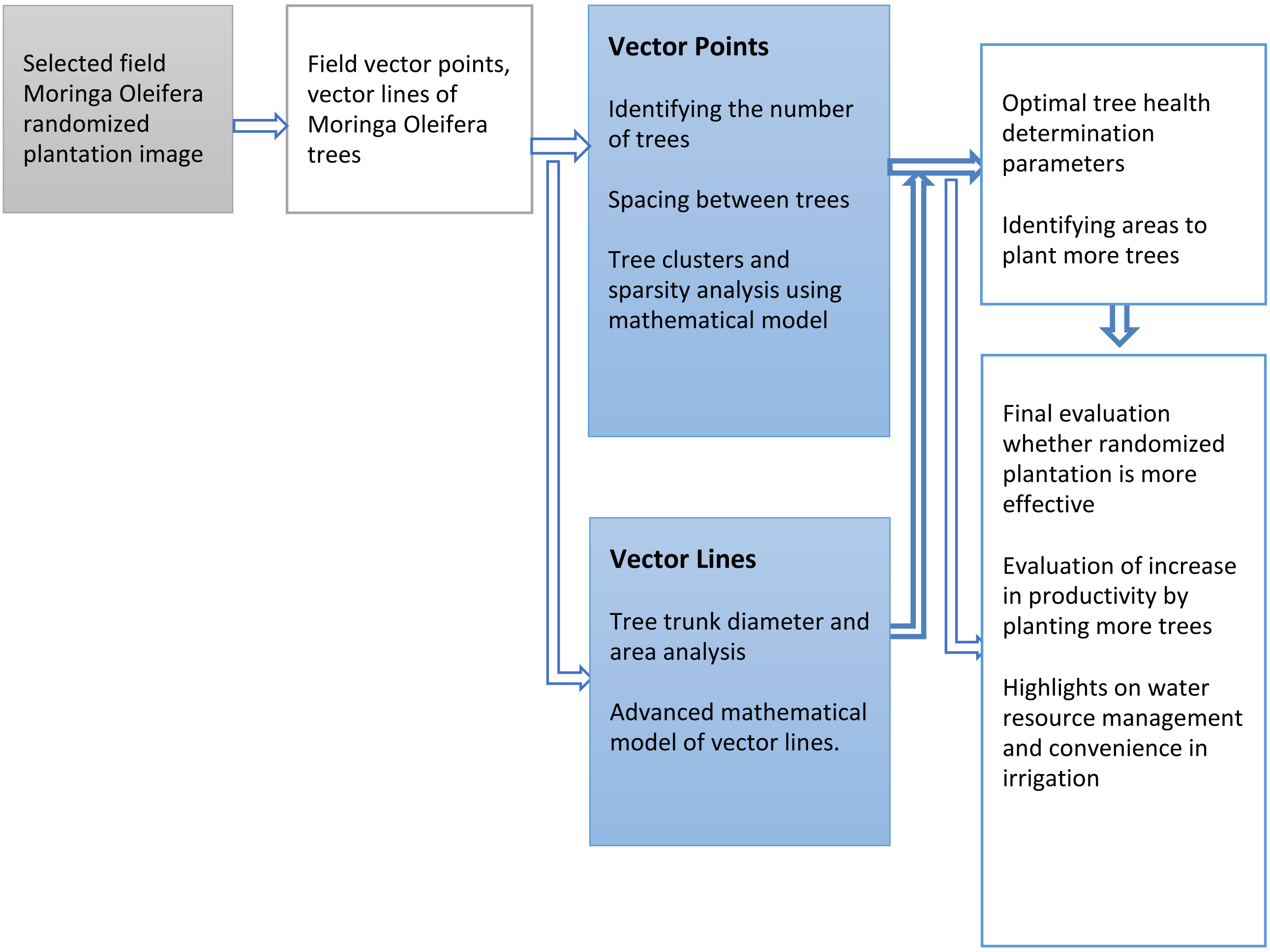

Fig.2 Flow chart of image data processing. In the first step, image is selected to continue our analysis. In the next step, vector points layer and vector lines layer files are created. Then, mathematics is used for vector points and vector lines. For optimal tree health determination distancing between the trees and tree trunk cross-sectional area are used. Final evaluation is a probable decision based on the analysis to justify effectiveness of the plantation, to increase productivity by planting more trees and better resource management for irrigation

Fig.3 Shows a vector layer of points placed over a raster layer of agricultural field. Moringa Oleifera trees are shown in this field. Various tree groups are shown in different coloured points and numbered which has been depicted clearly in figure 4

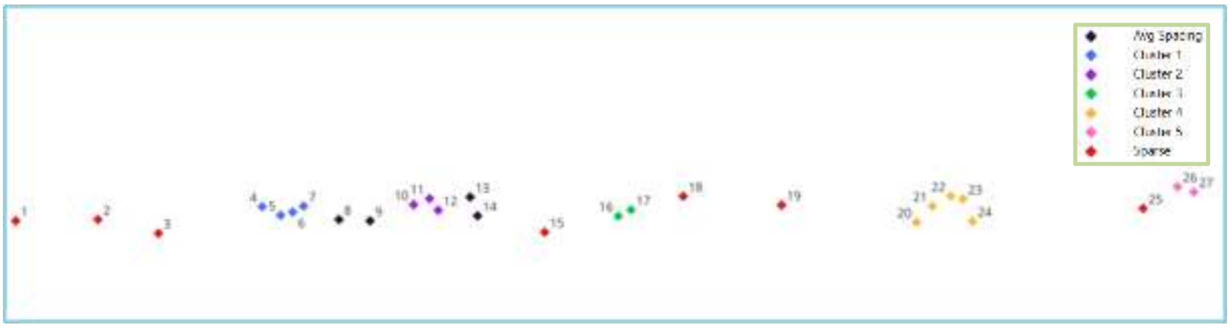

Fig. 4 A points vector layer with trees shown as points. Trees in sparsely grown area have been identified in red colour. Trees with average distancing are shown in black colour. Rest are trees in clusters

