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Artificial intelligence driven crop suitability mapping – Optimizing horticulture for the future

One of the key applications of Artificial Intelligence (AI) in agriculture is crop suitability mapping, which helps farmers identify the best crops for specific geographic areas by analyzing factors like soil type, climate, and the topography. For horticultural crops, AI-driven crop suitability mapping offers a transformative way to optimize land use and promote sustainable agriculture. By combining Machine Learning (ML), Geographical Information System (GIS), and Remote Sensing (RS) technologies, AI tools can process complex environmental data such as soil characteristics, climatic conditions and terrain to demarcate the most suitable regions for growing fruits, vegetables, and flowers. This data-driven approach improves decision-making accuracy, minimizes environmental risks, and aids farmers in adapting to evolving conditions. The role of AI in crop suitability mapping is particularly important for horticultural crops, which are highly sensitive to specific soil and climate requirements. This article explores the concept of crop suitability mapping, the role of AI in enhancing its precision and efficiency, and how AI is transforming the modern agriculture.

TRADITIONAL methods of crop suitability mapping have largely relied on historical data, expert insights, and manual observations. This process typically involves assessing soil characteristics (such as pH, texture, and organic content), temperature patterns, rainfall, and other climatic factors. However, these approaches can be time-consuming, labour-intensive, and sometimes prone to inaccuracies due to human error or incomplete data.

Advancements in crop suitability mapping

In recent years, advancements in data collection and analysis have transformed crop suitability mapping, making it far more efficient and accurate. Three key technologies–remote sensing, geographic information systems (GIS), and artificial intelligence (AI)–are now revolutionizing how farmers, researchers, and policymakers evaluate land for agricultural purposes.

Remote sensing for real-time data collection: Remote sensing involves collecting data about the Earth's surface from satellites, drones, or other aerial platforms. Through satellite imagery, it is possible to assess vegetation indices like the Normalized Difference Vegetation Index (NDVI), which indicates plant health. Drones, equipped with sensors, can further refine this data by capturing localized insights about soil moisture or crop stress.

Geographic information systems (GIS) for spatial analysis: GIS technology integrates data from remote sensing and other sources to create visual, interactive maps of specific regions. These maps offer spatial insights into the environmental characteristics of an area, enabling users to identify patterns and relationships that are critical for crop suitability. By layering different datasets such as soil type, topography, rainfall, and temperature, GIS provides a detailed understanding of how these factors influence the growth potential of specific crops.

Artificial intelligence for predictive modeling: This technology has brought a paradigm shift in crop suitability mapping by automating the analysis of complex environmental data. Machine learning and deep learning algorithms can process massive datasets, learn from historical data, and create predictive models. These models help forecast future conditions, optimize land use, and minimize risks in crop selection. In AI-driven crop suitability mapping, machine learning algorithms such as Random Forest or Neural Networks analyze variables like temperature, rainfall, and soil fertility to predict the best regions for specific crops. Deep learning models, particularly useful for image-based analysis, enhance the interpretation of satellite and drone data, identifying subtle patterns that may not be obvious through manual analysis. AI also has the capability to adapt to climate change by incorporating future weather scenarios into its predictions. This enables long-term planning and helps farmers adjust crop choices based on evolving environmental conditions.

Role of AI in crop suitability mapping

By harnessing the power of machine learning (ML), deep learning, and other AI technologies, now it is possible to develop highly accurate crop suitability maps. These tools excel at processing large amounts of data, identifying patterns, and making predictions that would be impossible or inefficient using traditional methods.

Data integration and analysis: One of the primary challenges in crop suitability mapping is the sheer volume of data involved. Soil characteristics, climate data, topographical maps, and water availability are just a few of the many factors that must be considered. AI tools such as machine learning algorithms can efficiently handle this complex data landscape, integrating diverse datasets from satellite imagery, weather stations, and soil sensors. For instance, an AI algorithm can analyze historical climate data and predict future weather patterns, which are crucial for determining crop viability. By using machine learning models, these tools can also adapt to changing conditions, continually refining their predictions as new data becomes available. This capability ensures that crop suitability maps remain up-to-date and accurate, providing farmers with the most relevant information for decision-making.

