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Leveraging cluster and PCA analysis to uncover key soil and environmental drivers for groundnut cultivation in the Kharif and Rabi seasons

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Abstract

The cultivation of groundnut, which is crucial for its protein-rich kernels and edible oil, is highly sensitive to variations in soil moisture, particularly under rainfed conditions. The objective of the present study is to improve the accuracy of soil moisture monitoring by using principal component analysis (PCA) and clustering to analyze data from sensor and satellite sources. In addition to the use of satellite images from SMAP, ERA5 and Sentinel 1A in addition to in situ sensor data, this study was carried out at the Oil Seed Research Station in Tindivanam. Important factors, such as soil moisture, potential evaporation (PET) and volumetric water content (VWC) were examined at various crop stages. According to PCA, VWC at different depths and soil moisture data clustered closely during the Kharif season, indicating substantial relationships. A significant loading on the first component (PC1) explained 51.26 % of the variance. The significance of soil moisture and PET was highlighted by cluster analysis, which revealed four major clusters with strong intracluster relationships. On the other hand, PCA for the Rabi season revealed that ERA5-SM, WS and ST were crucial, with PC1 accounting for 67.53 % of the variation. Three clusters were found in the cluster analysis for Rabi, highlighting the significance of ST and WS in crop development. A study of the seasons revealed that during Kharif, soil moisture and evaporation were crucial, whereas during Rabi, soil temperature and wind speed had greater impacts. This emphasizes how vital it is to apply season-appropriate agronomic techniques to maximize crop productivity and resource efficiency.

Keywords

groundnut; Kharif; Rabi; soil moisture; satellite; sensor; meteorology factors

Introduction

Groundnut (*Arachis hypogaea* L.) is a vital crop worldwide, serving both as a pulse and an oilseed, primarily cultivated for its edible oil, protein and fatty acids. The groundnut kernel is rich in protein (22-30 %) and contains a significant amount of edible oil (44-56 %), with oleic acid, linoleic acid and palmitic acid accounting for 90 % of its total fatty acid composition. High-oleic-acid groundnuts are particularly valued for their longer shelf life and superior flavor. In India, approximately 70 % of groundnut cultivation occurs under rainfed conditions, where intermittent soil moisture stress can significantly reduce both yield and quality. Improving the nutritional quality of groundnuts under these conditions requires studying the impact of soil moisture stress on crop performance (1).

Water scarcity significantly impacts crop performance in rainfed regions. The analysis of crop yield projections is crucial for understanding the influence of soil moisture and associated meteorological factors on crop growth. Effective planning and monitoring strategies help ensure sustainable farming practices despite changing environmental conditions (2). Climate plays a critical role in agricultural production, significantly influencing output. In addition to moisture, factors such as temperature, relative humidity, solar radiation, wind speed, pest and disease incidence and soil microbiology can affect production (3).

The principal components analysis (PCA) is highly useful in determining which environmental factors, such as soil moisture, temperature, potential evapotranspiration (PET) and wind speed, contribute most to groundnut yield. These key factors should be emphasized in crop management strategies. To analyze the variation among different environmental conditions, cluster analysis is employed. This method classifies locations or variables based on the similarity of their characteristics, aiming to minimize within-group variance and maximize between-group variance. It is also useful for selecting ideal environmental conditions for crop modeling and improving cultivation practices. Therefore, the present study was conducted to evaluate the variability in environmental factors influencing groundnut pod and dry fodder yield to identify the optimal conditions for future crop management strategies (4). Research on climate change is crucial for adapting agricultural crop management, particularly for crops sensitive to climatic variations such as groundnuts. Among the climate parameters, soil moisture, maximum and minimum temperatures, average temperature and solar radiation presented the highest R^2 values and the lowest RMSE values, indicating their strong influence (5). In contrast, wind speed and relative humidity had lower correlations and greater errors. The grid size of the NASA platform, which is kilometric in scale, can lead to low model adjustments due to the potential overlap of areas, which may particularly benefit growers lacking nearby surface weather stations (6).

The key objective of this research was as follows:

An in-depth comparative analysis of soil moisture data obtained from both satellite and sensor sources.