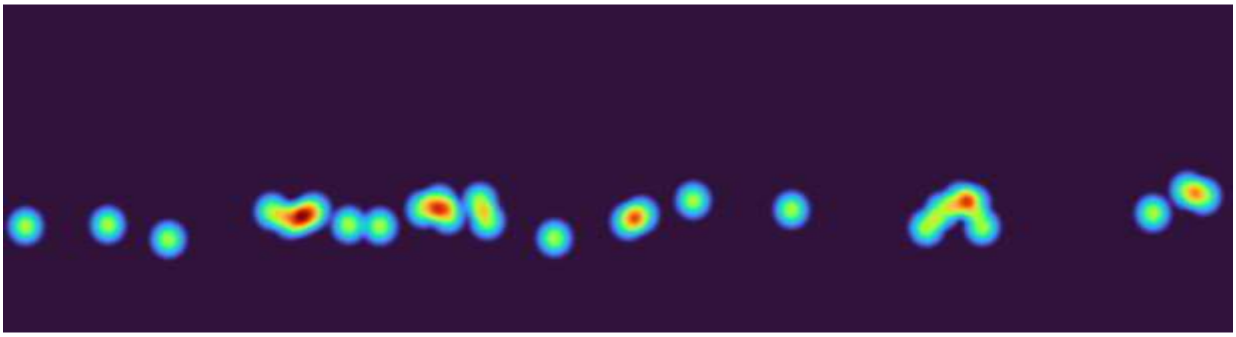

Fig. 5 Kernel density estimation heatmap. Sparse spots are visible not touching other spots. Clusters can be seen with dark brown nucleus. The average spacing spots are either touching or overlapping each other

Table 1 Unique tree id is given to each tree. The table shows the tree with the tree group to which it belongs

Tree ID	Tree Group	Tree ID	Tree Group	Tree ID	Tree Group
1	Sparse	10	Cluster 2	19	Sparse
2	Sparse	11	Cluster 2	20	Cluster 4
3	Sparse	12	Cluster 2	21	Cluster 4
4	Cluster 1	13	Avg Spacing	22	Cluster 4
5	Cluster 1	14	Avg Spacing	23	Cluster 4
6	Cluster 1	15	Sparse	24	Cluster 4
7	Cluster 1	16	Cluster 3	25	Sparse
8	Avg Spacing	17	Cluster 3	26	Cluster 5
9	Avg Spacing	18	Sparse	27	Cluster 5

Trees have been numbered 1 to 27 from left to right as shown in figure 4 which is a single vector layer of points representing trees. Three tree groups have been formed. One is sparse tree group, second is average spacing tree group and third is cluster tree group with trees in clusters. Five clusters have been identified named as cluster 1 to cluster 5 with each cluster given a unique colour (Fig. 4). Table 1 shows the three categories of tree groups. Points numbered in figure 3 are the unique tree id numbers in table 1 and can be correlated with three tree groups.

2.4 Heatmap

The heatmap (Fig. 5) is a density raster of an input points vector layer (Fig. 4) using Kernel density estimation. Heatmap has allowed easy identification of sparse spots, average spacing points and clustering of points. The density is calculated based on the number of points in a location with sparse spots resulting in smaller values and larger amount of cluster points resulting in larger values. Kernel shape is taken as quartic and output value scaling is taken as raw.

Kernal Function, $\boldsymbol{K(u)}$ with Kernel shape quartic (biweight) (Altman, 1992) :-

$$K(u) = \frac{15}{16}(1 - u^2)^2$$

Support: $|u| \leq 1$

has been used to create Kernel density estimation heatmap.

2.5 Vector layer model of tree trunk diameter

We have created a lines vector layer where each line indicates the diameter of tree trunk over which it is drawn (Fig. 6). With the help of vector lines data relative tree trunk diameter is determined and thereby calculating the relative tree trunk cross-sectional area. For trees having more than one trunk originating from ground, the trunks cross-sectional area for a particular tree id have been added up to determine tree trunks sum area and thereby the relative tree (cross-sectional) area as given in table 2. Relative tree area has been used to determine the width type.

Figure 7 shows a line vector layer with lines indicating the diameter of individual tree trunks. Colours of the lines have been categorized on the basis of width type in table 2.

The trees have been categorized in table 3 based on relative tree area range. The ranges have been decided based on visual inspection of Moringa Oleifera field and correlated with line density interpolation map created later.

2.6 Line density interpolation map

The line density interpolation takes the lines vector layer (Fig. 7) indicating the diameter of tree trunks as input applied and calculates a density measure of linear features which is obtained in a circular neighbourhood within each raster cell. Lines weight factor is optional and has not been applied by us. If applied, then the length of segment of each line that is intersected by circular neighbourhood is multiplied with the lines weight factor as first step. In next step, all the values of line lengths are summed and divided by the area of the circular neighbourhood. This process is repeated for all raster cells.

