Variability of Soil Fertility Using Geostatistical and Digital Soil Mapping Techniques : A Comprehensive Review of Northeastern India

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ABSTRACT

Soil fertility varies considerably across both space and time, and this variability is particularly pronounced in the fragile landscapes of Northeastern India. The region's diverse physiography, heterogeneous geology, shifting cultivation practices, and high-intensity rainfall create complex patterns of soil formation and nutrient distribution. Assessing such variability is crucial for sustainable land-use planning, efficient nutrient management, and the adoption of climate-smart agricultural practices. In recent years, geostatistical methods and digital soil mapping (DSM) have proven to be reliable frameworks for quantifying and predicting soil fertility patterns. These approaches, when combined with geographic information systems (GIS), remote sensing, and advanced computational tools, provide valuable insights into soil nutrient dynamics. This review brings together recent research conducted across states such as Tripura, Assam, Meghalaya, Nagaland, and Mizoram, as well as the Eastern Himalayan foothill areas. The studies highlight spatial heterogeneity in macronutrients, micronutrients, and soil organic carbon, demonstrating the role of terrain, land use, and management intensity in driving soil variability. Methodological advancements such as kriging, regression-kriging, and machine learning algorithms have further improved the accuracy of fertility prediction maps. These findings have direct implications for site-specific nutrient management and sustainable intensification in rain-fed and resource-constrained farming systems. Looking ahead, the integration of DSM with proximal sensing, big-data analytics, and artificial intelligence holds significant potential for refining soil fertility assessments and supporting resilient agricultural planning in Northeastern India.

Keywords : Spatio-temporal fertility variability, GIS, Remote sensing, Kriging, Machine learning, Proximal sensing, site-specific and Precision nutrient management.

Introduction

Soil fertility constitutes the cornerstone of agricultural productivity and ecological sustainability. It is not only a function of inherent soil properties but also of dynamic processes influenced by climate,

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topography, parent material, vegetation, and anthropogenic activities. In the humid tropics and sub-tropics, particularly in the fragile hill ecosystems of Northeastern India, soil fertility assumes greater significance because of its direct implications for food security, livelihoods, and environmental conservation (Lal, 2009; Reza *et al.,* 2012a; Bandyopadhyay *et al.,* 2015). The region, encompassing the states of Assam, Meghalaya, Tripura, Nagaland, Mizoram, Manipur, Arunachal Pradesh, and Sikkim, is characterized by high rainfall (2000–5000 mm annually), steep topography, shifting cultivation practices, and intense land-use pressures (Das *et al.,* 2021). These conditions foster rapid nutrient cycling and strong spatial heterogeneity in soil properties, making uniform management recommendations unsuitable.

Importance of Studying Spatial Variability of Soil Fertility

Traditional soil survey methods, though valuable, often fail to capture the fine-scale variability that arises from pedogenic processes and land-use interactions (Jenny, 1941; Webster and Oliver, 2007). Bulk sampling strategies average out localized variations, leading to blanket fertilizer recommendations that can result in nutrient deficiencies in some zones and surpluses in others (Reza *et al.,* 2017). Such inefficiencies are especially problematic in Northeastern India, where resource-poor farmers depend on thin soil fertility margins to sustain crop productivity. For example, Reza *et al.,* (2019a, 2019b, 2020a) demonstrated that even within relatively homogeneous geomorphic units in Tripura, soil organic carbon (SOC), nitrogen (N), and potassium (K) exhibited significant small-scale heterogeneity, influenced by micro-topography and land-use intensity.

The consequences of ignoring this variability are multi-fold: inefficient fertilizer use, soil acidification, nutrient imbalances, and environmental degradation through runoff and leaching (Srinivasarao, 2021). Moreover, the variability of soil fertility has implications beyond crop yield, it governs ecosystem services such as carbon sequestration, water regulation, and biodiversity conservation (Lal, 2004). Therefore, quantifying and mapping soil fertility variability is a prerequisite for developing site-specific nutrient management (SSNM), precision agriculture practices, and sustainable land-use strategies in the region (Baruah *et al.,* 2014).

Geostatistics in Soil Fertility Research

Over the past three decades, geostatistics has emerged as a powerful tool for quantifying and predicting spatial variability of soil properties (Webster and Oliver, 2007; McBratney and Pringle, 1999). Semivariogram analysis, kriging, and cokriging have been applied extensively to interpolate soil fertility parameters, assess uncertainty, and link soil variability to environmental covariates. In Northeastern India, Reza and colleagues (2010, 2012a, 2012b, 2016a, 2016b, 2019a, 2020a, 2021a, 2021b) pioneered the application of geostatistical models to characterize the variability of SOC, pH, macronutrients, and micronutrients in alluvial plains, piedmonts, and upland agro-ecosystems. These studies highlighted how sampling density, interval, and design critically influence the accuracy of semivariogram parameters and subsequent predictions.

For example, Reza *et al.,* (2016c) reported that suboptimal sampling inflates nugget values and obscure's multiscale structure, thereby reducing interpretability. Similarly, in the Brahmaputra floodplains, nutrient maps generated through ordinary kriging revealed strong spatial gradients linked to depositional processes and land-use intensity (Reza *et al.,* 2019b). Beyond interpolation, geostatistics has also facilitated multi-scale analysis, uncertainty quantification, and integration of auxiliary information (Goovaerts, 1997; Hengl *et al.,* 2007).

Digital Soil Mapping: A Paradigm Shift

The emergence of digital soil mapping (DSM) represents a paradigm shift in soil science, moving from traditional survey-based approaches toward predictive, data-driven models (McBratney *et al.,* 2003; Minasny and McBratney, 2016). DSM relies on the scorpan model [soil = f(s, c, o, r, p, a, n)] that relates soil properties to covariates such as soil samples (s), climate (c), organisms/vegetation (o), relief (r), parent material (p), age (a), and spatial position (n). Advances in geoinformatics, remote sensing, and machine learning have greatly enhanced the predictive capacity of DSM, enabling the production of high-resolution, reproducible soil property maps (Arrouays *et al.,* 2020).

In Northeastern India, DSM has been successfully applied to predict soil texture, SOC, and nutrient stocks using terrain derivatives, vegetation indices, and climate data as covariates (Jena *et al.,* 2023; Kumar *et al.,* 2023; Reza *et al.,* 2024a). Chattaraj *et al.,* (2025) integrated machine learning algorithms with environmental predictors to predict the soil texture and lithological discontinuity mapping for sustainable land use planning in a part of Eastern Himalayan foothills, India. Similarly, Shukla *et al.,* (2024) demonstrated that DSM-based approaches provide more detailed and reliable maps than conventional interpolation, particularly in heterogeneous landscapes.

DSM is not merely a mapping tool; it offers transformative potential for soil resource management. Its applications extend to soil fertility evaluation, erosion risk assessment, SOC stock estimation, and site-specific nutrient management. Importantly, DSM outputs can be periodically updated with new data, making them dynamic and adaptive under changing climate and land-use scenarios (Hengl *et al.,* 2015).