Predictive modeling and simulation: Another area where AI proves invaluable is in predictive modeling. Traditional crop suitability assessments often rely on static data, which may not account for dynamic factors such as climate variability or soil degradation over time. AI-powered predictive models, however, can simulate various scenarios, including changes in temperature, rainfall, and other environmental conditions, to forecast how crops might perform in the future. AI tools help to plan for the long term, optimizing crop selection based on future conditions.

Precision agriculture and real-time monitoring: AI also enhances crop suitability mapping through its application in precision agriculture. With the integration of Internet of Things (IoT) devices such as soil moisture sensors and drones equipped with multispectral cameras, AI algorithms can monitor crop health and environmental conditions in real time. This data can be fed back into crop suitability models, allowing for continuous refinement of predictions.

Automation and scalability: Automated AI systems can process satellite data, analyze soil samples, and predict climatic conditions without human intervention, dramatically reducing the time and cost associated with traditional methods. Furthermore, AI systems can scale to cover vast geographic areas, from small farms to entire countries. This scalability is particularly beneficial in regions with limited agricultural resources, where government agencies and international organizations can use AI-driven crop suitability mapping to guide large-scale agricultural planning and policy development. United States, Spain, and Italy are leading contributors for mapping in agriculture using AI tools. In majority cases (76%), machine learning (ML) techniques were utilized, while deep learning (DL) methods employed in about 24% applications. Key algorithms such as Random Forest (RF), Artificial Neural Networks (ANNs), and Support Vector Machines (SVMs) are frequently used in mapping activities related to agricultural management. Additionally, AI plays a vital role in various applications, including production enhancement, disease detection, crop classification, rural planning, forest dynamics, and improvements in irrigation systems.

CASE STUDIES

Oil palm

Given its high yield potential, oil-palm is a vital cash crop, especially in tropical regions. However, ensuring sustainable and economically viable oil palm cultivation requires careful assessment of land suitability to avoid environmental degradation and economic losses. Crop suitability mapping, enhanced by artificial intelligence (AI) tools, has emerged as a powerful approach to optimize land use for oil-palm cultivation.

Global perspective: In Northern Uganda, using parameters like rainfall, soil type, land cover, elevation, and slope through GIS techniques, suitability of land for oil-palm cultivation has been categorized into four classes viz. highly suitable, moderately suitable, marginally suitable, and unsuitable. The study found that 38.18% of the land was highly suitable, while only 4.87% was unsuitable. In a study in Peninsular Malaysia, utilizing Remote Sensing, GIS and Analytical Hier-Archy Process, a highly suitable climate is found around Selangor, Kelantan, Perak and Kedah. Climates that are unsuitable are predicted to increase by 5.6% (2040) and 5.72% (2080) from 1.77% in 2020. Climatic conditions will become unsuitable for oil palm production along the coast of Pahang and Selangor, and Perlis by 2080.