Figure 8 illustrates line density interpolation map with tree growth categorized with colours. Table 4 combines table 1 and table 2 with tree growth shown for all the tree groups.

Relative tree area range (Table 3) has been assessed by visual inspection of the Moringa Oleifera field which determines the tree growth for all the individual trees as shown in table 4. This tree growth has been correlated with the tree growth shown in line density interpolation map.

Fig.6 Shows a vector layer of lines placed over a raster layer of agricultural field study area. Lines have been drawn on individual tree trunks indicating their diameter. In figure 7 only vector layer of lines have been depicted clearly after categorizing the single coloured lines shown above into different colourss

Table 2 'Tree ID' is unique tree number with single or multiple tree trunks given by 'Trunk No.'. Each tree has 1 to 3 tree trunks originating from ground. 'Rel. Trunk Dia.' column is relative diameter used in calculating 'Rel. Trunk Area'. 'Rel. Tree Area' is the relative cross-sectional sum area of all the tree trunks of a single tree of Moringa Oleifera. 'Width Type' has been categorized according to data given in table 3 and 'Labels' have been given for each width type

Tree ID	**Trunk No.**	**Rel. Trunk Dia.**	**Rel. Trunk Area**	**Tree Trunks Sum Area**	**Rel. Tree Area**	**Width Type**	**Labels**
1	1	4.691	22.005	26.005	17.583	Broad	B
1	2	2	4	26.005	17.583	Broad	B
2	1	3.65	13.323	18.426	12.458	Broad	B
2	2	2.259	5.103	18.426	12.458	Broad	B
3	1	7.558	57.123	86.651	58.588	Very Broad	VB
3	2	4.64	21.53	86.651	58.588	Very Broad	VB
3	3	2.828	7.998	86.651	58.588	Very Broad	VB
4	1	2.868	8.225	9.319	6.301	Medium	M
4	2	1.046	1.094	9.319	6.301	Medium	M
5	1	3.171	10.055	10.055	6.799	Medium	M
6	1	1.569	2.462	3.462	2.341	Small	S
6	2	1	1	3.462	2.341	Small	S
7	1	2.563	6.569	16.241	10.981	Broad	B
7	2	2.304	5.308	16.241	10.981	Broad	B
7	3	2.089	4.364	16.241	10.981	Broad	B
8	1	3.302	10.903	20.687	13.987	Broad	B
8	2	3.128	9.784	20.687	13.987	Broad	B
9	1	3.997	15.976	25.34	17.133	Broad	B
9	2	3.06	9.364	25.34	17.133	Broad	B
10	1	3.388	11.479	11.479	7.761	Medium	M
11	1	3.046	9.278	13.625	9.212	Medium	M
11	2	2.085	4.347	13.625	9.212	Medium	M
12	1	3.838	14.73	14.73	9.959	Medium	M
13	1	2.479	6.145	8.591	5.809	Medium	M
13	2	1.564	2.446	8.591	5.809	Medium	M
14	1	6.169	38.057	43.589	29.472	Very Broad	VB
14	2	2.352	5.532	43.589	29.472	Very Broad	VB
15	1	3.306	10.93	10.93	7.39	Medium	M
16	1	5.628	31.674	33.372	22.564	Broad	B
16	2	1.303	1.698	33.372	22.564	Broad	B
17	1	3.042	9.254	12.914	8.732	Medium	M
17	2	1.913	3.66	12.914	8.732	Medium	M
18	1	3.562	12.688	12.688	8.579	Medium	M
19	1	1.216	1.479	1.479	1	Very Small	Z
20	1	7.349	54.008	54.008	36.517	Very Broad	VB
21	1	3.216	10.343	11.822	7.993	Medium	M
21	2	1.216	1.479	11.822	7.993	Medium	M

Tree ID	Trunk No.	Rel. Trunk Dia.	Rel. Trunk Area	Tree Trunks Sum Area	Rel. Tree Area	Width Type	Labels
22	1	1.631	2.66	2.66	1.799	Small	S
23	1	4.483	20.097	36.899	24.949	Broad	B
23	2	4.099	16.802	36.899	24.949	Broad	B
24	1	4.423	19.563	19.563	13.227	Broad	B
25	1	4.531	20.53	35.306	23.872	Broad	B
25	2	3.844	14.776	35.306	23.872	Broad	B
26	1	3.114	9.697	10.823	7.318	Medium	M
26	2	1.061	1.126	10.823	7.318	Medium	M
27	1	2.902	8.422	9.708	6.564	Medium	M
27	2	1.134	1.286	9.708	6.564	Medium	M

Table 3 Categorizing the trees on the basis of relative tree cross-sectional area range. Determining tree growth as directly proportional to width type category

Rel. Tree Area Range	Width Type	Tree Growth
25+	Very Broad	Very Good
10+ to 25	Broad	Good
5+ to 10	Medium	Average
1.5+ to 5	Small	Poor
1 to 1.5	Very Small	Very Poor

