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A review on bridging digital soil mapping and agricultural extension: Enhancing soil advisory services for sustainable farming

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Abstract

The accelerating impacts of climate change and land degradation now pose a potentially devastating threat to global smallholder crop production and its contribution to food security. At present, more than 500 million smallholder farms face a combined blow from climate variability and soil erosion. Technological advancements in the sector have nevertheless been tremendous, and yet yields have levelled off, and global average arable land per capita stands at only 0.2 hectares. To this effect, the global population stands at a projected 9.8 billion by the year 2050. "However, the impact of these conditions is most acutely felt by nearly 80% of smallholder producers in developing nations, who face multiple nutrient deficiencies, arid conditions, and fluctuating climate. Conditions such as these contribute to a degradation of basic ecosystem functions such as water and carbon storage in the soil. Soil assessment indices do not have the spatial, scalable, and timely requirements that underpin precision and climatically resilient land use and agriculture. In the South Asian region, the pressure of population as well as the intensive agricultural practices have further exacerbated the conditions of soil erosion, salinity, as well as nutrient deficiencies. Punjab, known as an agricultural rich region of India, is a witness to the stagnated production of wheat and rice, besides the depletion of Groundwater resources, and pronounced deficiencies of multiple nutrients. Despite the efforts of the Soil Health Card Scheme, the effectiveness remains confined due to the lack of precision in the regional soil classification. This chapter presents advanced digital soil mapping approaches developed under the iSOIL study, which integrating legacy soil data with targeted field sampling, environmental covariates, and multi-sensor proximal geophysical techniques, such as electromagnetic induction, ground-penetrating radar, magnetometry, and gamma-ray spectrometry. Machine learning, geostatistics, hyperspectral remote sensing, and pedo transfer functions are used to produce three-dimensional predictions of key soil properties. Results clearly show that increased accuracy in mapping soil organic carbon, bulk density, and texture at surface and subsurface depths across Punjab offers a robust means of identifying areas prone to soil degradation. These findings underpin evidence-based policymaking, sustainable land management strategies, and enhanced resilience of smallholder farming systems to climate change.

Keywords: Digital soil mapping, soil informatics, machine learning-based soil modeling, climate-resilient smallholder agriculture

1. Introduction

The earth's fragile layer of soil plays an essential and foundational role in the functioning of ecosystems and global agricultural systems, yet, globally, soil resources are threatened. Climate Change and Man-made land degradation are two of the current greatest threats to the health of our planet and to Food Security. The increased frequency of extreme weather events combined with poor management practices has accelerated the decline of soil health and therefore has ultimately damaged the foundation of 95% of Food Production. As soils continue to degrade, they pose an immediate threat to the ecological services they provide to us, such as Carbon Sequestration, Water Filtration, Water Storage, Nutrient Cycling and Diversity Support, which all have tremendous economic value, in fact, they cannot be replaced (IPBES, 2018) ^[8].

Due to their reliance on field surveys that are labor intensive and classification systems that are polygon based, traditional methods of soil assessment are beginning to be viewed as insufficient to fully address large-scale and dynamic issues related to soils. Even though they have provided substantial historic information regarding soils, traditional soil maps

had poor spatial resolution and provided only limited quantitatively-measured information about individual soil properties. Additionally, traditional soil maps do not allow for the easy and efficient update of soil mapping to reflect continual changes that occur (Lagacherie *et al.*, 2006) ^[2]. This is especially important for smallholder farmers to have access to site-specific, accurate information pertaining to soils, as these farmers have to manage both nutrient deficiency and water scarcity as well as salinity problems on many marginal lands. (Tiftonell *et al.*, 2010) ^[10].

As a response to the limitations associated with existing soil technology, and encouraged by the advancements in the digital world-all supported by the advancement of digital technologies, spatial statistics and data science within the field of soil informatics-this has created a merging of new ideas and the traditional soil science fields of soil technology. This discipline is based on the ability of scientists to collect, store, organize, analyze and interpret soil information, producing useful knowledge, but the Digital Soil Mapping (DSM) concept is a key component of soil informatics. Essentially, Digital Soil Mapping (DSM), represents a new predictive framework where statistical and

machine learning techniques are used to combine sparse field data with numerous environmental indicators, thus allowing scientists to derive predictive soil property maps over much larger areas (Drechsel *et al.*, 2001). The switch to continuous quantitative prediction instead of solely relying on the use of taxonomic soil classification has increased our ability to manage and monitor our soil resources at the appropriate levels for precision agriculture, and ultimately the policy level on a national scale.