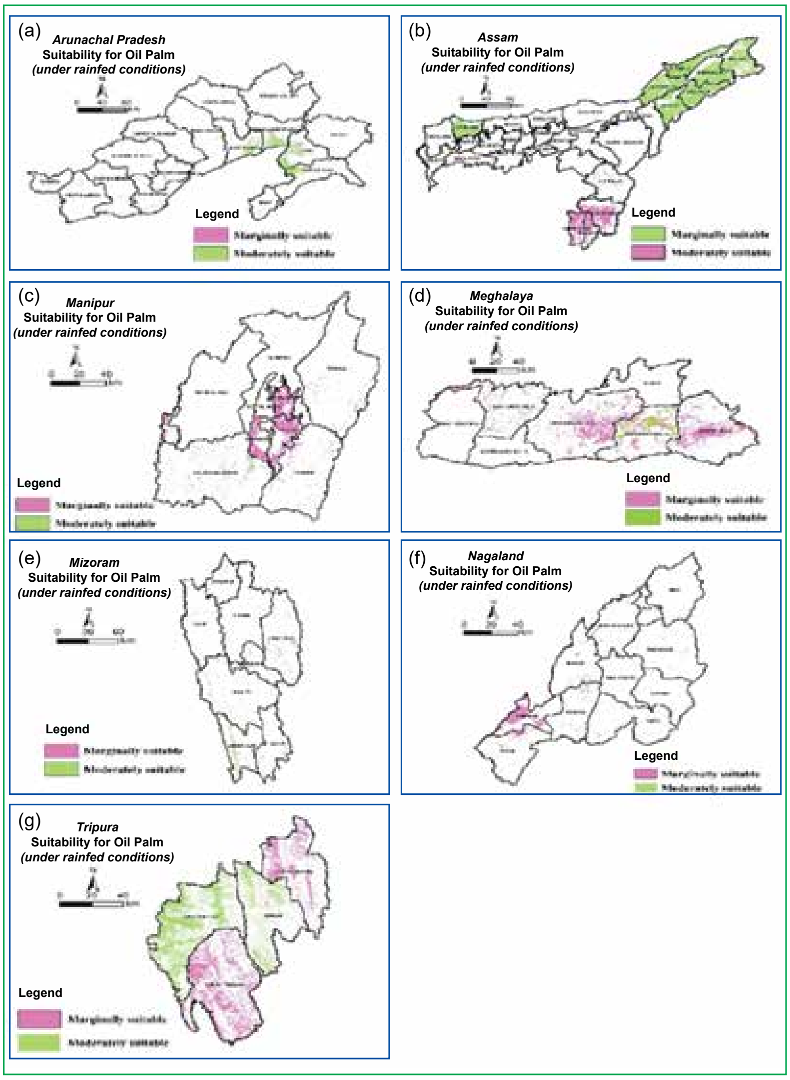
With advancements in remote sensing technology, high-resolution satellite data has become increasingly accessible, offering detailed insights into land cover, crop health, and spatial distribution of plantations. This evolution presents significant opportunities for optimizing agricultural practices and improving yield predictions. AI models have demonstrated high accuracy in detecting palm oil trees, with some studies reporting accuracy rates as high as 91%. However, this accuracy can still be influenced by factors such as changes in lighting conditions and image resolution. To further enhance the performance of these algorithms, gathering more diverse training data and fine-tuning the models can significantly improve detection accuracy.

In Southeast Asia, substantial progress has been made in mapping oil palm plantations through the application of machine learning (ML) models utilizing high-resolution satellite data. For example, impressive accuracy levels was achieved between 85 and 95% when mapping oil palm plantations with Sentinel-2 and Landsat-8 imagery. This study highlighted the effectiveness of integrating machine learning techniques with satellite data to create accurate and reliable land cover maps, which are essential for improved agricultural management and informed policy-making.

In Malaysia, the use of high-resolution imagery combined with labeled datasets for training deep learning (DL) models has shown a marked improvement in the accuracy and efficiency of oil palm tree detection. These DL approaches effectively tackle challenges such as varying tree sizes, overlapping canopies, and diverse environmental conditions, providing a scalable and precise solution for monitoring and managing oil palm plantations. Similarly, in Indonesia, a comparison between machine learning and non-machine learning techniques utilizing Sentinel-2 data revealed that while both methods yield satisfactory results, ML techniques significantly enhance mapping accuracy. This is attributed to their capability to manage complex, non-linear relationships within the data.

In Thailand, using convolutional neural networks (CNNs) with Sentinel-2 imagery, a notable accuracy range of 89 to 93% could be achieved in mapping both oil palm and rubber plantations. In Colombia also, Sentinel-2 data with CNNs was used to map oil palm plantations, achieving an accuracy of 90%. Similarly, in Indonesia, combined synthetic aperture radar (SAR) and optical satellite data using CNNs were employed to accurately map industrial oil palm plantations, reporting a 90% accuracy rate. This approach exemplifies the potential of integrating multiple data sources to enhance mapping precision.