Linking Soil Fertility Variability to Sustainable Agriculture

The integration of geostatistics and DSM has direct implications for sustainable agricultural management in Northeastern India. Site-specific nutrient management strategies, informed by spatial soil fertility maps, can optimize fertilizer use efficiency, reduce environmental losses, and enhance farm profitability (Parihar *et al.,* 2020; Srinivasarao, 2021). Moreover, soil organic carbon variability, as mapped by geostatistical and DSM techniques, provides insights into carbon sequestration potential, which is critical for climate change mitigation (Lal, 2004; Choudhury *et al.,* 2013; Reza *et al.,* 2024a).

Several case studies illustrate this potential. In Tripura, geostatistical mapping of SOC and nutrient variability was used to delineate management zones, facilitating precision fertilizer recommendations (Reza *et al.,* 2024a). Across the Brahmaputra plains, DSM-based nutrient maps have informed land capability classification and fertilizer targeting (Kumar *et al.,* 2023). Similarly, integration of soil fertility variability with land-use data has highlighted the impacts of shifting cultivation on nutrient depletion and soil degradation in Nagaland and Mizoram (Wapongnungsang *et al.,* 2021; Kumar *et al.,* 2023).

Objectives of the Review

In light of the above, this review aims to consolidate and critically assess the advances in understanding soil fertility variability in Northeastern India through geostatistical and DSM approaches. The specific objectives are: (1) to synthesize findings on the spatial variability of soil physical, chemical, and biological properties across the region, (2) to examine methodological advances in geostatistical and DSM techniques applied to soil fertility assessment, (3) to evaluate case studies linking soil variability to land-use, physiography, and management practices, (4) to highlight implications for sustainable agriculture, climate-smart nutrient management, and soil carbon sequestration and (5) to identify knowledge gaps and outline future research directions for soil fertility mapping in Northeastern India.

By integrating nearly four decades of research, this review contributes to a deeper understanding of soil fertility variability and demonstrates how geostatistical and DSM tools can transform soil resource management for the fragile yet vital agroecosystems of Northeastern India.

Physiographic and Agro-ecological Setting of Northeastern India

Northeastern India, comprising the eight states of Assam, Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland, Tripura, and Sikkim, represents one of the most distinctive physiographic and agro-ecological regions of the country. The region extends between 21°34′ –29°50′ N latitude and 88°05′ –97°30′ E longitude, covering nearly 262,179 km² (about 8% of India's geographical area) (Figure 1), and is characterized by a diverse topography ranging from floodplains to rugged mountains (Velayutham *et al.,* 1999; Reza *et al.,* 2022).

Physiography

The physiography of Northeastern India is dominated by three broad units (Figure 2) :

(1) The Eastern Himalayas – spanning Arunachal Pradesh and Sikkim, characterized by steep slopes, high relief, and young, fragile mountains formed mainly of crystalline and sedimentary rocks.

(2) The Meghalaya Plateau – an extension of the Indian Peninsular shield, comprising Archean gneisses and granites, interspersed with sandstone and limestone formations. This plateau is dissected by numerous rivers and is prone to high-intensity rainfall.

(3) The Brahmaputra and Barak Valleys – low-lying floodplains with fertile alluvium, subject to annual flooding and sediment deposition, making them agriculturally productive but also

ecologically fragile (Choudhury *et al.,* 2022; Jakhmola *et al.,* 2023; Reza *et al.,* 2021a).

The physiographic diversity leads to pronounced differences in soil depth, texture, drainage, and erosion susceptibility, which directly influence fertility and land-use potential.

Climate

The climate of the region is predominantly humid subtropical to perhumid, governed by the southwest monsoon. Annual rainfall ranges from 1200 mm in rain-shadow zones to more than 11000 mm in Cherrapunji and Mawsynram, making it one of the wettest places on Earth (IMD, 2022). The rainfall is highly seasonal, with more than 70–80% concentrated between May and October. Temperature varies from alpine conditions in the Eastern Himalayas (below 0 °C in winter) to humid subtropical in the valleys (average 24–27 °C in summer). Agroclimatic variability creates multiple cropping systems, ranging from temperate horticulture in Sikkim to rice-based intensive agriculture in Assam and shifting cultivation (*jhum*) in Mizoram and Nagaland (Birthal *et al.,* 2006; Kumar *et al.,* 2020).

Soils

The soils of Northeastern India are diverse and closely linked to physiography, parent material, and climate. According to Velayutham *et al.,* (1999), the major soil orders include :

(1) Inceptisols – dominant in valleys and piedmonts, moderately fertile, but erosion-prone.

(2) Ultisols and Alfisols – widespread on uplands and hill slopes; acidic, with low base saturation and strong leaching losses.

(3) Entisols – found in floodplains, alluvial deposits, and shifting river courses; variable fertility depending on sediment load.

(4) Mollisols – restricted occurrence in pockets of Sikkim and Arunachal Pradesh.

The soils are generally acidic (pH 4.5–6.0), rich in organic carbon in surface horizons due to forest cover, but deficient in available phosphorus, exchangeable bases, and micronutrients such as boron and zinc (Reza *et al.,* 2010; Panwar *et al.,* 2011; Reza *et al.,* 2014a, 2014b, 2014c; Manpoong and Tripathi, 2019; Dutta *et al.,* 2021). Soil erosion and nutrient depletion are key challenges in uplands, while sedimentation and fertility buildup are common in floodplains.

Agro-ecological Zones

The Planning Commission and ICAR (Sehgal *et al.,* 1992; Velayutham *et al.,* 1999) have delineated the region into three agro-ecological subregions (AESRs) within the broader hot-humid to perhumid ecosystem:

(1) AESR 17.1 (Eastern Himalayas, Arunachal Pradesh, Sikkim): Cool to cold perhumid climate, steep slopes, soils prone to landslides; supports temperate horticulture (apple, orange, large cardamom) and shifting cultivation.

(2) AESR 17.2 (Meghalaya Plateau, Nagaland, Manipur, Mizoram): Humid perhumid climate, moderate to steep slopes, acidic Ultisols and Alfisols; supports rice, maize, pulses, ginger, and pineapple. Jhum remains a dominant land-use.

(3) AESR 17.3 (Brahmaputra and Barak Valleys, Tripura, plains of Assam): Humid climate, alluvial Inceptisols and Entisols, highly fertile but flood-prone; supports intensive rice, tea, sugarcane, and vegetable cultivation.

This agro-ecological diversity underpins the complexity of soil fertility management. For instance, while nitrogen and organic matter are generally adequate due to biomass recycling, phosphorus deficiency, soil acidity, and micronutrient imbalances are widespread across zones (Reza *et al.,* 2012b, 2016a, 2024b; Singh *et al.,* 2020).

Soil Fertility Variability: Physical, Chemical, and Biological Dimensions

Soil fertility is a multi-dimensional property that emerges from the combined behaviour of physical, chemical, and biological soil attributes. In Northeastern India, this complexity is accentuated by the region's unique physiographic and agro-ecological setting, which includes steep altitudinal gradients, humid subtropical to per-humid climates, and highly heterogeneous lithological formations. These environmental factors, coupled with diverse land-use practices such as shifting cultivation, terrace farming, plantation crops, and intensive rice-based systems, generate pronounced horizontal (spatial) and vertical (depth-wise) variability in soil properties (Reza *et al.,* 2012a; Choudhury *et al.,* 2013; Reza *et al.,* 2021b).