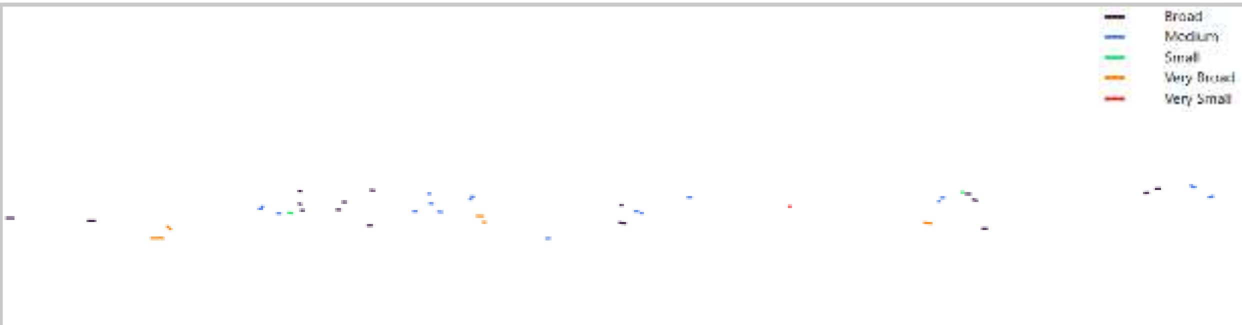

Fig.7 Line vector layer. Lines have been categorized into 5 colours based on 5 width types. Width type has been selected on the basis of relative tree area range as shown in table 3

Table 4 Tree growth analysed for tree id with tree group to which the tree belongs and relative tree area

Tree ID	Rel. Tree Area	Tree Group	Tree Growth	Tree ID	Rel. Tree Area	Tree Group	Tree Growth
1	17.583	Sparse	Good	15	7.39	Sparse	Average
2	12.458	Sparse	Good	16	22.564	Cluster 3	Good

3	58.588	Sparse	Very Good
4	6.301	Cluster 1	Average
5	6.799	Cluster 1	Average
6	2.341	Cluster 1	Poor
7	10.981	Cluster 1	Good
8	13.987	Avg Spacing	Good
9	17.133	Avg Spacing	Good
10	7.761	Cluster 2	Average
11	9.212	Cluster 2	Average
12	9.959	Cluster 2	Average
13	5.809	Avg Spacing	Average
14	29.472	Avg Spacing	Very Good
17	8.732	Cluster 3	Average
18	8.579	Sparse	Average
19	1	Sparse	Very Poor
20	36.517	Cluster 4	Very Good
21	7.993	Cluster 4	Average
22	1.799	Cluster 4	Poor
23	24.949	Cluster 4	Good
24	13.227	Cluster 4	Good
25	23.872	Sparse	Good
26	7.318	Cluster 5	Average
27	6.564	Cluster 5	Average

Fig.8 Line density interpolation map of line vector layer (Fig. 7). Tree growth very good is shown in colour blue, good in green or greenish yellow, average in mostly yellow, poor in orange and very poor in vermillion

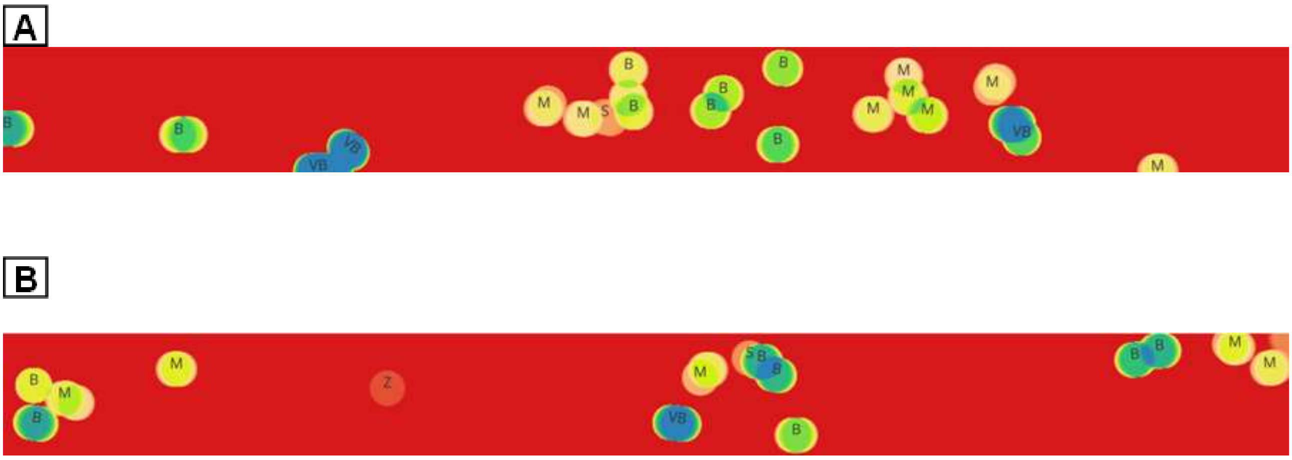

Fig.9 Enlarged view of figure 8 with labels applied to coloured spots. Labels can be correlated with colour of the spots showing tree trunk cross-sectional area range. A Left half section of figure 8 is shown here. B Right half section of figure 8 is shown here

Labels have been applied on the line density interpolation map which can be seen on the coloured spots in the map (Fig. 9). Except for some of the spots which are partially visible being behind the other spots all the labels are visible. Figure 9 also gives an enlarged view of figure 8 into two sections.