Offering insights that could improve the accuracy of soil moisture monitoring and prediction, with a focus on agricultural practices, particularly for groundnut crops.

Materials and Methods

The study was carried out at the Oil Seed Research Station in Tindivanam at 12°213886′N latitude and 79°672351′E longitude. Groundnut is a soil moisture-sensitive crop that is sown in both predominant seasons of Tamil Nadu-Kharif and Rabi (7). The crop variety TMV 14 was chosen for this study. The soil moisture and weather parameters were monitored and observations were taken at critical crop stages, such as the seedling (15 days after sowing), vegetative (30 DAS), flowering (45 DAS), pegging (60 DAS), pod filling (75 DAS) and harvesting (105 DAS) stages. The soil moisture sensor tower installed at the site is shown in Fig. 1.

In situ soil moisture sensor (Cr 300) data are used to validate seasonal observations of satellite data (8). At regular intervals, the logger data are collected from the flux sensor. Satellite datasets such as the SMAP (Soil Moisture Active Passive) is combined sensor satellite to monitor soil moisture, ERA5 (European Reanalysis Version 5) is a dataset providing high-resolution climate and weather information from the European Centre for

Fig. 1. Experimental site with *in-situ* sensor.

Medium-Range Weather Forecasts and Sentinel 1A (S1A) is synthetic aperture radar helps to capture the soil and environmental status were used for the comparative analysis. Satellite data were processed and downloaded from the Google Earth Engine (GEE). The parameters utilized are detailed below in Table 1.

The statistical analysis of clustering and principal component analysis (PCA) was performed to study the relationship between each parameter and the sources of satellite data used. PCA relies heavily on eigenvalues and loadings to help with data structure identification. Greater values of eigenvalues indicate a greater amount of variance explained by each principal component. Since they can account for more variance than a single original variable, eigenvalues larger than one are typically regarded as noteworthy. A stronger relationship is indicated by higher values (close to 1 or -1) for loadings, which show how much each variable contributes to a principal component. An indication of a significant impact of the variable on the component would be a loading of 0.7 or higher. Complex datasets can be made easier to access and understand by analyzing these values, which help identify which variables are most crucial in explaining data patterns. The parameters concerning the stages of crop phenology were weighed. The sense of reinforcement and balancing leads to the establishment of a favorable environment at the regional level/field itself. The analysis was performed via SAS JMP Pro 17 software (9).

Table 1. Details of the sources and meteorological parameters.

Source	Parameters and units
Soil moisture tower (Cr 300)	Volumetric water content at 10 cm, 30 cm and 45 cm (VWC; %)
	Soil temperature at 10 cm, 30 cm and 45 cm (ST; °C)
	Horizontal wind speed (WS; m/s)
	Horizontal wind direction degree (WDV; °)
	Rain (mm)
	Relative humidity (RH; %)
	Net radiation (NR; Watts/m^2)
SMAP (Soil Moisture Active Passive) (27)	Soil Moisture (SM; %)
	Root Zone Soil Moisture (RZSM; %)
Sentinel 1A (28)	Backscatter Vertical-Vertical (VV; σ^0)
	Backscatter Vertical-Horizontal (VH; σ^0)
ERA5 (29)	Soil Moisture (SM; %)
	Forecast Albedo (Albedo; No unit)
	Surface Net Solar Radiation (SNSR; J/m^2)
	Potential Evaporation (PET; m)

