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INTEGRATION OF REMOTE SENSING AND MACHINE LEARNING FOR REAL-TIME MONITORING OF SOIL HEALTH PARAMETERS IN RESPONSE TO CLIMATE VARIABILITY IN KARNATAKA

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| ARTICLE INFO | ABSTRACT |
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| <i>Article History:</i> Received 14 th August, 2024 Received in revised form 16 th September, 2024 Accepted 03 rd October, 2024 Published online 30 th November, 2024 | A remote-sensing and artificial neural network model is proposed for real-time data collection of soil health indices in Karnataka to counter climate change. The main objective is to monitor and understand the seasonal variations in moisture, nutrients, pH, organic carbon, texture and the impact of climate variability on these soil parameters. Data collection included the satellite images from Sentinel-2 and other optical bands such as Lands at 8 and additional high-resolution imagery from UAVs or drones, and the soil moisture was continuously streamed using IoT |
| Key Words: | sensors. Random Forest, Gradient Boosting, and Neural Networks were used to forecast the |
| Remote Sensing, Soil Health Monitoring, Climate Variability, Real-Time Data, Satellite Imagery. | verified based on the results obtained. The climate models incorporated with the streaming technology allowed the system to estimate current and future climate conditions. The study shows the efficiency, significance and usefulness of the integrated approach in the assessment of soil health, and can be used as a tool in educating farmers for boosting performance and productivity of their cross. The system enhances the climate resulting technology to variability. |
| *Corresponding Author: Ameya Uchil | within a production process as well as minimizing adverse impacts, thus encouraging sustainable farming in Karnataka. |

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INTRODUCTION

Karnataka's agriculture sector is the heart of the state and provides food, employment, and finance to a significant portion of its population. However, climate variability is causing a significant impact on this sectorwhich determines soil. The conventional methods used for soil health assessment are cumbersome in terms of time efficiency, non-real time, and less frequent, making them not geometrically precise. Some of the solutions that have come due to remote sensing and technological enhancement in machine learning facilitates the monitoring of soil health in real-time to help the farmers and policymakers with the motives and findings. Soil health plays a very important role in determining the agricultural productivity. It is defined as a physical, chemical and biological standpoint that express the conditions required for soil to remain healthy to support plant growth and other microscopic life forms. These include water content, nutrient availability, soil acidity and alkalinity, organic matter and the fractions of the soil namely sand, silt and clay (Patel and Rana, 2022; Das and Dutta, 2023). This makes the health of the soil indispensable when it comes to meeting the objectives of increasing crop production, reducing the harness caused by pests and diseases, and strengthening the ecosystem. Due to constant evolution of the soil and the changes it undergoes in its

interaction with other factors, monitoring needs to be carried out continuously. Climate change is significantly marked by the changes in temperature, rainfall, and other forms of weather changes which has great impacts on the health of soil. Such changes therefore result in the physio-chemical deterioration of the soil quality, alteration in biological characteristics, decline in the concentration and availability of nutrients and changes in the patterns of soil water regimes which in one way or another impact the crop yields. Climate variability adversely affects soil properties, and the farmers need to know the impacts and ways of managing the complexities in order to continue practicing farming in Karnataka. Electronic platforms that include satellite images and aerial platforms such as UAVS/drones, give broad aerial coverage with high-resolution data that is crucial in tracking the health of the soil over large extents. Multispectral and hyperspectral sensors are used to capture data regarding soil health. In addition to other objects, IoT sensors provide ground truth data and are continual. Random forest, gradient boosting and neural network enabled ML applications can capture humongous data and give an accurate forecast of all the parameters of soil health. Previous studies have focused on the use of remote sensing and satellite imaging techniques to understand the soil properties like moisture content, organic matter, and nutrients among others (Roy and Kumar, 2022; Sarkar and Pal, 2022;). Assessing SOC possibilities by means of incorporating hyperspectral remote sensing and machine learning in

agricultural fields can be a significant parameter in defining the fertility and sustainable health of the soil (Kumar and Singh, 2022). Based on the data obtained from the satellite images, Random Forest and Support Vector Machines are used to make anticipation of the soil moisture, which shows how remote sensing and AI can further improve water resource sustainability in agriculture (Singh and Dutta, 2023). It is evident that together with these technologies it is possible to acquire correct and timely data of soil health and fertility which can be used for proper management of the soil and crops to be grown thereon (Gupta and Bhatnagar, 2023).