3. Results and Discussions

3.1 Above average growth percentage

In figure 10 there are 3 trees showing very good growth with one growing in sparse growth area, one growing with average spacing and one growing in a cluster signifying that trees with very good health can grow irrespective of the group.

Out of 9 trees having good health 2 are growing in sparse growth area, 2 are growing with average spacing and 5 are growing in clusters. Out of 16 trees in clusters 37.5% are showing above average growth. 50% of trees with average spacing and 42.9% in sparsely grown area show above average growth result. Here average spacing are giving best result but since the trees in clusters are closely packed in terms of space used by them, then taken all the trees in a cluster together and then comparing will be a better idea.

3.2 Below average growth percentage

In Figure 11 total trees growing in sparse growth area with below average growth is 1 out of 7 sparse trees. This is 14.3% below average result. For average spacing this result is 0% and for clusters this result is 12.5%. Highest percentage of below average growth is shown by sparse group.

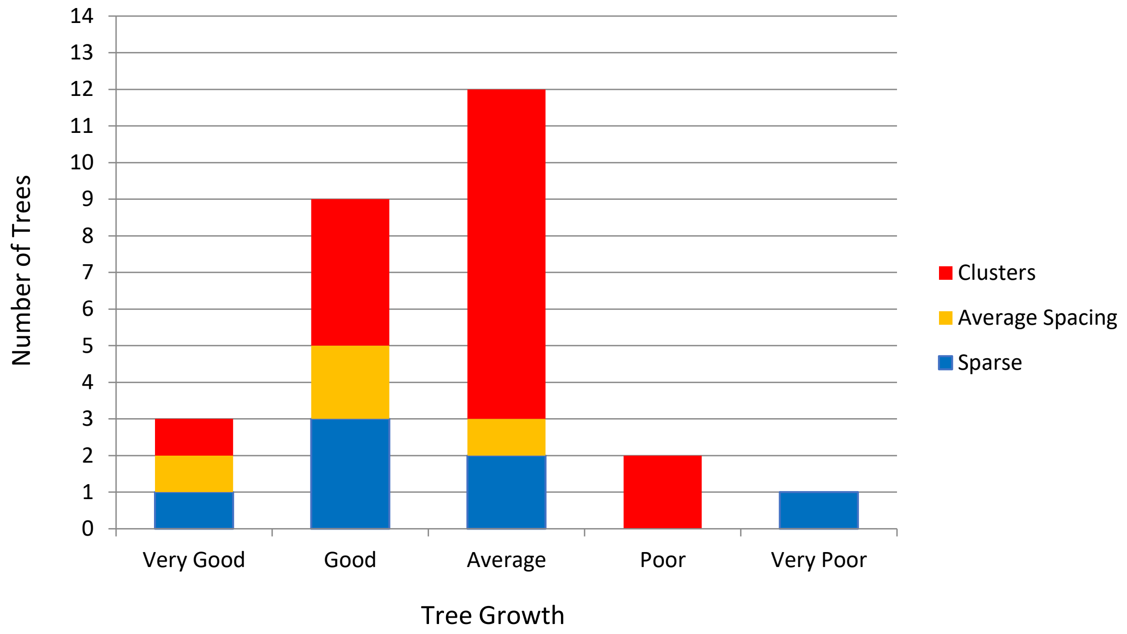

Fig.10 Number of trees versus tree growth for three types of tree groups

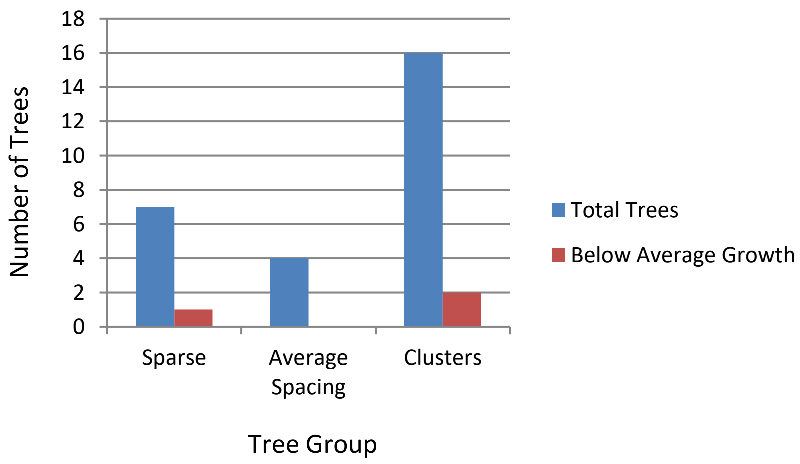

Fig. 11 Depicts the ratio of below average growth trees to the total trees in each of the three tree groups

3.3 Analysis of tree growth percentage taken all the trees in a cluster together as one

Relative cross-sectional area of cluster 1 by adding up for all the trees in that cluster is 26.422 (>25). Similarly very good growth (>25) is shown in figure 12 for clusters 2, 3 and 4. Cluster 5 is showing good growth (>10). 80% of clusters are showing very good growth and rest 20% good growth. This result is in itself appealing, seeing that the space occupied by a cluster in line density interpolation map is comparable to or less than that of sparse trees. About sparse trees 1 out of 7 shows very good growth that is 14.3% and 42.9% show good growth. Now result for clusters from figure 12 give 100% as above average cluster growth as compared to 57.2% for spare trees. The result is growing in clusters is a clear advantage over growing trees sparsely.