Soil Physical Properties

Soil physical properties form the structural foundation of fertility by regulating soil-water-plant interactions, root penetration, aeration, and ultimately nutrient cycling. In Northeastern India, the diverse physiography, from Brahmaputra floodplains to Tripura uplands and Eastern Himalayan foothills-creates pronounced spatial and vertical heterogeneity in texture, bulk density (BD), and soil moisture regimes. Studies combining classical laboratory analysis, geostatistics, and digital soil mapping (DSM) approaches have provided insights into the patterns and processes governing these attributes (Reza *et al.,* 2012a; 2016c; 2017; 2021b; Jena *et al.,* 2023).

Texture and Particle-Size Distribution

Soil texture, determined by the relative proportions of sand, silt, and clay, plays a central role in controlling water retention, infiltration, drainage, nutrient-holding capacity, and soil aeration. It is therefore considered a fundamental determinant of soil fertility. In Northeastern India, strong physiographic and lithological gradients shape texture distribution at both horizontal and vertical scales.

Reza *et al.* (2016c) used a geostatistical framework to characterize spatial variability in alluvial soils, showing that landform and depositional processes strongly influenced texture. Subsequent work in Tripura (Reza *et al.,* 2021b) demonstrated systematic depth-wise variability, where lowland alluvial plains displayed finer textures with higher silt and clay content in subsoil horizons, while upland hill soils remained sandier and coarser throughout the profile. Such differences directly influence infiltration capacity and nutrient storage potential. Beyond traditional laboratory approaches, DSM methods have expanded the scope of texture mapping in the region. Jena *et al.,*

(2023) predicted particle-size fractions across the North Eastern Region using digital covariates (DEM derivatives, terrain indices, vegetation indices) and machine learning algorithms. They found that terrain derivatives such as slope curvature, elevation, and parent material were the strongest predictors for clay and silt fractions, demonstrating the utility of covariates in capturing textural variability over large areas. *Chattaraj et al.* (2025) similarly highlighted lithological discontinuities as key controls on textural patterns in the Eastern Himalayan foothills.

These findings indicate that spatial heterogeneity in soil texture necessitates differentiated management of irrigation, tillage, and nutrient application. Fine-textured zones require careful regulation of water infiltration and nutrient retention, whereas coarse-textured soils benefit from more frequent irrigation and organic matter additions to improve their water-holding and nutrient-use efficiency.

Bulk Density

Bulk density (BD), a measure of soil compaction and porosity, directly affects root growth, soil aeration, and water availability. In Northeastern India, BD shows significant horizontal and depth-wise variability due to landform, management practices, and parent material.

Reza *et al.* (2016c) applied a geostatistical approach to characterize BD variability in alluvial soils, demonstrating that BD increased with soil depth and was significantly higher in intensively cultivated lands compared to undisturbed forest soils. Later, Reza *et al.* (2021b) showed fine-scale spatial patterns of BD in Tripura, where terrace cultivation and human-induced compaction led to localized "hotspots" of elevated BD, while natural forest sites exhibited lower values. Such mapping is critical as localized compaction zones restrict rooting volume and impede nutrient and water uptake. Techniques such as variogram modeling and kriging have proven effective in delineating small-scale BD variability, enabling site-specific amelioration. The identification of localized high-BD zones allows targeted interventions such as deep tillage, sub-soiling, or the incorporation of organic amendments (e.g., farmyard manure, biochar) to reduce compaction, improve porosity, and restore soil fertility (Das *et al.*, 2019; Choudhury *et al.,* 2018; Gogoi *et al.,* 2017).

Soil Moisture and Water-Holding Capacity

Soil moisture dynamics are particularly critical in the monsoonal climate of Northeastern India, where rainfall is intense but seasonal, and water availability fluctuates widely. While short-term moisture is highly dynamic, long-term patterns exhibit strong spatial dependence linked to soil texture, slope, drainage, and landform position.

Reza *et al.* (2021b) investigated soil moisture variability in Tripura and found that fine-textured lowland soils retained significantly higher moisture during dry periods, whereas sandy upland soils showed rapid drying. Seasonal monitoring revealed that moisture variability followed a structured spatial pattern, with inter-annual stability at the same sites, suggesting that soil–landform interactions impose persistent controls on moisture availability. The integration of geostatistics and DSM further enhances moisture mapping. For instance, remote sensing–derived indices (NDVI, LST) and DEM-based attributes have been successfully applied as covariates for predicting soil water-holding capacity (Kaya *et al.,* 2023). Similar approaches have been demonstrated in Northeastern India, where DEM derivatives, rainfall surfaces, and vegetation indices were integrated with geostatistical methods to predict soil moisture and hydrological parameters across Tripura, Assam, and the Brahmaputra plains (Agarwal *et al.,* 2023; Jena *et al.,* 2023). Such approaches offer practical tools for planning irrigation, selecting drought-tolerant crop varieties, and minimizing crop failure risks under climate variability

Soil Chemical Properties

Soil chemical attributes define the reservoir of nutrients available for plant growth and strongly influence crop productivity and sustainability. In Northeastern India, the interplay of physiography, rainfall regimes, parent material, and land management practices generates substantial heterogeneity in the spatial and vertical distribution of soil macronutrients and micronutrients. Among these, nitrogen (N), phosphorus (P), and potassium (K) remain the most critical for crop growth, yet their availability is highly variable across agro-ecological zones.

Macronutrients (N, P, K)

Macronutrient distributions in Northeastern India show marked spatial heterogeneity driven by parent material, depositional processes, land use intensity, cropping systems, and fertilizer management history. Studies employing both geostatistical and digital soil mapping (DSM) approaches have helped quantify and visualize these patterns, allowing for the delineation of nutrient management zones (Reza *et al.,* 2012b; 2019c; 2020a; 2020b; Ramachandran *et al.,* 2025).

Nitrogen (N) : Nitrogen, being highly mobile in soils and closely tied to organic matter, shows strong surface enrichment but declines sharply with depth. Reza *et al.* (2019c) reported that available N in the Brahmaputra plains was significantly higher in surface horizons (0–15 cm), reflecting organic matter additions, root biomass turnover, and manure application. Similarly, in Tripura, Reza *et al.* (2020a) demonstrated spatial hotspots of N enrichment associated with organic matter-rich soils under shifting cultivation and lowland rice fields. Conversely, upland soils with continuous cultivation and reduced organic input showed depleted N status.

Spatial variability studies using kriging interpolation revealed a high nugget effect for N, reflecting strong microscale variability and the influence of management practices (Reza *et al.,* 2016b, 2017). DSM-based prediction models, incorporating covariates such as NDVI, elevation, and land use, improved prediction accuracy and helped in delineating N-deficient and N-rich management zones (Jena *et al.,* 2022).