Results

Soil and environmental factors during the Kharif season

Biplot and PCA Analysis

The biplot of the Kharif season (Fig. 2) illustrates the relationships among the variables through PCA. The first principal component (PC1) accounts for a substantial proportion of the variability in the data, allowing us to observe which variables contribute most significantly to the overall variance. Key variables, such as VWC at different depths (30 cm and 45 cm), ERA5-SM, PET and SMAP-SM, cluster closely together, indicating a strong positive correlation. This graphical representation helps identify clusters of variables that behave similarly, providing insight into the underlying data structure. By the analysis, the first principal component, with an eigenvalue of 9.739, accounted for 51.26 % of the total data variability, while the second, third and fourth components, with eigenvalues of 5.722, 2.392, and 1.145, explained 30.12 %, 12.59 % and 6.03 % of the variance respectively. Soil moisture variables were most influential in the first component; SMAP-RZSM (loading of 0.316) had the strongest influence, followed closely by SMAP-SM (0.315) and various VWC depths (ranging from 0.253 to 0.308). ERA5-SM also contributed with a loading of 0.207. In the second component, which explained 30.12 % of the variance, key variables included WDV (0.405), S1A-VH (0.397), rainfall (0.362) and albedo (-0.321). These results show that while soil moisture variables dominate the first component, weather and remote sensing indicators exert a greater influence on the second. This distinction underscores the importance of considering both meteorological and soil variables to better understand the factors driving variability in groundnut cultivation.

Cluster analysis and squared cosines of variables

Table 2 provides a detailed summary of the clustering analysis for the Kharif season. Clusters are formed on the basis of the R^2 values of the variables within each cluster, the R^2 values with the next closest cluster and various cluster coefficients. The analysis identified 4 distinct clusters, which were summarized with their contributing factors. Cluster I (proportion: 0.895) includes VWC at 45 cm and 30 cm, ERA5-SM, PET and SMAP-SM. The high R^2 values within this cluster (ranging from 0.781-0.962) indicate a strong intracluster correlation. For example, the VWC at 45 cm has an R^2 value of 0.962, demonstrating its strong relationship with the other variables in this cluster. The low 1-R^2 ratios and cluster coefficients further confirm the robustness of this cluster. In Cluster II (proportion: 0.794), the variables in this cluster are WDV, S1A-VH, NR, Rain, S1A -VV and albedo. With R^2 values ranging from 0.547 to 0.956, this cluster shows moderate to high intracluster correlations. For example, WDV has an R^2 value of 0.956, indicating a strong relationship within the cluster. Cluster III (proportion: 0.883) contains WS, ST at 10 cm and 45 cm, SMAP-RZSM, VWC at 10 cm and RH. High R^2 values (e.g., WS at 0.972) signify strong intracluster correlations, demonstrating the tight grouping of these variables. Cluster IV (proportion: 0.932) compared with ST at 30 cm