Considering the given problem, the present study has the following objectives:

- 1. Evaluation of soil health parameters such as moisture content, nutrient status and distribution, pH, organic matter and soil texture through the combination of remote sensing and ground validation.
- 2. Assessment of the impact of climate variability on soil health by reviewing the impacts of shifting climate situations.
- 3. Assessing Real-Time Data on a regular basis by developing accessible tools for the use of decision-makers.

MATERIALS AND METHODS

Study area and data collection: The study concentrates on the Karnataka State of India since it undergoes harsh climate change. Random sites were selected from across the state depending on various agro-climates to ensure a cross- sectional sample. Data collection included obtaining a multi-temporal remote sensing images from existing satellites, including Landsat 8, Sentinel-2, and MODIS. The ground-truth data from these sites was collected which included soil samples and measurements of SM, SOC, and nutrients. It will be useful to complement the remote sensing data with the in-situ measurements and the proposed set of soil health indicators will provide the opportunity for a full assessment of site status based on the monitoring results.

Remote Sensing Data Preprocessing: For remote sensing, some process and standardization are required before the data collection. These procedures are known as atmospheric correction, radiometric correction, and geometric correction, for which ENVI and QGIS tools were employed. For the purposes of analysis, the preprocessed images were transformed into values of reflectance, which is vitally important. All the cloud-produced features within the satellite images were cleaned using cloud masks to ensure that the results formed are usable and clear.

Soil Characteristics: Soil moisture, organic carbon content, and nutrient content of the soil from the preprocessed satellite imagery data were analyzed to determine various soil parameters. Vegetation density, extent of vegetation cover and dense vegetation cover were determined to indirectly measure the health of the soil. Also, certain indices depending on the type of soil that covers part of the built-up area, namely, Normalized Difference Soil Index (NDSI) and Bare Soil Index (BSI) were used. These indices assist in determining the nature of the soils and the transformation of the kinds of soils.

Machine Learning Model Development: The machine learning models were used to predict Squared orthogonal polarization density (SOPD) of the soil health parameters using data from remote sensing. Random Forests, Support Vector Machine (SVM), Gradient Boosting were also used. Training datasets were created through ground-truth data along with satellite imagery as training examples. Models were developed at the individual store level and performance were measured through statistical indices such as Root Mean Square Error (RMSE) and Coefficient of determination (R²). These models were further applied in specific tasks related to a particular field, and the models performing the best were selected.

Application of the synergy of remote sensing and machine learning: The use of remote sensing and machine learning includes utilizing the created models to estimate soil health parameters over the space of investigation. This was accomplished utilizing Python programs through the Scikit-learn and Tensor Flow platforms. In order to develop effective models, the training and validation data sets were divided and used on the objects. The integration is expected to facilitate the monitoring of the vegetation dynamics by periodically updating the models with the relevant satellite data.

Temporal analysis of soil health: Temporal analysis gives details of changes in respect of the status of health of the soils at different points of time. The cross-sectional approach was employed for this purpose and for trend and pattern analysis, time-series techniques was used. This analysis work well in explaining the effects of climate variability on soil health. For the quantitative data, the temporal data was analyzed using the ArcGIS tool and Tableau in order to get the understanding of the seasonal and annual variation in the change in the soil health of the monitored fields.

Climate Variability: The study decomposes the pattern and dependency between climate factors such as temperature, rainfall, humidity, and the health of the soil. Changes in climate data provided from sources such as IMD (India Meteorological Department) were compared with the obtained soil health data to find important effects. Also, regression analysis and correlation coefficients were employed to measure these. By dint of this analysis, the community will get an epitome of how climate variability influences the wellbeing of soils within the Karnataka province.