Phosphorus (P) : Phosphorus availability is especially constrained in Northeastern India due to the predominance of acidic soils with high concentrations of Fe and Al oxides that immobilize P through fixation (Reza *et al.,* 2012b; Kumar, 2015). Many plateau and upland soils exhibit severe P deficiency, while depositional plains show somewhat better availability due to alluvial inputs. Ramachandran *et al.* (2025) mapped available P in Barpeta district (Assam) and highlighted deficiency patches coinciding with strongly acidic soils and erosion-prone uplands. In Brahmaputra plain, Reza *et al.* (2012b) observed similar patterns, with upland soils exhibiting critically low P (<10 kg ha^{-1}) while floodplains maintained moderate levels. Geostatistical mapping demonstrated that P variability followed a moderate spatial structure, with range values reflecting the influence of lithology and landform. DSM approaches using terrain derivatives and parent material as covariates significantly improved the mapping of P distribution (Jena *et al.,* 2022).

Potassium (K) : Potassium, though less mobile than N, also displays notable spatial variability across Northeastern India. In alluvial soils of the Brahmaputra plains, available K levels were found to be sufficient or moderately high (Reza *et al.,* 2016b), reflecting mineralogical contributions from parent material. However, in eroded uplands and hill slopes of Tripura, Reza *et al.,* (2020b) reported K depletion due to intensive cropping, leaching losses, and low clay content.

Geostatistical analyses revealed that K variability often displayed a stronger spatial structure than N, suggesting the importance of inherent soil properties (texture, mineralogy) over short-term management effects. DSM studies further confirmed that covariates like slope, elevation, and vegetation indices are strong predictors of K distribution (Ramachandran *et al.,* 2025). The observed heterogeneity in macronutrient availability underscores the need for site-specific nutrient management (SSNM). Nitrogen hotspots can be managed with precision fertilizer application to avoid overuse and leaching. Phosphorus-deficient uplands require liming, integrated use of P fertilizers, and organic amendments to reduce fixation. Potassium management must focus on supplementing eroded uplands with mineral K sources and recycling crop residues. Geostatistical and DSM-based nutrient maps can thus directly inform precision agriculture and climate-smart nutrient management practices in the region.

Soil pH, Acidity, and Cation Exchange Capacity (CEC)

Soil reaction (pH) and cation exchange capacity (CEC) are critical chemical properties that regulate nutrient availability, microbial functioning, and soil fertility sustainability (Al-Shammary *et al.,* 2024). In Northeastern India, the predominance of high rainfall, leaching-prone environments, and weathered parent materials leads to widespread soil acidity and variable CEC across landscapes. The interaction between soil acidity, exchange complex characteristics, and organic matter inputs determines the capacity of soils to supply and retain nutrients for crop production (Maiumdar *et al.,* 2022).

Most soils of Northeastern India are acidic, with pH values commonly ranging between 4.5 and 6.0, especially in upland and plateau soils derived from granitegneissic and sandstone parent materials (Reza *et al.,* 2012c; Baruah *et al.,* 2014; Bandopadhyay *et al.,* 2015; Choudhury *et al.,* 2024). Strong leaching of bases under humid tropical conditions, coupled with intense weathering, results in base cation depletion (Ca^{2+}, Mg^{2+}, K^{+}) and dominance of exchangeable acidity (H^{+} and Al^{3+}). Reza *et al.* (2012c) analyzed acidity patterns in Assam soils and reported that upland and shifting cultivation sites were strongly acidic (pH <5.0), while lowland paddy soils maintained relatively higher pH (5.5–6.0) due to deposition and management. Choudhury *et al.* (2024) mapped soil acidity and micronutrient availability across the Meghalaya Plateau using geostatistics. They demonstrated strong spatial correlations between pH, parent material, and elevation-granite-derived uplands showed more severe acidity than sedimentary-derived valleys. Gangopadhyay *et al.* (2015) reported that more than 85% of Tripura's cultivated soils are acidic, constraining P availability and creating conditions for Fe and Mn toxicity in waterlogged sites.

Cation exchange capacity (CEC) reflects the soil's ability to retain and exchange nutrient cations such as Ca^{2+}, Mg^{2+}, K^{+}, and NH_4^{+}. It is mainly controlled by clay mineralogy and soil organic matter. Soils with smectitic or illitic clays generally show higher CEC, while kaolinitic and sesquioxide-rich soils are lower (Yunan *et al.,* 2015). Organic matter contributes significantly in acidic, weathered soils, which dominate Northeastern India (Babu *et al.,* 2020). In this region, CEC is generally moderate to low but highly variable across physiographic units and land uses. Reza *et al.* (2021b, 2022) showed that in Tripura, CEC correlated positively with clay and SOC, with alluvial plains recording higher values than sandy uplands. In Arunachal Pradesh, Reza *et al.* (2024b) reported that shifting cultivation reduced organic matter, which in turn lowered CEC and nutrient retention. Choudhury *et al.* (2024) found that in Meghalaya, forest soils maintained higher CEC due to organic inputs, while cropped uplands showed depleted exchange capacity. Similarly, Hazarika *et al.* (2019) noted that Brahmaputra floodplain soils with finer textures and higher organic matter exhibited higher CEC compared to sandy levees. The variability of CEC has important management implications. Low-CEC soils are more prone to leaching and nutrient depletion, requiring organic matter additions, conservation tillage, or agroforestry to maintain fertility (Chatterjee *et al.,* 2015). In strongly acidic soils, liming and biochar can enhance base saturation and cation retention. Geostatistical and DSM approaches now allow precise mapping of CEC variability, supporting site-specific nutrient management in the fragile agro-ecosystems of Northeastern India.

Micronutrients (Zn, Fe, Mn, B, etc.,)

Micronutrients, though required in trace amounts, are indispensable for plant metabolic functions, enzymatic activities, and overall soil–plant health. Deficiencies or toxicities in these elements have direct implications for crop productivity and nutritional quality. In Northeastern India, micronutrient variability is a persistent issue, arising from the dominance of acidic soils, intense monsoonal leaching, diverse parent materials, and contrasting topographic and hydrological conditions (Reza *et al.,* 2016a; Bandyopadhyay *et al.,* 2018).

Spatial assessments across the region consistently demonstrate high heterogeneity in micronutrient availability. Reza *et al.* (2021a) quantified the spatial variability of zinc in Brahmaputra alluvial soils and showed localized deficiency pockets that did not align with blanket fertilizer recommendations, highlighting the need for site-specific interventions. Similarly, Shukla *et al.* (2024) employed multivariate tools such as principal component analysis (PCA) and fuzzy clustering to delineate management zones for multiple micronutrients (S, B, Zn, Mn, Fe, Cu) across the Northeastern hill ecosystem. Their findings emphasized the strong co-variation among nutrients and the necessity of integrated management strategies.