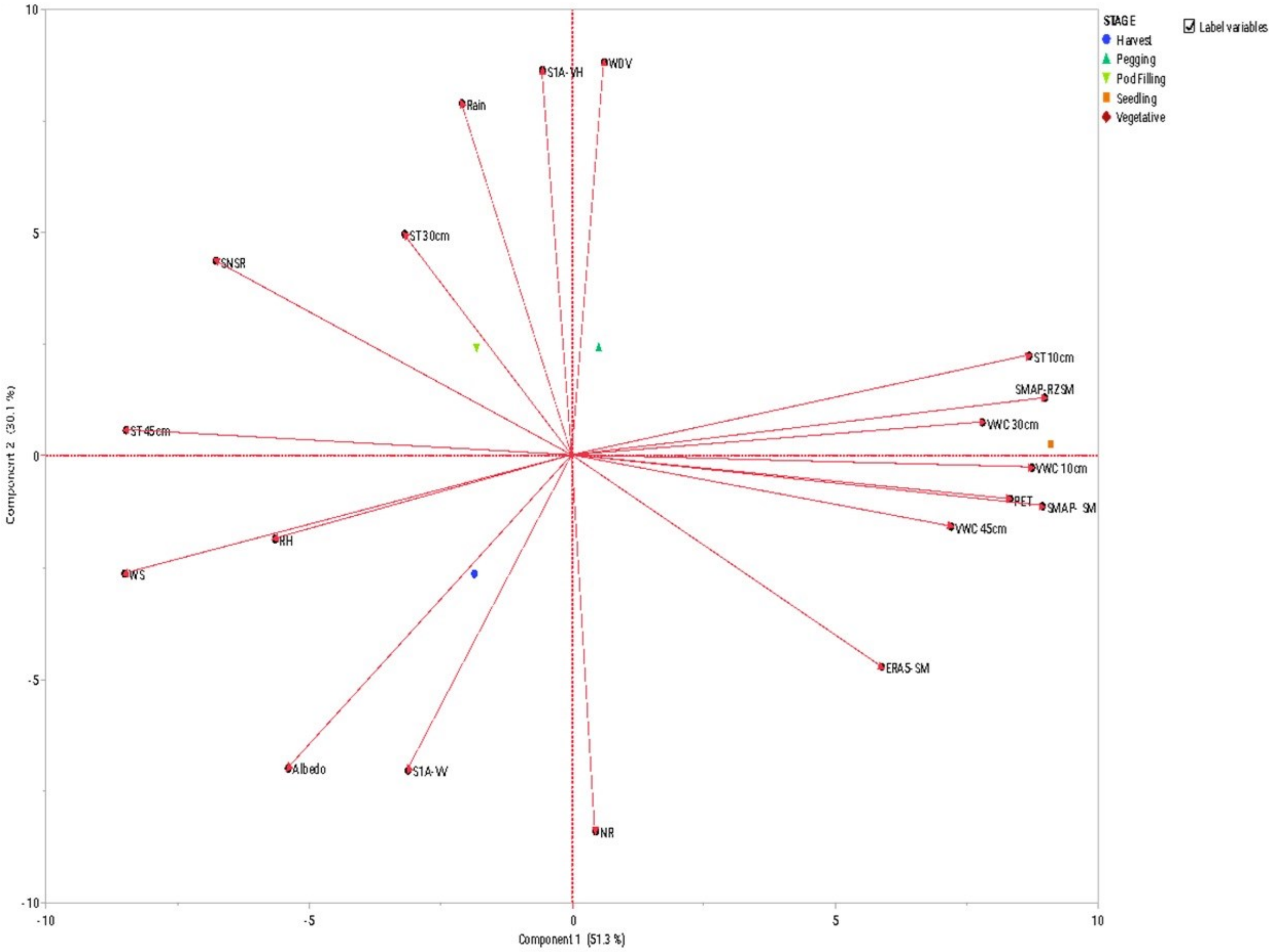

Fig. 2. Biplot of covariates in groundnut crop under the Kharif season.

Table 2. Clustering summary of the Kharif season

Clusters (Proportion)	Variables	R^2 of own cluster	R^2 of the next closest	1-R^2 ratio	Cluster coefficient I	Cluster coefficient II	Cluster coefficient III	Cluster coefficient IV
I (0.895)	VWC 45 cm	0.962	0.365	0.06	0.463	0	0	0
	VWC 30 cm	0.928	0.519	0.15	0.455	0	0	0
	ERA5-SM	0.781	0.256	0.295	0.417	0	0	0
	PET	0.898	0.659	0.298	0.448	0	0	0
	SMAP- SM	0.906	0.809	0.494	0.449	0	0	0
II (0.794)	WDV	0.956	0.109	0.049	0	0.447	0	0
	S1A-VH	0.933	0.253	0.089	0	0.442	0	0
	NR	0.873	0.369	0.201	0	-0.428	0	0
	Rain	0.78	0.141	0.256	0	0.404	0	0
	S1A-VV	0.547	0.227	0.586	0	-0.338	0	0
	Albedo	0.676	0.533	0.693	0	-0.376	0	0
III (0.883)	WS	0.972	0.493	0.055	0	0	-0.428	0
	ST 10 cm	0.951	0.581	0.118	0	0	0.423	0
	ST 45 cm	0.929	0.58	0.168	0	0	-0.418	0
	SMAP-RZSM	0.929	0.749	0.283	0	0	0.418	0
	VWC 10 cm	0.873	0.72	0.454	0	0	0.406	0
	RH	0.641	0.287	0.503	0	0	-0.347	0
IV (0.932)	ST 30 cm	0.932	0.211	0.087	0	0	0	0.707
	SNSR	0.932	0.494	0.135	0	0	0	0.707

and SNSR, this cluster has very high R^2 values (both 0.932), indicating excellent intracluster correlation and a clear grouping distinct from those of the other clusters.

Fig. 3 shows the squared cosines of the variables for the Kharif season. Squared cosines measure the quality of representation of each variable in the factor space defined by the principal components. Higher squared cosine values indicate better representation. For example, variables such as VWC at various depths, ERA5-SM, PET and SMAP-SM have higher squared cosine values, indicating that they are well represented in the principal component space. This helps in assessing the importance and influence of each variable within the dataset.