Out of 4 trees with average spacing, 2 lie in good growth range and 1 in very good range which is 75% above average growth and lower as compared to 100% for clusters.

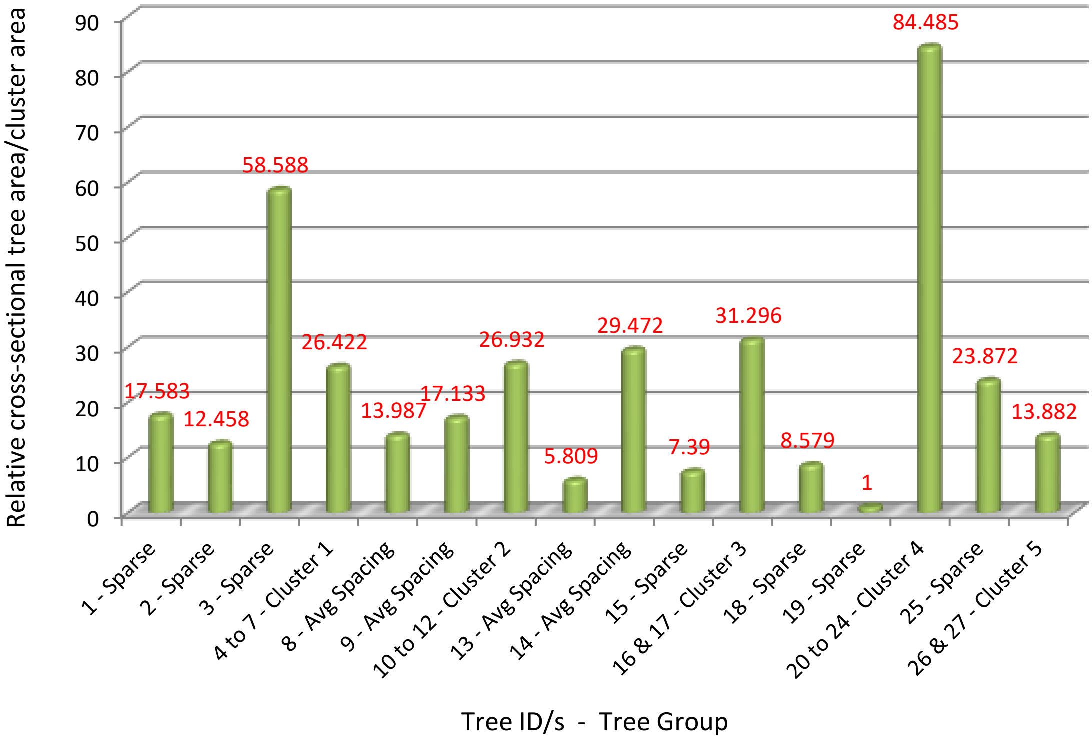

Fig. 12 Tree id/s with their group on x-axis and relative cross-sectional tree area/cluster area on y-axis. Relative cross-sectional area of all trees in a cluster was added to determine the cluster area

3.4 Identifying the field area to plant more trees

By visualizing the line density interpolation map of figure 8 and data from figure 12 the field areas with sparse trees can be selected for planting more trees.

Keeping maximum 5 trees in a cluster, as our analysis supports that, sparse tree id 25 can be converted into a cluster of 5 trees by planting 4 more trees to the left and in front. Sparse tree id 19 can also be converted into a cluster of 5 trees by planting 4 more trees around it. Sparse tree id 18 can be converted into a cluster of 4 trees by planting 3 more trees to the right and in front of it. Not converting sparse tree id 15 into a cluster as next to tree id 14 with very good growth and tree id 16 with good growth. Sparse tree id 3 need not be converted into a cluster as already showing very good and highest growth. Not converting sparse tree id 2 into a cluster as next to sparse tree id 3. Sparse tree id 1 can be converted into a cluster of 4.

Above discussion leads to introduction of 4 new clusters by planting 14 more trees. Increase in efficiency of farm produce by planting more trees can be attained.

3.5 Increase in produce by planting more trees

x = Percentage increase in number of trees

y = Extra trees to be planted

z = Total number of trees already planted

$$x = \left[\frac{y}{z}\right] \times 100$$

Percentage increase in number of trees was evaluated as 51.85%. Since tree growth is assumed to be proportional to cross-sectional area of trees the increase in growth of farm is proportional to increase in relative cross-sectional area by adding up for all trees to be planted in the farm.

RCS area = Relative cross-sectional area

Total RCS area of all trees in the farm is 378.888 by adding up the RCS area of 27 trees present, where tree ID 19 area being the minimum area has been taken as 1 for relative area calculations.

a *= total RCS area of all trees in the farm*

p *= total RCS area of all trees in clusters*

q *= total number of trees in clusters*

r *= average RCS area per tree among total trees in clusters*

s *= total number of trees in new clusters to be formed containing the existing sparse trees and new trees to be planted*

t *= predicted total RCS area of new clusters to be formed*

$$t = \left[\frac{p}{q}\right] \times s = r \times s$$

The predicted total RCS area of 4 new clusters to be formed including the RCS area of 4 existing sparse trees was evaluated as 205.894.

u *= sum of sparse trees RCS area which are to be converted into new clusters*

v *= predicted increase in RCS area of farm with new trees to be planted*

$$v = \left(\left[\frac{p}{q}\right] \times s\right) - u$$

The predicted increase in RCS area of farm with 14 new trees to be planted in 4 new clusters to be formed was evaluated as 154.86.

w *= predicted percentage increase in RCS area of farm*

$$w = \left[\frac{\left(\left[\frac{p}{q}\right] \times s\right) - u}{a}\right] \times 100$$

The above formula, which has been derived solely by first author of this paper, can be used in context of randomized tree plantations as "Prashant's equation on precision farming", is given on the name of first author.

$$w = \left[\frac{v}{a}\right] \times 100$$

The predicted percentage increase in RCS area of farm was evaluated as 40.87%.Foregoing analysis resluted in predicted growth of Moringa Oleifera farms to be 140.87% by using randomized tree plantation field.