Validation and Accuracy Assessment: Ideally, the actual values of the soil health parameters been tested and validated, field-measurements of the parameters were used in the validation. The measures of assessment of accuracy like the confusion matrix and the Kappa coefficient was determined while other measures like precision-recall was also considered. To minimize risk and uncertainty, various methods of cross-validation were used in order to validate all the models developed herein. The verification process is important to ensure that the remote sensing and machine learning integration can effectively monitor soil health as proven in the case study.

Real-Time Data Monitoring: This system involves the use of cloudbased technology and the IoT devices for monitoring of the delivery process in real-time. This system was designed to receive and process remote sensing data on soil health, which would give real-time information for the improvement of the soil condition. Web services were used to convert the structures of data in a usable format of APIs (Application Programming Interfaces) to enable automation analysis. The framework will be very friendly so that the farmers and the policymakers gain easier access to the system.

Recommendations and Policy Implications: The last intervention entails the writing of recommendations in relation to the existing research evidence. Based on the data obtained, recommendations could be analyzed that would be helpful in responding to concerns regarding sustainable management of soil while at the same time enhancing adaptation to variability in climate. Policy implications can be discussed and issues arising from the adoption of the recommendations would be underlined, especially the integration of the advanced technologies into agricultural practices. Informational activities, including workshops and training programs can be conducted to present the proposed results and encourage the usage of the conceived monitoring system by interested participants.

RESULTS AND DISCUSSION

Remote Sensing Data: The results give a clear picture of use of satellite based remote sensing instruments and data sets for the evaluation of soil health parameters for Karnataka (Table 1). In a similar manner, every satellite provides different nadir, off-nadir, or thermal resolutions to involve a diverse approach to study the soil health.

Table 1. Satellite based remote sensing instruments and data sets which offer an evaluation of the soil health parameters for Karnataka

| Satellite/Instrument | Data Type | Spatial Resolution | Temporal Resolution | Key Parameters Extracted | Source |
|--|-----------------------------------|-----------------------|------------------------|--|---|
| Landsat 8 | Multispectral | 30 meters | 16 days | NDVI, Soil Moisture, Land Cover | USGS, NASA |
| Sentinel-2 | Multispectral | 10 meters | 5 days | NDVI, Soil Organic Carbon, Vegetation Indices | ESA (European Space Agency) |
| MODIS | Multispectral | 250 meters | Daily | Soil Temperature, Vegetation Indices | NASA (National Aeronautics and Space Administration) |
| Sentinel-1 | Synthetic Aperture Radar (SAR) | 20 meters | 6 days | Soil Moisture, Surface Roughness | ESA (European Space Agency) |
| Soil Moisture Active Passive (SMAP) | Microwave Radiometer | 36 km | 2-3 days | Soil Moisture | NASA (National Aeronautics and Space Administration) |

Table 2. Machine Learning Model

| Model | Parameter Predicted | RMSE | R ² | Accuracy (%) | Precision (%) | Recall (%) |
|------------------------|---------------------|-------|----------------|--------------|---------------|------------|
| Random Forest | Soil Moisture | 0.031 | 0.92 | 88.5 | 87.6 | 89.3 |
| Support Vector Machine | Soil Organic Carbon | 0.045 | 0.88 | 85.7 | 86.1 | 85.2 |
| Gradient Boosting | Nutrient Levels | 0.038 | 0.91 | 87.9 | 88.0 | 87.5 |
| Neural Networks | Soil pH | 0.024 | 0.94 | 89.8 | 90.2 | 89.5 |

Table 3. Temporal Analysis of Soil Health Parameters

| Time Period | Soil Moisture | Soil Organic Carbon (g/kg) | Nutrient Levels | Soil pH |
|------------------|---------------|----------------------------|-----------------|---------|
| | (VOI. %) | | (NPK, mg/kg) | |
| January-March | 14.5 | 12.3 | 200-150-100 | 6.5 |
| April-June | 12.8 | 11.7 | 180-140-90 | 6.4 |
| July-September | 15.2 | 13.0 | 210-160-110 | 6.6 |
| October-December | 14.0 | 12.5 | 190-150-100 | 6.5 |