Soil and environmental factors during the Rabi season

Biplot and PCA Analysis

The biplot for the Rabi season (Fig. 4) provides a visual representation of the relationships between variables via PCA. The PC1 captures a significant portion of the variance, highlighting the contribution of each variable. Variables such as ST at 45 cm, WS, ERA5-SM and VWC at 30 cm form distinct clusters, reflecting their strong correlations. This visualization aids in understanding how different variables group together and contribute to the overall variability in the data. The analysis revealed that the first principal component, with an eigenvalue of 12.831, explained 67.53 % of the total data variability, while the second, third, fourth and fifth components, with eigenvalues of 3.107, 1.747, 0.920 and 0.393, accounted for 16.36 %, 9.20 %, 4.84 % and 2.07 % of the variance respectively. During the Rabi season, soil moisture variables played a dominant role in the first component, with ERA5-SM being the most significant (loading of 0.272), followed by VWC at 30 cm (0.269), VWC at 45 cm (0.262), S1A-VH (0.242), SMAP-RZSM (0.215) and VWC at 10 cm (0.214). In the second component, which contributed 16.36 % to the variance, major influencing factors were WDV (0.382), rainfall (0.258), albedo (0.251) and S1A-VV (-0.416). These findings suggest a transition from soil moisture as the key factor in the first component to a stronger influence of weather and remote sensing indicators in the second. This shift highlights the need to consider both meteorological and soil-related factors to better understand the dynamics impacting groundnut cultivation throughout the seasons.

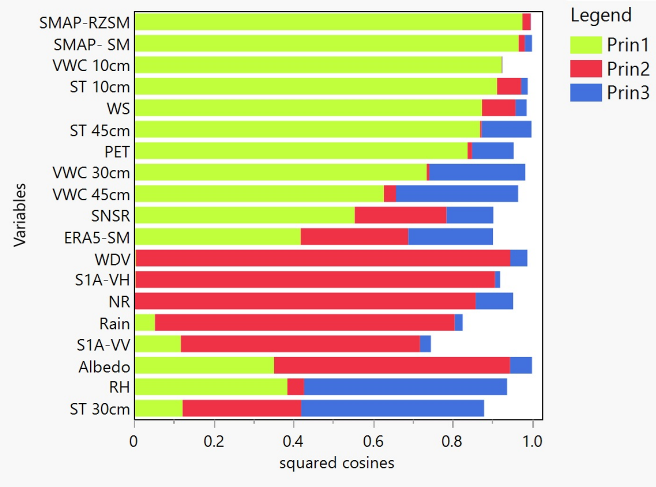

Fig. 3. Plot of squared cosines of variables in groundnut crop under the Kharif season.

Cluster analysis and squared cosines of variables

Table 3 details the cluster analysis for the Rabi season, categorizing variables into clusters on the basis of their R^2 values and cluster coefficients. Three clusters were identified. Cluster I (proportion: 0.879) includes ST at 45