Ease of irrigation is achieved by keeping space between clusters. Clusters can be connected with mud canal and mud bed prepared for each cluster. This way water can be given easily at one point with minimal maintenance cost. Thus saving upon water as well.

4. Conclusion

It can be concluded for Moringa Oleifera tree plantation that distancing between the trees is not a significant factor that is affecting the tree health but there is an advantage of growing trees in clusters with spacing between clusters to grow more trees in same area and enhancing the produce of farms thereby using the space economically. Distancing between the clusters allows for precision farming of areas where clusters are grown. Sparse trees with very good health need not be converted into clusters and that can only be decided once they grow up.

Initially randomized plantation of Moringa Oleifera benefits that later it can be decided better using tools of precision farming where to plant more trees. The predicted growth of Moringa Oleifera farms by the model created in this study should be examined for it's variations with photographs from different farms with randomized tree plantations using high resolution mobile cameras.

This study can be applied to similar agricultural field areas with different species of plants or fields with Moringa Oleifera plantations. Tree plantation spicies can be identified which are showing good growth in clusters and our study can be very useful in such cases. Potential savings in form of agricultural produce and irrigation can be achieved.

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Author Contributions

Conceptualization: [PKA], [AA], [PA]; methodology on GIS/Agricultural land and tree plantation growth analysis: [PKA], [AA], [PA]; formal analysis on GIS/Agricultural land and tree plantation growth analysis: [PKA]; writing─ original draft preparartion on GIS/ Agricultural land and tree plantation growth analysis: [PA], [AA]; writing─ review and editing on Agricultural land and tree plantation growth analysis: [PKA], [PA], [AA]; supervision: [AA], [PA].

Data availability

The datasets generated during and/or analysed during the current study are provded in this article.

1. Declarations

Competing interest

The authors declare that they have no conflict of interest

5. References

Adhikari, K., Smith, D. R., Hajda, C., and Kharel, T. P. (2023). Within-field yield stability and gross margin variations across corn fields and implications for precision conservation. *Precision Agriculture, 24*, 1401–1416. https://doi.org/10.1007/s11119-023-09995-7

Akinci, H., Ozalp, A. Y., Turgut, B. (2013). Agriculture land use suitability analysis using GIS and AHP technique, *Comput. Electron. Agric. 97* (2019) (2013) 71–82. https://doi.org/10.1016/j.compag.2013.07.006

Ali, Md. I., Borah, A., Singh, M., Srivastava, R. P. (2024). A Comprehensive Review of Recent Advances in Agronomy Research. *International Journal of Research Publication and Reviews, 5*(1), 934-940.

Altman, N. S. (1992). "An introduction to kernel and nearest neighbour nonparametric regression". *The American Statistician*. *46*(3): 175–185. doi:10.1080/00031305.1992.10475879. hdl:1813/31637.

Bandyopadhyay, S., Jaiswal, R. K., Hegde, V. S., Jayaraman, V. (2009). Assessment of land suitability potentials for agriculture using a remote sensing and GIS based approach, *Int. J. Remote Sens. 30* (4) 879–895.

Bochtis, D., and Oksanen, T. (2009). Combined coverage and path planning for field operations. In *Proceedings of the 7th European Conference on Precision Agriculture. Wageningen, The Netherlands: Wageningen Academic Publishers*. pp. 683–690

Bongiovanni, R., & Lowenberg-Deboer, J. (2004). Precision agriculture and sustainability. *Precision Agriculture, 5*(4), 359–387. https://doi.org/10.1023/B:PRAG.0000040806.39604.aa

Capmourteres, V., Adams, J., Berg, A., Fraser, E., Swanton, C., & Anand, M. (2018). Precision conservation meets precision agriculture: A case study from southern Ontario. *Agricultural Systems, 167*, 176–185. https://doi.org/10.1016/j.agsy.2018.09.011

Crookston, K. (2006). A top 10 list of developments and issues impacting crop management and ecology during the past 50 years. *Crop Science 46*, 2253-2262.

Duc, T. T. (2006). Using GIS and AHP technique for land-use suitability analysis, in: *International Symposium on Geoinformatics for Spatial Infrastructure Development in Earth and Allied Sciences, GIS-IDEAS 2006*, 9–11 November, Ho Chi Minh City, Vietnam, 2006.

El Baroudy, A. A. (2016). Mapping and evaluating land suitability using a GIS-based model, *Catena 140*, 96–104.

Filip, M., Zoubek, T., Bumbalek, R., Cerny, P., Batista, C. E., Olsan, P., et al. (2020). Advanced computational methods for agriculture machinery movement optimization with applications in sugarcane production. *Agriculture-Basel, 10*, 20.