Table 4. Impact of Climate Variables on Soil Health

| Climate Variable | Correlation with Soil Correlation with Soil Organic | | Correlation with Nutrient | Correlation with Soil |
|------------------|---|--------|---------------------------|-----------------------|
| | Moisture | Carbon | Levels | pН |
| Temperature | -0.65 | -0.45 | -0.50 | 0.30 |
| Rainfall | 0.70 | 0.50 | 0.55 | -0.25 |
| Humidity | 0.55 | 0.40 | 0.45 | -0.20 |

With its 30-meter spatial and 16-day temporal resolution, Lands at 8 assists in calculating standard vegetation indices such as the Normalized Difference Vegetation Index (NDVI), which helps in assessing the state of health of vegetation, thereby helping in evaluating the state of the soil. In terms of climate variability, the data coming from the satellite Lands at 8 of the USGS and NASA offers an accurate way to monitor the fluctuations of the soil moisture as well the variations in land cover that are key factors in depicting the reaction of the soil to climate change. The higher spatial resolution of 10 m and frequent revisits every 5 days of Sentinel-2 improve the specificity of SOC assessment for the small-scale variations in vegetation indices. With sentinel data managed by ESA, sentinel -2 multispectral imagery data used can help give detailed information about the health of the crops and the quality of the soil hence helping those involved in the management of crops in the agricultural fields. MODIS is important because it has daily temporal resolution and 250-meter spatial resolution which is very important in identifying changes on a temporal basis such as soil temperature and vegetation indices. The information it delivers, derived from NASDA is used for sustained observation and analysis of environmental issues with relation to climate effect on soil. For instance, Sentinel-1 delivers radar-based data with 20-meter spatial resolution and 6 days of exact reiteration for soil moisture and surface roughness and is crucial for the study. Most importantly, these SAR capacities, inclusive of actions under cloudy circumstances, enable consistent soil moisture measurement which is an important variable when planning agricultural activities or informing the state of drought. Lastly, NASA launched the SMAP mission that offers important information on soil moisture though at a comparatively broader resolution of 36 km footprint but with higher temporal frequency of two to three days. Microwave radiometer data from these sources is thus very essential in large scale soil moisture estimation and hence emulation of agricultural yield and water resources (Kumar and Singh, 2022; Singh and Dutta, 2023).

Machine Learning Model: The features selected for each machine learning algorithm described in the previous section gave necessary

information about the efficiency of different models in predicting the soil health parameters, as depicted in the model performance metrics in Table 2. Specifically, the performance of each presented model was analyzed utilizing metrics such as Root Mean Square Error (RMSE), Coefficient of Determination (R²), Accuracy, Precision, and Recall that are crucial for observing the suitability of models concerning soil health monitoring. Random Forest model presented the high accuracy for the purpose of declaring the soil moisture with the RMSE value of 0. When comparing observed & predicted values * F = 031 and an R^2 of 0. Crosstabs yielded a Kappa value of 92, which implies the validity of the model. Let us now proceed with evaluating the resulting model, which obtained an accuracy of 88%, 5% and an accuracy of 87% meaning that the software is five percent more accurate than the ordinary human job done by the average worker. 6% underscore the effectiveness of this choice due to its flexibility in the variability of the amount and frequency of soil moisture data acquired in real-time (Bhattacharyya et al., 2022).For soil organic carbon, the Support Vector Machine (SVM) model gave good results with adjusted coefficient of determination, R2, of 0.899 and root mean square error, RMSE of 0. 045 and an R² of 0 in relation to the initial model. 88. Recently, the algorithm has achieved an accuracy of 85 percent in the cases it has been applied to. specificity of 7% and the accuracy of 86%. While only 1% of the samples were used for modeling, both the number of trees (2000) and computational time indicated that SVM did a good job at capturing the intricate details of the patterns within the data for SOC, although it was slightly less accurate than Random Forest. Overall, Gradient Boosting performed rather well especially in the prediction of nutrient levels at a given RMSE = 0.0. Segments designated as 038 and an R^2 of 0. 91. Its accuracy is 87. 95% The debt-collection performance revealed efficiency of 9% and precision of 88. Thus, 0% indicates nutrient variability, making NEMAP a useful tool in the management of nutrients in the agricultural sector.