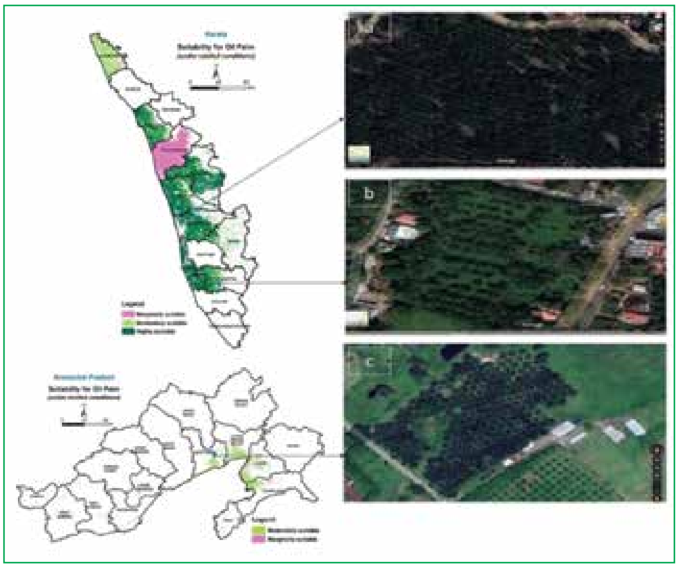
Machine learning techniques, including random forests, support vector machines (SVM), and neural networks, have consistently achieved impressive accuracy rates between 85 and 95% in mapping major plantation crops. The integration of advanced satellite data, particularly from Sentinel and Landsat imagery, is revolutionizing agricultural monitoring and management practices. These advancements significantly contribute to sustainable agricultural development and informed decision-making in the plantation sector. As a result, farmers are now able to adopt more precise agricultural practices, leading to better resource utilization and enhanced environmental sustainability in the region.



Oil-palm suitability maps under rainfed conditions in different Indian states

Indian context: India has recognized the need to boost domestic palm oil production due to its heavy reliance on imports. In India, the use of GIS and MCDA techniques were explored to identify suitable areas for oil-palm cultivation. These studies integrate various factors such as soil characteristics, climatic conditions, topography, and land use into the decision-making process to create suitability maps. By combining spatial data with weighted criteria, the authors developed a model that evaluates potential sites for oil palm production under rainfed conditions. This method provides a systematic and transparent approach to land suitability analysis, considering the ecological and socio-economic factors critical for sustainable cultivation of oil palm under rainfed conditions. Thematic rasters, representing key factors influencing land suitability, were created in a GIS. Utilizing MCDA techniques, a digital suitability map was generated in ArcGIS 10.3, delineating three distinct classes over an extensive area of 10.5 million. Further, with an aim to focus on actual locations that can be readily planted with oil palm, the suitable locations identified were restricted to eight selected land use/land cover (LULC) classes.

This strategic limitation aimed to facilitate the expansion of OP cultivation exclusively to areas deemed most suitable based on the identified criteria. The results of the study show that the integration of GIS and MCDA is highly effective in producing accurate suitability maps for oil palm. The maps generated highlight the most favourable regions for oil-palm cultivation based on



Validating suitability maps of Kerala and Arunachal Pradesh with real time data specific criteria, helping policymakers and land managers make informed decisions about agricultural expansion. The approach not only enhances the precision of land-use planning but also minimizes the environmental and social impacts of oil palm farming by avoiding unsuitable or vulnerable areas. This methodology can be adapted and applied to other crops and regions, contributing to sustainable agricultural practices worldwide.

Litchi

As climate change and land degradation continue to impact agricultural productivity, identifying suitable regions for growing fruit crops has become crucial. Litchi *(Litchi chinensis),* along with other fruit crops like mango, citrus, and apple, require specific climatic and soil conditions for optimal growth. Crop suitability mapping is emerging as an advanced method to assist farmers, researchers, and policymakers in making data-driven decisions for sustainable fruit crop cultivation.