Element-specific patterns have also been documented. Zinc and boron deficiencies are widespread in upland and highly weathered soils, particularly under continuous cropping and shifting cultivation systems (Shukla *et al.,* 2019). In contrast, iron and manganese often show elevated availability in poorly drained or waterlogged valley soils, sometimes reaching toxic levels for sensitive crops (Choudhury *et al.,* 2024). Hazarika *et al.* (2019) further reported that floodplain soils of the Brahmaputra exhibited strong spatial gradients in Fe and Mn linked to drainage and depositional processes.

The interaction between soil acidity and micronutrient status is a recurring theme. Acidic conditions ($pH < 5.5$) commonly enhance Fe and Mn solubility while limiting the availability of Zn, B, and Mo (Choudhury *et al.,* 2024). This dual challenge of toxicity in lowland soils and deficiency in uplands complicates fertilizer management across the region. Recent advances in geostatistics and digital soil mapping (DSM) have improved micronutrient mapping accuracy, enabling the delineation of site-specific deficiency zones and supporting precision nutrient management (Reza *et al.,* 2021a; Shukla *et al.,* 2024).

Overall, micronutrient variability in Northeastern India reflects a complex interplay of parent material, land use, soil acidity, and hydrology. Site-specific recommendations, organic amendments, liming, and micronutrient-enriched fertilizers are crucial to overcome these limitations. Mapping-based approaches not only capture the fine-scale heterogeneity but also provide actionable insights for enhancing crop productivity and soil health in the fragile agro-ecosystems of the region.

Soil Organic Carbon and Biological Indicators

Soil organic carbon (SOC) and biological indicators together form the backbone of soil fertility assessment, as they integrate the physical, chemical, and ecological processes that determine soil functioning. SOC serves as the primary reservoir of energy and nutrients for soil organisms, influencing aggregation, porosity, and water-holding capacity, while simultaneously regulating nutrient cycling and long-term carbon sequestration. Biological indicators such as microbial biomass carbon and nitrogen, enzymatic activities, and soil fauna diversity act as sensitive proxies of soil health, reflecting changes in land use, organic matter inputs, and management intensity much earlier than many chemical properties. Their combined assessment provides a holistic view of ecosystem resilience, since soils with high SOC and active biological functioning can better buffer against erosion, nutrient depletion, and climatic variability. In agro-ecosystems like those of Northeastern India, where fragile hill slopes, shifting cultivation, and high rainfall intensities create inherent instability, the joint monitoring of SOC and biological indicators becomes essential for designing sustainable soil fertility strategies that balance productivity with ecological stability.

Soil Organic Carbon (SOC) Stocks and Fractions

Soil organic carbon (SOC) forms the foundation of soil health, underpinning critical functions such as nutrient supply, aggregate stability, water retention, and long-term carbon sequestration (Lal, 2019). In Northeastern India, the variability of SOC is strongly mediated by physiographic heterogeneity, intense rainfall regimes, diverse land uses, and traditional management practices such as *jhum* (shifting cultivation). Multiple regional studies confirm that SOC stocks and fractions vary significantly across land-use systems, topographic positions, and soil depths.

Reza *et al.* (2019b, 2020b) quantified SOC variability in Tripura and reported that forest soils and less-disturbed grasslands maintained higher SOC stocks than cultivated and *jhum* fields, particularly in the upper horizons. This aligns with the findings of Sanjita and Binoy Singh (2018), who highlighted that sacred groves of Manipur preserve higher SOC concentrations compared with surrounding agricultural landscapes, emphasizing the conservation role of traditional ecological sanctuaries. Similarly, Choudhury *et al.* (2016) documented SOC variation across altitudinal gradients in the northeastern Himalayan region and found that both altitude and associated agro-physical factors influenced SOC concentrations.

Several studies highlight the impact of land-use transitions on SOC depletion. Saplalrinliana *et al.* (2016) and Sahoo *et al.* (2023) observed that the conversion of forests to shifting cultivation in Mizoram led to significant SOC loss, driven by biomass burning and reduced litter inputs. Nath *et al.* (2018, 2021) also noted rapid SOC decline in degraded *jhum* cycles, with marked reductions in labile carbon fractions. In a regional-scale study, Ray *et al.* (2021) demonstrated how shifting cultivation accelerates soil degradation and SOC depletion across the northeastern hill region, and emphasized the role of geospatial techniques in land-use planning to mitigate carbon losses. In Assam, Hota *et al.* (2022) reported that continuous cultivation in the Brahmaputra floodplains reduced SOC content, while forest and pasture systems retained higher labile pools.

Soil Biological and Functional Indicators

Biological indicators provide dynamic insights into soil fertility because they directly reflect soil processes such as nutrient cycling, organic matter turnover, and resilience to disturbances (Bünemann *et al.,* 2018). Unlike static physical and chemical properties, biological attributes are sensitive to land-use change, management practices, and climate variability, making them critical tools for soil quality assessment in Northeastern India.

Microbial biomass carbon (MBC) and nitrogen (MBN) are widely recognized as labile pools of nutrients and as indicators of soil biological activity. Lungmuan *et al.* (2017) documented significant spatial variation of MBC and MBN across land uses in Mizoram, with higher values under forest and grasslands compared to cropped uplands and shifting cultivation fields. Lalmuansangi *et al.* (2022) found that microbial biomass was highly responsive to land-use intensity in Meghalaya, where forest soils supported greater microbial pools than cultivated terraces. Similar trends were reported by Nath *et al.* (2021) in degraded *jhum* cycles, where microbial pools were reduced by repeated burning and shortened fallow periods, indicating loss of biological resilience.

Soil enzyme activities provide functional measures of nutrient cycling potential. Acid and alkaline phosphatase, dehydrogenase, and urease activities have been widely studied in Northeastern India. Lungmuana *et al.* (2019) observed that enzyme activities were significantly higher in forest soils compared to shifting cultivation and cropped lands in Mizoram, demonstrating the depletion of functional potential with disturbance. Reza *et al.* (2014c, 2018b) reported that phosphatase activity strongly correlated with available phosphorus in Assam soils confirming its utility as a biological indicator of P dynamics. De *et al.* (2022) also highlighted the role of enzyme assays in constructing soil quality indices (SQIs), which captured the impacts of land use and elevation on soil functioning.

Soil macro- and mesofauna, including earthworms, termites, and nematodes, contribute to litter decomposition, aggregate stability, and nutrient mineralization. Zodinpuii *et al.* (2019) reported that earthworm abundance and diversity were significantly reduced under shifting cultivation in Mizoram compared to natural forests, which supported higher soil faunal biomass. Sanjita and Binoy Singh (2018) noted that sacred groves in Manipur not only conserved higher SOC but also maintained diverse soil faunal communities, underlining the link between biodiversity conservation and soil function.

Overall, the synthesis of physical, chemical, and biological dimensions reveals that soil fertility variability in Northeastern India is strongly scale-dependent and process-driven, reflecting interactions between geomorphic setting, climate forcing, and anthropogenic interventions. Table 1 and 2 summarize the key studies quantifying variability across these three dimensions, offering a compact reference for understanding soil fertility heterogeneity in the region.