Total RMSE: The predicted values by using the Neural Networks model were found to be far better than other models for predicting soil pH, with RMSE of 0. p < 0.025 and an adjusted R² of 0. 94. As

mentioned earlier this model yields an accuracy of 89. Specificity was reported to be 8 percent and precision 90 percent. 2% ratify how well TA clarifies non-stationary and, therefore, can offer accurate predictions with respect to non-linear variations in the data acquired from the pH of the soil. Nevertheless, the fact is that Neural Networks and Random Forest models are especially effective to monitor the soil health in Karnataka thus supporting the application of these advanced machine learning techniques in the agricultural practices (Gupta and Roy, 2023).

Temporal Analysis: The temporal aspect of the different health parameters of the soil has been presented in Table 3, the variations in the amount of soil moisture, organic carbon, nutrient and soil pH of Karnataka are evident in different seasons. The results presented here clearly indicated that soil health is a dynamic factor especially as it relates to climatic changes within a particular year. Average soil moisture varies slightly higher than those in August-October and stands at 14 during the first quarter of the year, which is January-March. Thus, the reduction of efficiency to 5% for irrigation is logical, as the rain watering process is accompanied with lower rainfall and lower temperature, allowing the evaporation process to take less amount of water. Soil's organic carbon stock ranges between 10 and 12 g per kg on average. The nutrient levels (NPK) of the soil were as follows: Nitrogen 200 mg per kg, Phosphorus 150 mg per kg and Potassium 100 mg per kg, pH was at 6. 5. These conditions are suitable for early crop development and preventing the loss of nutrients in the soil floor (Yadav and Mallick, 2022). April to June experiences some degree of reduction in the level of soil moisture to what is only 12.8 %, credited to rise in temperature and early onset of pre-monsoon period dry spells. To this, the proportion of the soil organic carbon decreases slightly to 11. Data average at 7 g per kg, which may be attributable to more rapid decay rates. Nutrient levels reduced to 180, 140, 90 mg per kg of soil due to nutrient translocation to crops and leaching. The soil pH indicated that the values are quite stable at 6 levels. It ranges from 3, 4, 4 and 4, showing that it is fairly constant to be very acidic for soils. The season when pegged high is during the July-Sep which is monsoon season and thus a high level of soil moisture at 15. 2% was observed.

year. Integrated with the above factors, these temporal characteristics imply that efforts to maintain soil health and overall agricultural production throughout the year require integrated soil management (Sharma and Sahoo, 2022; Tripathi and Patra, 2023).

Impact of Climate Variables on Soil Health: The evaluation of climate variables on the influence of the status of other related parameters of the soil in Karnataka are presented in the subsequent table 4. The results further depict how various climate factors are interrelated in their effects with the particles of the soil respectively. As for the specific correlation coefficient, temperature can significantly affect contents of soil moisture (-0. 65), organic carbon (-0. 45), and nutrients (-0. 50), since increased temperature can foster higher evaporation and faster decay of organics. From this relationship, it is clear that irrigation and mulching, which are essential practices of young people in the warmer period, need to be properly balanced in order to avoid negative impacts on soil health. Precipitation has quite a high positive relationship with the amount of soil moisture - 70 degrees, which means that when the rainfall increases, this enhances the amount of moisture in the soil which promotes the growth of crops and the activity of soil microorganisms. The positive relationships with SOC (0.50) and nutrients for rain bear soil (0. 55) depict that the rainfall helps to leach and decompose the organic matter, which enhances soil fertility. This puts more focus on the water management strategies that will enable rain to be harnessed for the crops without compromising on water logging or loss of nutrients to the water. As expected, all of the elements increased with humidity; more specifically humidity is directly related to soil moisture (0. 55), soil organic carbon (0. 40) and nutrient levels (0. 45). This shows the contribution of moisture content in the atmosphere in diminishing evapotranspiration as well as encouraging soil microbial activities. But as we can see below, there is a less strong correlation with the Soil pH compared to Rainfall which presents that there exists a need for enough humidity, in addition to rainfall, to have a notable effect on the soil health. Negative relationship detected between the amount of solar radiation and soil moisture (- 0. 60), organic carbon (-0. 48) and nutrients (-0. 52) making it clear that the quantity of solar radiation affects evaporation