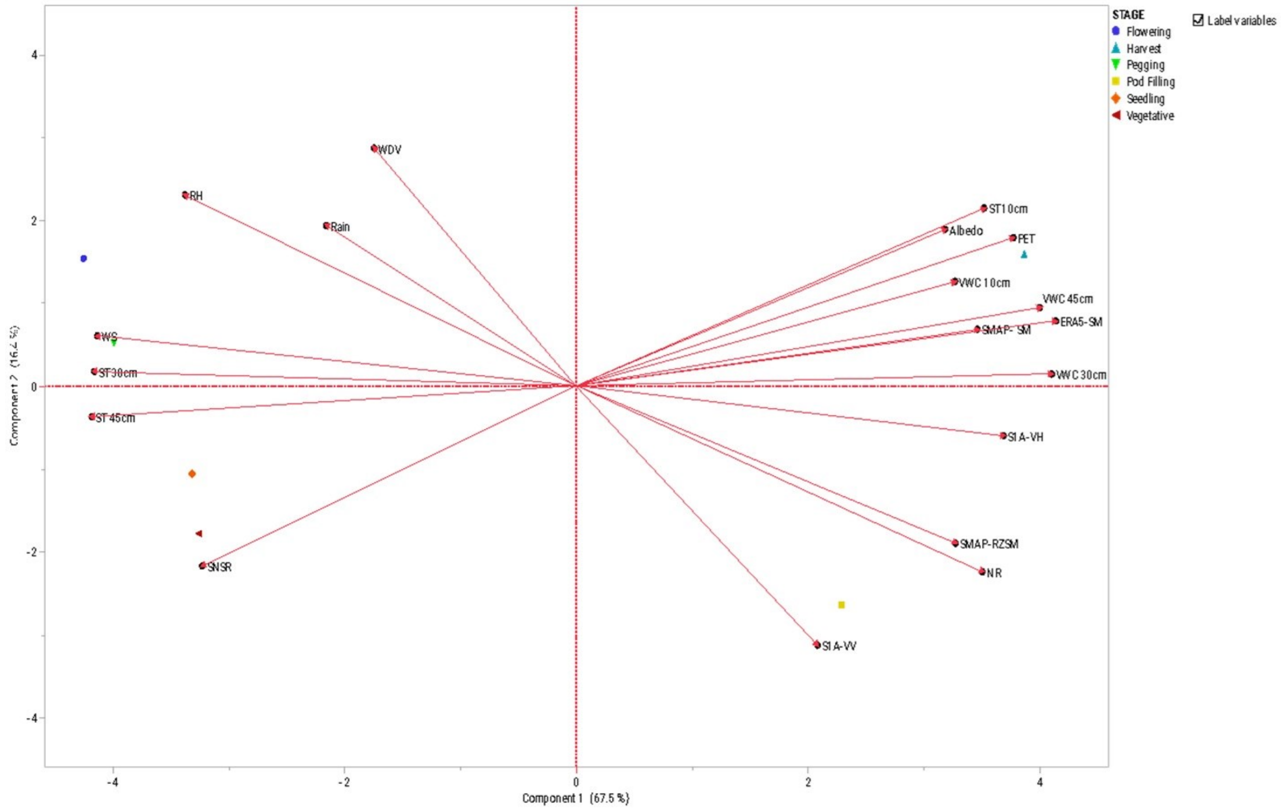

Fig. 4. Biplot of covariates in groundnut crop under the Rabi season.

Table 3. Clustering summary of the Rabi season.

Clusters (Proportion)	Variables	R^2 of own cluster	R^2 of the next closest	1-R^2 ratio	Cluster coefficient I	Cluster coefficient II	Cluster coefficient III
I (0.879)	ST 45 cm	0.966	0.758	0.142	-0.370613	0	0
	WS	0.934	0.652	0.19	-0.364435	0	0
	ERA5-SM	0.955	0.828	0.265	0.3684542	0	0
	VWC 30 cm	0.916	0.706	0.285	0.3610237	0	0
	SMAP- SM	0.831	0.414	0.288	0.3438175	0	0
	S1A-VH	0.825	0.475	0.333	0.3425581	0	0
	ST 30 cm	0.883	0.721	0.42	-0.354345	0	0
	VWC 10 cm	0.722	0.478	0.533	0.3203433	0	0
II (0.738)	RH	0.954	0.502	0.091	0	-0.464186	0
	NR	0.955	0.581	0.107	0	0.4643568	0
	S1A-VV	0.739	0.16	0.311	0	0.4083417	0
	WDV	0.573	0.147	0.501	0	-0.359529	0
	Rain	0.551	0.161	0.535	0	-0.352698	0
	SMAP-RZSM	0.658	0.656	0.993	0	0.3853625	0
III (0.927)	ST 10 cm	0.991	0.63	0.024	0	0	0.4623148
	SNSR	0.957	0.483	0.083	0	0	-0.45434
	PET	0.93	0.784	0.325	0	0	0.4478376
	VWC 45 cm	0.931	0.798	0.34	0	0	0.4482202
	Albedo	0.827	0.493	0.341	0	0	0.4223507