Geostatistical and DSM Approaches to Soil Fertility

Geostatistics and digital soil mapping (DSM) have emerged as powerful tools to unravel spatial variability of soil fertility, particularly in the heterogeneous landscapes of Northeastern India. Geostatistical techniques such as variogram modeling and kriging allow quantification of spatial dependence and creation of high-resolution fertility maps that capture fine-scale variability across land uses, topographic positions, and management intensities (Reza *et al.,* 2016c; 2017). Complementing this, DSM integrates field observations with covariates derived from remote sensing indices (e.g., NDVI, LST), digital elevation models, and climatic datasets to predict soil properties and delineate management zones with greater accuracy (Kaya *et al.,* 2023; Reza *et al.,* 2024a;). Together, these approaches provide robust frameworks for identifying nutrient-deficient hotspots, guiding site-specific nutrient management, and supporting sustainable land-use planning in regions where conventional blanket fertilizer recommendations are ineffective due to sharp biophysical gradients.

Geostatistical Approach to Soil Fertility

Geostatistical techniques provide a rigorous framework to quantify, model, and predict the spatial variability of soil fertility in heterogeneous landscapes such as those of Northeastern India. The central element of geostatistics is variography, which characterizes the spatial dependence of soil attributes through semivariogram parameters (range, sill, nugget). Studies in the region (Reza *et al.,* 2016c, 2017; Bhunia *et al.,* 2018) have shown that variograms reveal the scale of spatial correlation in soil properties such as pH, organic carbon, macronutrients, and micronutrients, with shorter ranges often observed in upland and *jhum*-cultivated soils due to high anthropogenic disturbance, and longer ranges in alluvial plains where depositional processes dominate.

Once spatial structure is established, kriging and its variants (ordinary, universal, indicator, regression kriging) are widely used for interpolation and mapping of soil fertility indicators. For example, Reza *et al.* (2016b, 2019a) applied ordinary kriging to delineate nitrogen, phosphorus, and potassium distribution in the Brahmaputra plains and Tripura, successfully identifying nutrient-deficient zones for targeted management. Similarly, indicator kriging has been used to map soil acidity and micronutrient deficiencies, improving the delineation of critical thresholds for fertilizer recommendations (Choudhury *et al.,* 2024).

Digital Soil Mapping (DSM) Approach to Soil Fertility

Digital Soil Mapping (DSM) has emerged as a powerful approach for predicting and visualizing soil fertility indicators in complex and data-scarce landscapes such as Northeastern India. Unlike traditional survey methods, DSM integrates georeferenced soil observations with spatially exhaustive covariates derived from terrain, remote sensing, and climate data to produce high-resolution soil property maps. These tools are particularly suited for the region's rugged topography, heterogeneous parent material, and diverse land uses.

The increasing availability of high-resolution environmental covariates has supported the application of digital soil mapping (DSM) frameworks. DSM integrates field observations with predictors such as remote sensing indices (NDVI, LST), digital elevation model (DEM)-

derived terrain attributes (slope, curvature, topographic wetness index), and climatic surfaces to model fertility indicators. For instance, Reza *et al.* (2024a) demonstrated the utility of DSM in delineating soil organic carbon hotspots across the Northeastern Himalayas, while Jena *et al.* (2022) combined DSM with terrain covariates to map soil pH and micronutrient availability. These approaches enhance prediction accuracy, especially in areas with sparse sampling, by capturing soil–landscape–climate interactions.

In recent years, machine learning algorithms such as Random Forest (RF), Support Vector Machines (SVM), Gradient Boosting Machines (GBM), and Cubist models have been increasingly integrated into DSM frameworks. Their ability to handle nonlinear relationships and high-dimensional data makes them suitable for predicting soil fertility parameters in the complex physiographic settings of Northeast India. Studies (Reza *et al.,* 2024a) report that ensemble models such as RF and GBM outperform traditional regression approaches in predicting SOC, especially when combined with remote sensing and climatic covariates.

Finally, the credibility of geostatistical and DSM outputs depends on robust validation. Commonly used methods include cross-validation, RMSE (Root Mean Square Error), ME (Mean Error), and concordance statistics. Validation exercises in the region (Reza *et al.,* 2019c; Choudhury and Mandal, 2021) indicate that while kriging provides reliable interpolations for densely sampled datasets, DSM and machine learning approaches offer superior performance in data-sparse and heterogeneous terrains. Integrating these methods has been shown to improve soil fertility mapping and support site-specific management, climate-resilient agriculture, and sustainable land-use planning in the region. Table 3 and 4 summarize the key studies quantifying variability across these three dimensions, offering a compact reference for understanding soil fertility heterogeneity in the region using geoatatisitical and DSM approaches.

Implications and Future Perspectives

The synthesis of soil fertility variability research in Northeastern India underscores several implications for sustainable land management. First, the pronounced spatial heterogeneity of macronutrients and micronutrients highlights the need for site-specific nutrient management (SSNM) rather than blanket fertilizer application. Geostatistical and DSM-based fertility maps provide a scientific basis for delineating management zones, improving fertilizer use efficiency, reducing input costs, and minimizing environmental risks such as nutrient leaching and eutrophication. Adoption of precision agriculture tools tailored to the Northeast's diverse cropping systems can directly improve farm productivity and livelihoods.

Second, the mapping of soil organic carbon (SOC) stocks and fractions points to significant opportunities for enhancing carbon sequestration. Forests, wetlands, and traditionally managed agroecosystems act as SOC reservoirs, while shifting cultivation and intensive cropping have led to SOC depletion in vulnerable landscapes. High-resolution SOC maps can be integrated into carbon credit schemes and climate-smart agriculture programs, ensuring that the Northeast contributes to India's climate mitigation targets while enhancing soil health.

Third, these findings have strong implications for sustainable agriculture and land use planning. By integrating soil fertility data with agro-ecological zoning, policymakers and planners can optimize land allocation, identify degraded hotspots, and prioritize restoration strategies. In erosion-prone uplands and *jhum* areas, targeted interventions such as agroforestry, contour farming, and organic amendments can stabilize soils and restore fertility. Similarly, integrating geostatistics and DSM outputs into watershed-level planning supports resource-efficient irrigation, crop diversification, and climate-resilient farming systems.

Finally, several research gaps and future directions remain. There is a need for more high-density, harmonized soil sampling networks to improve the robustness of geostatistical and DSM predictions. Multi-temporal soil monitoring under different land-use trajectories is critical for understanding fertility dynamics under climate change. The integration of proximal sensors, UAV-based hyperspectral imaging, and big-data analytics could significantly advance predictive modeling of soil properties. Moreover, participatory approaches involving local farmers and indigenous knowledge should complement technical assessments to ensure context-specific management strategies.

The future of soil fertility research and management in Northeastern India lies in bridging advanced spatial technologies with local realities, enabling evidence-based policies, resilient farming practices, and sustainable natural resource use in this ecologically sensitive and agriculturally vital region.