Hamano, M., Kitaki, Y., Kurata, Y., & Watanabe, O. (2022). Development of measuring method of paddy field ridges in hilly and mountainous areas: Application of geographic information system software and precision digital elevation data (DEM). *Japanese Journal of Farm Work Research, 57*(1), 41–48.

Her, Y., Chaubey, I., Frankenberger, J., & Smith, D. (2016). Effect of conservation practices implemented by USDA programs at field and watershed scales. *Journal of Soil and Water Conservation, 71*(3), 249–266. https://doi.org/10.2489/jswc.71.3.249

Hofstee, J. W., Spätjens, L. E. E. M., & Ijken, H. (2009). Optimal path planning for field operations. In *"Proceedings of the 7th European conference on precision agriculture"*. Wageningen Academic Publishers The Netherlands. pp. 511–519

Jin, J., & Tang, L. (2010). Optimal coverage path planning for arable farming on 2D surfaces. *Transactions of the ASABE, 53*, 283–295.

Jones, G., Gee, C., & Truchetet, F. (2009). Modelling agronomic images for weed detection and comparison of crop/weed discrimination algorithm performance. *Precision Agriculture, 10*, 1–15.

Kalogirou, S. (2002). Expert systems and GIS: an application of land suitability evaluation. *Comput. Environ. Urban Syst. 26* (2–3) 89–112.

Kotam, V. R., Vinayak, B., Suhas N & Rohini N (2024). Farm_Era: Advanced Gis Field Mapping, Precision Crop Planning, Input Tracking, AI-Powered Pest Management, Real-Time Weather Updates, Smart Irrigation, and Powerful Data Analytics for Optimized Farming. *International Journal of Research Publication and Reviews*, *5*(1), 1510-1521.

Kumar, R. (2022). Remote Sensing and GIS-Based Land Use and Land Cover Change Detection Mapping of Jind District, Haryana. *International Journal of Research Publication and Reviews*, *3*(3), 869-874.

Kyushik Oh and Seunghyun Jeong (2007). Assessing the spatial distribution of urban parks using GIS, *Landscape and Urban Planning 82* (2007) 25–32. https://doi.org/10.1016/j.landurbplan.2007.01.014

Machiwal, D., Katara, P. & Mittal, H.K. (2015). Estimation of Soil Erosion and Identification of Critical Areas for Soil Conservation Measures using RS and GIS-based Universal Soil Loss Equation. *Agricultural Research 4*, 183–195. https://doi.org/10.1007/s40003-015-0157-7

McConnell, M., & Burger, L. W. (2011). Precision conservation: A geospatial decision support tool for optimizing conservation and profitability in agricultural landscapes. *Journal of Soil and Water Conservation, 66*(6), 347–354. https://doi.org/10.2489/jswc.66.6.347

Nigam, G.K., Tripathi, M.P. (2020). Generation of Groundwater Zones for Selection of Prospective Suitable Water Harvesting Structure Sites for Sustainable Water Supply Towards the Agricultural Development. *Agricultural Research 9*, 148–160. https://doi.org/10.1007/s40003-019-00430-w

Nyeko, M. (2012). GIS and multi-criteria decision analysis for land use resource planning, *J. Geogr. Inform. Syst. 4*, 341–348.

Oksanen, T., & Visala, A. (2009). Coverage path planning algorithms for agricultural field machines. *Journal of Field Robotics, 26*, 651–668.

Oliver, M., Bishop, T., & Marchant, B. (2013). *Precision agriculture for sustainability and environmental protection*. Routledge. https://doi.org/10.4324/9780203128329

Oyoshi, K., Tomiyama, N., Okumura, T., Sobue, S., & Sato, J. (2016). Mapping rice-planted areas using time-series synthetic apertureradar data for the Asia-RiCE activity. *Paddy and Water Environment, 14*(4), 463–472. https://doi.org/10.1007/s10333-015-0515-x

Pereira, J. M., Duckstein, L. (1993). A multiple criteria decision-making approach to GIS-based land suitability evaluation, *Int. J. Geogr. Inf. Sci. 7* (5) 407–424.

QGIS (2023). QGIS geographic information system. Open source geospatial foundation project. http://qgis.org.

Ragini, H.R., Debnath, M.K., Gupta, D.S. et al. (2023). Modelling and Monitoring Land Use: Land Cover Change Dynamics of Cooch Behar District of West Bengal using Multi-Temporal Satellite Data. *Agricultural Research 12*, 387–396 (2023). https://doi.org/10.1007/s40003-023-00657-8

Rizzo, G., Monzon, J.P., Tenorio, F.A., Howard, R., Cassman, K.G. and Grassini, P. (2022). Climate and agronomy, not genetics, underpin recent maize yield gains in favorable environments. *Proceedings of the National Academy of Sciences of the United States of America, 119*(4):e2113629119. doi: 10.1073/pnas.2113629119.

Schwilch, G., Bestelmeyer, B., Bunning, S., Critchley, W., Herrick, J., Kellner, K., et al. (2011). Experiences in monitoring and assessment of sustainable land management, *Land Degrad. Dev. 22*, 214–225.

Wang, R., Zhang, S., Yang, J., Pu, L., Yang, C., Yu, L., et al. (2016). Integrated use of GCM, RS, and GIS for the assessment of hillslope and gully erosion in the Mushi River Sub-Catchment Northeast China. *Sustainability, 8*, 317.