cm, WS, ERA5-SM, VWC at 30 cm, SMAP-SM, S1A-VH, ST at 30 cm and VWC at 10 cm. The high R^2 values (e.g., ST at 45 cm with an R^2 of 0.966) indicate strong intracluster correlations, demonstrating a robust grouping of these variables. Cluster II (proportion: 0.738) comprises RH, NR, S1A-VV, WDV, Rain and SMAP-RZSM; this cluster shows a range of R^2 values with moderate to high intracluster correlations. For example, RH has an R^2 of 0.954, indicating a strong relationship within the cluster. Cluster III (proportion: 0.927) contains ST at 10 cm, SNSR, PET, VWC at 45 cm and albedo. High R^2 values (e.g., ST at 10 cm with an R^2 of 0.991) demonstrate strong intracluster correlations, indicating a tight grouping of these variables.

Fig. 5 illustrates the squared cosines of the variables for the Rabi season, providing insights into the quality of their representation in the principal component space. Higher squared cosine values indicate that variables such as ST at 45 cm, WS, ERA5-SM and VWC at 30 cm are well represented, emphasizing their importance in the dataset.

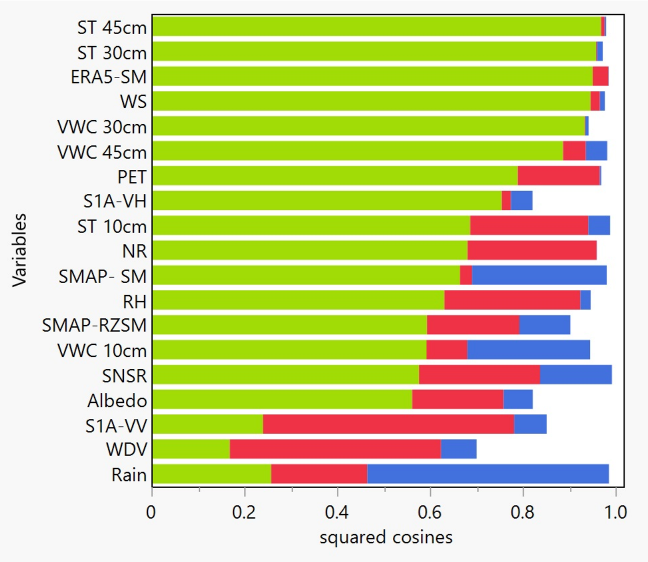

Fig. 5. Plot of squared cosines of variables in groundnut crop under the Rabi season.

Discussion

This study explores the intricate interrelationships between soil and environmental variables during the Kharif and Rabi seasons. This probing employs PCA and cluster analysis to reveal significant patterns in the interactions of these variables. The biplot analysis effectively revealed crucial insights for comprehending crop performance and environmental dynamics.

Kharif season

During the Kharif season, the PC1 accounted for 51.26 % of the total variance. This underscores the importance of variables such as the volumetric water content (VWC) at different depths, ERA5-SM, PET and SMAP-SM which are closely clustered and strongly positively correlated. This correlation signified that soil moisture at various depths plays a crucial role in determining crop yield during the monsoon season, especially for rice and maize (10). Furthermore, the substantial loadings of VWC at 45 cm (0.253) and SMAP-SM (0.315) in PC1 underscore their vital role in soil moisture retention, directly impacting Kharif crops such as rice and maize, as supported previous study (11). This correlation emphasized the role of deep soil moisture in sustaining crop growth during periods of water scarcity (12). The results of the cluster analysis confirmed the findings by grouping similar variables. Cluster I consisted of VWC at 45 cm and 30 cm, ERA5-SM, PET, and SMAP-SM, which showed strong correlations within the cluster, with R^2 values ranging from 0.781-0.962. This indicates a strong interrelationship between these variables, collectively influencing soil moisture dynamics and crop growth during the Kharif season. These results highlighting the critical role of soil moisture and evaporation in determining the yield of water-intensive crops such as rice (13). The influence of PET on crop water demand, particularly in Kharif, has been assured its role in irrigation planning for sustainable agriculture (14). Additionally, the significance of soil moisture and its impact on root development and nutrient uptake in monsoon-fed crops was emphasized by (15).