Conclusion

This review highlights the significant progress made in understanding the spatial variability of soil fertility in Northeastern India, an ecologically sensitive region marked by complex physiography, diverse parent materials, and highly dynamic land-use systems. Across physical, chemical, and biological dimensions, soils in the Northeast display strong heterogeneity that is shaped by topography, lithology, intense monsoonal rainfall, and human interventions such as shifting cultivation and intensive cropping. These patterns underscore the limitations of blanket fertilizer recommendations and call for site-specific, evidence-based soil management.

The synthesis of soil physical properties reveals pronounced spatial gradients in texture, bulk density, and soil moisture regimes, each exerting a strong influence on root growth, nutrient dynamics and water availability. Chemical properties including macronutrients, micronutrients, pH and cation exchange capacity are equally variable, with deficiencies of nitrogen, phosphorus, potassium, zinc, and boron emerging as recurrent challenges. Biological indicators such as soil organic carbon, microbial biomass, enzyme activities, and soil quality indices further demonstrate how fertility interacts with land use, conservation practices, and climate variability.

Geostatistical approaches have provided critical insights by quantifying spatial structures through semivariograms and kriging, while digital soil mapping (DSM) has leveraged environmental covariates, remote sensing, and machine learning to produce high-resolution fertility maps. Together, these techniques have enabled the delineation of nutrient management zones, identification of SOC hotspots, and prediction of fertility constraints across scales. The integration of geostatistics with DSM has proven particularly valuable in enhancing predictive accuracy, reducing uncertainty, and linking soil properties to terrain and land-use drivers.

From a management perspective, the implications are clear. Site-specific nutrient management (SSNM), carbon sequestration strategies, precision agriculture practices, and climate-smart interventions are urgently needed to balance productivity with sustainability. At the same time, several research gaps persist, including the need for denser sampling networks, multi-temporal monitoring, the incorporation of proximal and UAV-based sensing, and participatory approaches that embed local knowledge into spatial decision-support frameworks.

Geostatistical and digital soil mapping (DSM) approaches have substantially advanced soil fertility evaluation by enabling spatially explicit predictions; however, several critical limitations constrain their reliability and broader applicability. The effectiveness of these methods is strongly dependent on sampling density and design, with sparse or uneven datasets often yielding unstable variogram models and uncertain kriging estimates, particularly in heterogeneous agricultural landscapes. Moreover, classical geostatistical assumptions of stationarity and isotropy are frequently violated under intensive land use, leading to biased representation of nutrient distributions. While DSM leverages environmental covariates and machine learning to enhance spatial resolution, the indirect and often non-stationary relationships between soil properties and covariates limit model transferability across regions and time. Scale mismatches between point-based soil observations and coarse-resolution remote sensing or terrain data further obscure fine-scale nutrient variability, especially for management-sensitive attributes such as available nitrogen, phosphorus, and potassium. The predominantly static nature of DSM products also fails to capture temporal dynamics driven by fertilization, cropping systems, and climate variability. Although machine learning improves predictive accuracy, its black-box nature reduces interpretability and hampers process-based understanding and practical adoption. Additionally, uncertainty quantification remains incomplete, as combined uncertainties arising from sampling, covariate quality, and model structure are rarely fully propagated. High data and computational demands further restrict application in data-poor regions. Collectively, these limitations highlight that geostatistics–DSM frameworks, while powerful, should be complemented with temporal monitoring, agronomic knowledge, and field-scale validation to ensure robust and actionable soil fertility assessments.

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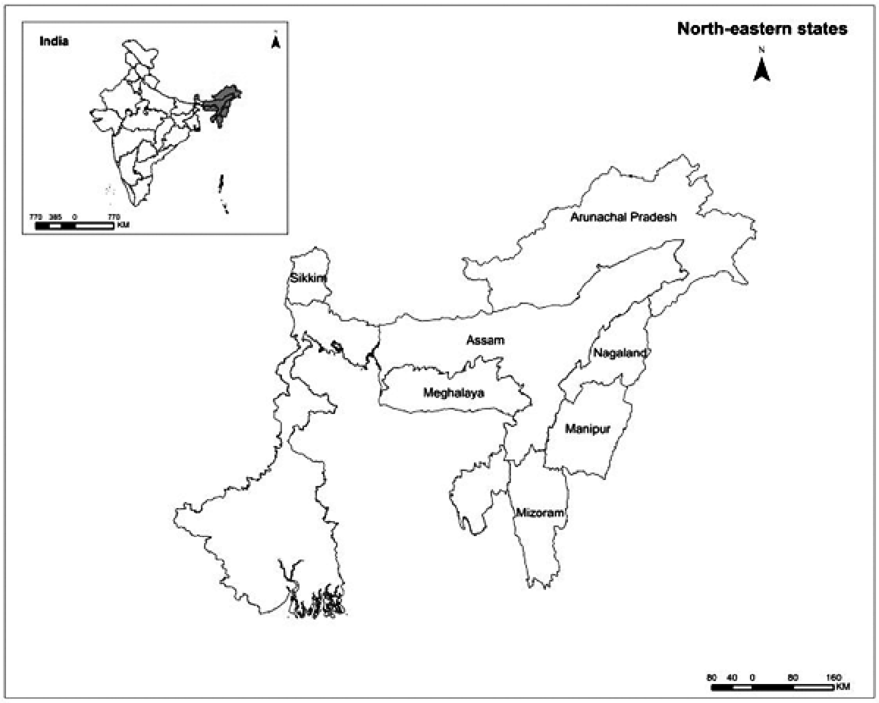