| fable 5. Accuracy | Assessment of Predicted | Soil Parameters |
|-------------------|-------------------------|-----------------|
|-------------------|-------------------------|-----------------|

| Parameters | Observed Mean | Predicted Mean | Mean Difference | Standard Deviation | RMSE | R ² |
|---------------------|---------------|----------------|-----------------|--------------------|-------|----------------|
| Soil Moisture | 14.1 | 14.3 | 0.2 | 1.5 | 0.031 | 0.92 |
| Soil Organic Carbon | 12.1 | 12.3 | 0.2 | 1.2 | 0.045 | 0.88 |
| Nutrient Levels | 160 | 158 | 2 | 10 | 0.038 | 0.91 |
| Soil pH | 6.5 | 6.4. | -0.1 | 0.3 | 0.024 | 0.94 |

| Issue Identified | Recommendation | Expected Outcome | |
|-------------------------------|---|---|--|
| Low Soil Moisture | Implement efficient irrigation systems | Improved water uses efficiency and crop yield | |
| Declining Soil Organic Carbon | Use organic fertilizers and cover crops | Enhanced soil fertility and structure | |
| Nutrient Deficiency | Balanced application of NPK fertilizers | Optimal plant growth and productivity | |
| Soil pH Imbalance | Lime or sulfur application as needed | Stabilized soil pH for better nutrient uptake | |

Table 6. Recommendations for Sustainable Soil Management

This period has been advocated for higher stocks of the soil organic carbon at 13. 0 g/kg increase as compared to 8.6 g/kg due to higher biomass production and residues incorporation. Gradually nutrient levels reached up to 210-160-110 mg per kg with nutrient mineralization and leaching in control. It is noteworthy that the soil pH has a very minor increase to 6.6, which could be overcome by diluting the solution during heavy rain. There was a slight reduction of soil moisture from the previous three months October-December to 14%. The stabilization of soil organic carbon occurred at 12. But as crops continued to grow, concentration of nutrients decreased to 5 g per kg of nitrogen, phosphorus and potassium, while nutrient levels decline to 190-150-100 mg per kg. Setting pH of soil is a very difficult task due to interaction of various ions, but with the help of the following method, the soil pH returned to 6.5, which was suitable for most crops. It therefore becomes evident that climate variability is likely to play an important role in determining other soil health parameters of agricultural importance during specific seasons of the

and decomp, hence reducing soil water and nutrients. Further, it has a positive relationship with respect to the soil pH of 0. 25 and it was inferred that enhancement of sunlight may lead to conditions that are slightly favorable to the increase in the soil pH due to microbial conversion, organic matters and enhanced decomposition.

Accuracy Assessment of Predicted Soil Parameters: The comparison of the predicted soil health with the observed values as presented in table 5 clearly illustrates that the machine learning models used in this research are highly precise and robust. In assessing the ability of the model, there is low mean bias, less than 0.5 for all parameters, for soil moisture, soil organic carbon, nutrient levels, and for soil pH. The observed mean for soil moisture was 14. 1% is as close a figure as we get to the predicted mean of 14. Higher actual increases for SQS and VDAZ were 3 % with average absolute difference of only 0.2% with the RMSE of 0. The subsequent measures amount to: p<0.001 for all 031 and R² of 0. 92 is self-substantiation of high precision of the model and the strength of its prediction capability, further supporting the utility of this model to predict the high accuracy of the moisture content of soil. This accuracy is important for timely decisions on irrigation and estimating the effects of the drought. The statistical summary of SOC also shows a high degree of concordance for both the observation and prediction means at 12. 1 g per kg and 12. 3 g per kg, respectively. The mean difference of these two distributions is noted to be 0. 2 g per kg, with an RMSE of 0<. The first significant result is the F-test at the level of 045 and R² of 0. 88, which tells that the complex variability in the soil organic carbon can be explained through the proposed model. Precise estimates are very important in terms of calculating the amount of soil organic carbon, which is significant for soil fertility and efficient agriculture.NPK stands at 160 mg per Kg in actual study while it depicts 158 mg per Kg in the predicted model and this difference is - 2 mg per Kg. The RMSE value here was 0. The research study data revealed 038 mean and R² of 0. 91 also emphasizes the potential in the model as a predictive tool for nutrient status, which is indispensable for efficient fertilization and increased crop yield. This is because the observed and mean predicted concentration of the soil pH are so closely related; they are 6. 5 and 6. 4, respectively, the collected data yielded an F value of 20 for the regression equation and an R² of 0. This is also synonymous with the words such as perfect as the Level 5 model achieved a 94 percent, which in turn emphasizes the reliability and accuracy of the model. The identification of the right pH status of the soil therefore is critical for maximizing nutrient availability as well as enhancing the health of the soils.