Rabi Season

In the Rabi season, PCA identified a specific set of influential variables. The PC1 represented 67.53 % of the variance, with significant contributions from soil temperature (ST) at 45 cm, wind speed (WS), ERA5-SM and VWC at 30 cm. These variables formed distinct clusters, reflecting their strong correlations and collective impact on soil and crop dynamics during the winter season. The significance of ST and WS during the Rabi season is demonstrated that these variables significantly affect the growth of wheat and mustard, which are crops that are sensitive to temperature and wind conditions (16). This finding reported that soil temperature significantly influences nutrient availability and root development in wheat (17). Cluster analysis for the Rabi season revealed three main clusters, with Cluster I (proportion: 0.879) including ST at 45 cm, WS, ERA5-SM, VWC at 30 cm, SMAP-SM and S1A-VH. High R^2 values, such as 0.966 for ST at 45 cm, indicate strong intracluster correlations, suggesting that these variables are closely linked in influencing crop growth during the Rabi season. This observation showed that the soil temperature at deeper layers plays a critical role in maintaining soil health and crop yield, particularly for wheat (18). Furthermore, the role of wind speed in modulating microclimatic conditions and its impact on crop transpiration rates during the Rabi season has been emphasized by earlier worker (19).

Comparison of the seasonal variations

The comparison between the Kharif and Rabi seasons reveals the varying significance of soil and environmental variables during different cropping periods. During the Kharif season, soil moisture and evaporation were more influential, while soil temperature and wind speed were critical during the Rabi season. These seasonal variations in variable influence align with findings that suggest the pivotal role of soil moisture and temperature dynamics in determining crop yield and quality, especially in semiarid regions (20). The influence of soil moisture in the Kharif season and soil temperature in the Rabi season has also been demonstrated, with both variables significantly impacting the physiological processes of crops and overall productivity (21). The importance of wind speed during the Rabi season, particularly its effect on evaporation rates and microclimatic conditions essential for crops like wheat and mustard, has been highlighted (22).

Additionally, studies have shown that seasonal changes directly impact nutrient availability and soil microbial activity, both of which are crucial for crop growth (23). Variations in temperature and moisture across seasons have been found to significantly influence nutrient cycling in soils. The effects of soil temperature and moisture on root development and crop yield across seasons further support the seasonal dynamics observed in this study (24). These insights are essential for optimizing agronomic practices, such as irrigation scheduling, fertilization and crop selection, which must be tailored to the specific needs of crops during different seasons (25). Understanding the key variables influencing crop growth across seasons can help farmers optimize irrigation, fertilization, and other practices to enhance crop yield and sustainability. Moreover, this understanding is valuable for developing predictive models of crop performance, contributing to better resource management and decision-making in agriculture. The importance of incorporating environmental variables into crop management practices has been emphasized as such integration has been shown to significantly improve crop productivity and resource use efficiency (26).

Conclusion

This study identifies key environmental and soil variables affecting groundnut cultivation across seasons. During the Kharif season, soil moisture and potential evaporation (PET) are crucial for managing water stress, with strong correlations between measures like SMAP-SM and VWC highlighting their importance. Accurate soil moisture monitoring and informed irrigation plans are essential to mitigate water shortages and enhance productivity. In the Rabi season, soil temperature and wind speed become more significant. PCA results show that ERA5-SM, VWC, wind speed and soil temperature at deeper levels are critical for crop growth. These findings underscore the need for season-specific agronomic strategies to improve fertilization and irrigation, ultimately supporting better crop management and yield. The study advocates for the development of prediction models to refine agricultural practices and adapt to changing environmental conditions, promoting both productivity and sustainability.

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Authors' contributions

GP carried out the data curation, formal analysis, investigation and visualization and drafted the original manuscript. MD contributed to the conceptualization, data curation, formal analysis and methodology, validated the results and participated in reviewing and editing the manuscript. KP participated in reviewing and editing the manuscript. PS, PPC and RKP contributed to reviewing and editing the manuscript. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interest to declare.

Ethical issues: None

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Quill Bot and AI assistance in order to enhance the readability and flow of content; after the original drafting. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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