Figure 1. Map showing northeastern India

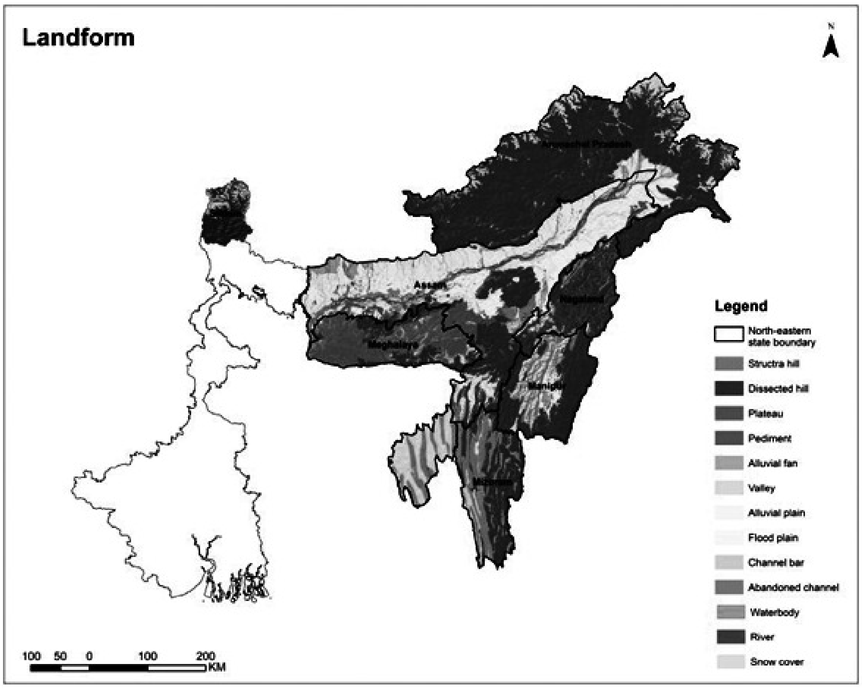

Figure 2. Physiography map of northeastern India

Table 1. Summary of soil physical variability studies in Northeastern India

Study area	Soil properties	Method/Approach	Key findings	Reference
Lower Brahmaputra plains; alluvial soils	Texture, bulk density	Geostatistics, GIS mapping	Alluvial depositional patterns create spatial gradients in texture; sampling design critically affects semivariogram interpretation.	Reza *et al.,* 2016b, 2017
Assam (Tinsukia district)	Various physical properties	Geostatistics	Spatial structure identified with moderate-range variograms; implications for sampling design.	Reza *et al.,* 2019a
Tripura	Bulk density, particle-size distribution, soil moisture (horizontal & vertical)	Field profiles, laboratory particle-size, geostatistics (variogram, kriging)	Demonstrated significant horizontal & vertical heterogeneity; BD increases with depth; micro-topography influences moisture and texture distribution.	Reza *et al.,* 2021b
Tripura (Purvanchal range)	Bulk density, texture, moisture	Landform and soil analysis	Strong landform–soil relationships; vertical stratification of texture and bulk density	Reza *et al.,* 2022
Nagaland (Wokha district)	Soil texture, bulk density	Field sampling, GIS	Variation in soil texture and BD across land-use systems	Ray *et al.,* 2022
Meghalaya state (Ri-Bhoi district)	Particle size distribution (sand, silt and clay)	DSM, environmental covariates, Random Forest model	Soil texture was significantly more precise and they accurately depicted the spatial variations spatial variations of particle-size fractions.	Jena *et al.,* 2023
Eastern Himalayan foothills	Texture, lithological discontinuity	DSM using covariates (DEM, RS indices)	Improved mapping of texture using machine learning; lithological control on soil variability, useful for land-use planning.	Chattaraj *et al.,* 2025

Table 2. Summary of soil nutrient variability studies (macronutrients and micronutrients)

Study area	Nutrients analyzed	Method/Approach	Key findings	Reference
Assam (Brahmaputra plains)	Available N, P, K	Multivariate statistics, Geostatistics, GIS	Strong spatial dependence of macronutrients, tied to floodplain processes	Reza *et al.,* 2012a, 2012b, 2015a, 2016b
Assam (Industrial/ coal-mine affected areas)	Heavy metals (Fe, Mn, Pb, Cd)	Geostatistics, pollution indices	Identified hotspots near industrial sources; spatial heterogeneity influenced by proximity to proximity pollution sources.	Reza *et al.,* 2013, 2014d, 2015, 2018c
Nagaland & Mizoram	SOC, micronutrients	SQI, biological indicators	Decline in SOC and micronutrients under shifting cultivation	Reza *et al.,* 2014c, 2018b; Mukhopadhyay *et al.,* 2025
Tripura (Bishalgarh blocks)	SOC, bulk density	Soil profile sampling, GIS	Significant vertical variability of SOC	Reza *et al.,* 2019b
Tripura (Charilam block)	SOC, SOC fractions	Soil profile sampling, GIS	SOC stratification by land use	Reza *et al.,* 2020b
Brahmaputra plains	Available Zn	Semivariogram, kriging	Patchy distribution of Zn; moderate spatial dependence	Reza *et al.,* 2021a
Assam (Biswanath district)	Macro- and micronutrients	GIS-based mapping	Heterogeneous nutrient availability; need for site-specific nutrient management	Bhuyan *et al.,* 2023
Upper Brahmaputra Valley	Soil organic carbon SVM, GBM)	DSM with ML (RF,	RF outperformed others; SOC strongly controlled by elevation and vegetation	Kumar *et al.,* 2023
Meghalaya Plateau	Soil acidity, micronutrients Zn, B, Mn, Fe, Cu)	DSM, covariates (DEM, RS)	Strong link between acidity and micronutrient availability; DSM improved spatial prediction	Choudhury *et al.,* 2024
Sub-tropical NE India (multi-state)	S, B, Zn, Mn, Fe, Cu	PCA, fuzzy clustering, DSM	Delineated nutrient management zones using multivariate clustering; useful for precision nutrient management.	Shukla *et al.,* (2024)
Assam (Barpeta district)	Soil nutrient status (NPK & others)	GPS-guided sampling, GIS mapping, statistical analysis	Mapped nutrient-rich and deficient zones to inform sustainable fertilizer management.	Ramachandran *et al.,* (2025)

Table 3. Summary of geostatistical applications in Northeastern India

Study area	Soil properties	Methods	Key findings	Reference
Brahmaputra Valley, Assam	SOC, N, P, K	Semivariogram, OK	Moderate–strong dependence; SOC strongly structured	Reza *et al.,* 2016b
Tripura	N, P, K	OK, UK	Hotspots aligned with intensive cropping zones	Reza *et al.,* 2019a
pH, micronutrients	OK	Short-range variability; site-specific liming needed	pH, micronutrients	Reza *et al.,* 2019a
Mizoram (jhum land)	SOC, N	Cokriging with slope & NDVI	Reduced prediction error	Saha *et al.,* 2020
Brahmaputra Plains	SOC, nutrients	Regression Kriging	SOC as major predictor of fertility gradients	Singh *et al.,* 2021

Table 4. DSM applications in Northeastern India (soil property, dataset, method, performance metrics)

Study area	Soil properties mapped	Key covariates used	Method / Model	Performance (R^2 / RMSE)	Key outcomes	Reference
NE hill region (West Bengal–Assam border)	N, P, K	DEM, LULC, rainfall	Regression-Kriging	R^2 = 0.55–0.62	Effective for delineating nutrient variability under mixed land uses	Bhunia *et al.,* 2018
NER (multi-state)	Particle-size fractions (sand, silt, clay)	Terrain attributes, parent material, land use	Random Forest, Cubist	R^2 = 0.70–0.76	Terrain and lithology strong predictors of silt/ clay fractions; upland–lowland contrasts well captured	Jena *et al.,* 2023
Meghalaya Plateau	Soil pH and micronutrients (Zn, B, Fe)	Elevation, slope, land use, NDVI	Regression-Kriging, RF	R^2 = 0.60	Identified strong spatial dependence of acidity and micronutrients with parent material and elevation	Choudhury *et al.,* 2024
Sub-tropical NE India	Multi-micronutrients (Zn, Mn, Fe, Cu, B, S)	Remote sensing indices, DEM attributes	PCA + Fuzzy Clustering with DSM	Not reported	Management zones for micronutrients delineated, capturing co-variation among nutrients	Shukla *et al.,* 2024
Northeastern Himalayas	Soil organic carbon (SOC)	DEM derivatives (slope, curvature, TWI), NDVI, LST	Random Forest, Regression-Kriging	R^2 = 0.68	High-resolution SOC management zones; identified SOC-rich forest vs. SOC-depleted jhum fields	Reza *et al.,* 2024a