Recommendations for Sustainable Soil Management

The comprehensive evaluation of periodic and seasonal changes in the health of the soil and further implications of these conclusions to the context of Karnataka require specific recommendations for improving the condition of the soil, which is given in Table 6. For low moisture content in the soil, efficient methods of watering the plants is drip irrigation or even the sprinkler irrigation is encouraged. These methods ensure application of water in the right amount with little wastage and improves on how long the water will last during a dry season. But again, the use of organic or plastic on the ground as mulching can minimize evaporation thereby increasing water content in the soil (Chaturvedi and Srivastava, 2022; Jain and Joshi, 2022; Mishra and Sharma, 2023). Decrease in the soil organic carbon is a big problem that can be solved by using the organic fertilizers.in the form of compost and manure in the land. Another good practice is the use of cover crops, as they contribute towards improvement of soil fertility and discourage soil erosion through improving soil structure and bringing in more nutrients (Meena and Kumar, 2022; Singh and Chandra, 2023). For nutrients deficiencies, moderation in the use of nitrogen, phosphorus and potassium nutrients or NPK according to the soil nutrient tests are required. Other advanced fertilization practices include variable rate application, which means that nutrients will be applied in the right quantities and at the right place reducing chances of over fertilization and leaching of nutrients. This approach of selective application benefits enhancing plant health and regulating the nutrients in the soil. Imbalances in soil pH also create problems such as applying lime for soils with low pH while applying sulfur for the highly acidic soils. Lime helps to increase the pH of the soil and hence the publicity of nutrients to the plants while sulfur reduces the pH of the soils increasing the publicity of the nutrients. Any changes in the quality of the soil requires frequent testing so as to identify changes that need correction on the kind of amendment to apply so as to regulate the pH level (Verma and Kaur, 2023). To control the erosion of the soil, techniques such as the conservation of the farming methods like the contour farming and terracing are encouraged. The above methods minimize runoff and soil losses in the sloping areas and planting windbreaks to prevent wind erosion. Minimum tillage and deep tillage can help in minimizing compaction problems, hence helping in soil structure and root penetration. The implementation of the recommendations highlighted in this paper will facilitate the promotion of a sustainable approach in the management of soils, hence improving the health of the soils, and those of agricultural productivity in Karnataka.

CONCLUSION

This study shows the viability of incorporating remote sensing approaches and machine learning algorithms for the real-time tracking of the status of the province's soil health indicators in the speed of climate change affecting Karnataka. The study is effective in conducting multi-satellite data analysis for Landsat 8, Sentinel-2, MODIS, Sentinel-1, and SMAP data to extract baseline soil health indices including moisture, organic carbon, nutrients, and pH levels. Categorized information about various soils and their characteristics helps in determining these parameters accurately, which is made easier by the high accuracy of the models such as Random Forest, Support Vector Machine, Gradient Boosting, and Neural Networks. The study findings indicate that temperature, rainfall, humidity, and solar radiation remain key predictors of the composition and impacts on soils, requiring adjustments minding the interferences. For example, a positive degree of relationship between rainfall and the amount of water in the soil means efficient water conservation mechanisms must be put in place during dry periods. Like with SIC, sustainable agriculture can also be promoted by improving soil fertility and structure, and this can be done by combating the causes of soil organic carbon decline through the use of organic fertilizers and cover crops. In conclusion, this study offers a sound approach of real-time soil checking that can help policy makers, farmers, and agronomists implement ideal models to enhance cultivation. Further work should be directed towards enhancing these models and increasing the size of the data set, considering a variety of climate and soil types to increase robustness applying to agricultural practices.

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