India is one of the largest producers of litchi, with key production areas located in the states of Bihar, West Bengal, Uttar Pradesh, and Assam. However, the expansion of litchi cultivation is constrained by regional variations in climate and soil quality. In a study using Geomatic tools and AHP technique, approximately 47% of India's total geographic area (TGA) was found unsuitable for litchi cultivation, while 3.7 and 9.98% were classified as very suitable and suitable, respectively. States like Bihar, Uttar Pradesh, Jharkhand, West Bengal, Chhattisgarh, and Madhya Pradesh were identified as leading regions for litchi cultivation within the very suitable category. Some smaller suitable areas were found in Maharashtra, Gujarat, Andhra Pradesh, Kerala, Karnataka, and Tamil Nadu. However, most of southern and central India was deemed unsuitable for litchi.

This study also highlighted the potential impact of climate change, suggesting that traditional litchi-growing regions in eastern India (Bihar, West Bengal, and eastern Uttar Pradesh) may become less suitable in the future. A northward and upward (altitude) shift in litchi suitability zones was observed. The methods used to develop the litchi crop potential zonation (LCPZ) map can be applied to other crops and regions globally. These findings are crucial for policymakers, planners, and growers, though future modifications to the map will be necessary to accommodate the development of new litchi cultivars and the effects of climate change, along with access to more precise climate and soil data.

Future prospects

While AI-powered crop suitability mapping has tremendous potential, it faces several challenges. A major hurdle is the availability and quality of data, especially in regions with limited technological infrastructure. AI models depend heavily on accurate, timely data to produce reliable predictions, but in many developing areas, access to such data remains difficult. Furthermore, the complexity of environmental variables like climate change, soil degradation, and water availability makes it challenging to create models that are universally applicable across diverse regions. However, with ongoing advancements in AI, remote sensing, and IoT technologies, these tools could become increasingly effective for suitability mapping and predictive modeling. Such tools can also help develop more robust adaptation strategies for climate change. Digital maps created through GIS, remote sensing, and AHP techniques can be enhanced by incorporating AI for predictive modeling, enabling the development of suitability maps that account for future climate scenarios. To make these technologies widely accessible and impactful, governments, research institutions, and private organizations must collaborate to ensure that AI-driven solutions reach farmers around the world, helping to realize the full benefits of AI in agriculture.

SUMMARY

AI-driven approaches offer several advantages, including the ability to process vast datasets, predict outcomes under changing climatic conditions, and provide real-time insights to farmers. By automating the process, AI tools can significantly enhance the precision of suitability assessments, ensuring that land use is optimized for crop cultivation. However, the use of artificial intelligence (AI) tools for the direct suitability mapping of horticultural crops in India remains limited. Most suitability mapping efforts for crops like, oil palm, litchi, and other horticultural species have relied on traditional methods such as GIS, remote sensing, and analytical hierarchy processes (AHP). These techniques assess environmental variables like soil, temperature, and rainfall to identify potential cultivation zones. While AI has revolutionized various areas of agriculture, its application in crop suitability mapping for horticulture is yet to be fully explored in India. Instead, AI tools have primarily been leveraged for broader applications like monitoring plantations, detecting disease and pest incidence, and identifying nutrient deficiencies in crops like oil palm, tea, and sugarcane. These models effectively utilize satellite imagery, high-resolution data, and sensor inputs to provide real-time insights, significantly improving precision agriculture practices. For instance, ML algorithms such as random forests and neural networks have shown high accuracy in identifying nutrient deficiencies and pest outbreaks, which directly enhance crop yields and productivity. The potential for AI in crop suitability mapping is immense. With continuous advancements in data collection through remote sensing and AI technologies, India has the opportunity to implement AI-driven tools to increase the precision and accuracy of horticultural crop management. Such advancements would optimize resource utilization, boost productivity, and promote sustainable agricultural practices by identifying the best-suited areas for specific crops under varying climatic conditions.

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