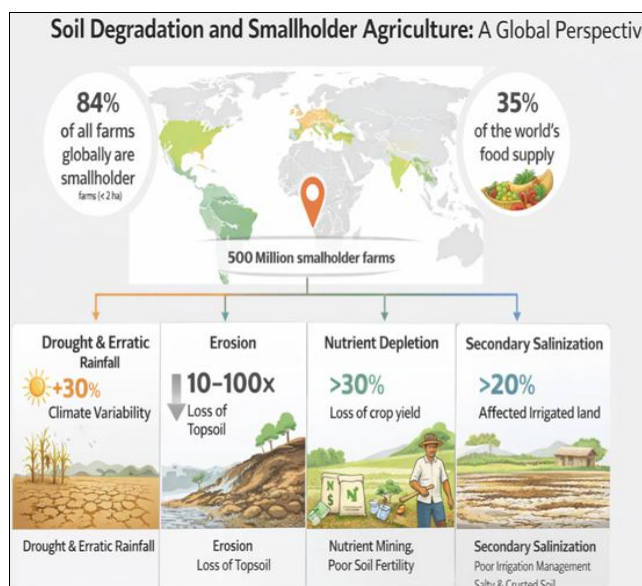
In this chapter, we review the world-wide demand for these new techniques and how they can promote resilient, sustainable agriculture among smallholders. The chapter begins by outlining the interaction between soil degradation, food security, and smallholders. This is followed by the creation of conceptual and technical elements of soil informatics, soil degradation, and the development of an integrated DSM framework for smallholder agriculture, and lastly, the case study from Punjab, India (which demonstrates the interactions between soil sustainability and agricultural intensification) will provide insights into the practical application of an integrated DSM framework for smallholder agriculture that can be globally adopted in the 21st century.

2. Soil Degradation and Smallholder Agriculture: A Global Perspective

About 84% of all farms globally are identified as smallholder farms (less than 2 ha). This type of farm

provides about 35% of the total food quantity globally but provides a much larger percentage of local 500 million smallholder farms in developing countries. Tropical and sub-tropical locations have the highest density of these farms and are affected by both climate change and soil degradation (Morton, 2007) ^[12]. The vulnerability of these farm systems can be attributed to many factors such as physical environment constraints, social/economic difficulties, inadequate access to information and technological resources.

Climate Change and Climate Variability exacerbate existing soil constraints. The change in precipitation patterns from Climate Variability can increase the risk of Drought and Erosion. Climate Variability also causes changes in Temperature, which may increase mineralization of soil organic carbon (SOC) and decrease both fertility and water-holding capacity of soils (Lal, 2020). Nutrient Depletion is a widespread problem; continuous cropping without nutrient replenishment has resulted in widespread deficiencies of nitrogen, phosphorus, and potassium throughout sub-Saharan Africa and South Asia. In addition, the erosion of topsoil from the action of water and wind exceeds natural formation by 10-100 times the global average loss of topsoil (P. *et al.*, 2017). Secondary Salinization (due to poor Irrigation Management) has affected over 20% of the world's irrigated land, resulting in losses of up to 50% in crop yield (Qadir *et al.*, 2014) ^[3].



A key issue in how smallholder farmers make decisions and understand their agricultural support systems is the lack of accurate, timely, and spatially detailed soil data (Tittone *et al.*, 2010) ^[10]. Many countries do produce national soil surveys, but they tend to be outdated, have a relatively low level of detail (e.g., 1:1,000,000), and are based on classification systems which do not give farmers any indication as to how to manage their lands with respect to the macro-level nutrient or soil health parameters. As a result, the weak availability of reliable soil data reduces the effectiveness of fertilizer subsidy programs, extension programs, and climate change adaptation programs, leading to the use of broad and/or generic solutions which are

financially and environmentally detrimental (Tittone *et al.*, 2014) ^[10].

3. Digital Soil Mapping and Soil Informatics: Concepts and Advances

The SCORPAN model is a quantitative representation of Jenny's traditional factorial model of soil development and is considered the theoretical foundation of Digital Soil Mapping (DSM). The SCORPAN model proposal states that one should be able to estimate the value of a given soil property (S) at a location by using data from seven distinct types of influential environmental conditions.

s = Other known soil properties present at the site.

c = Climatic characteristics, e.g., temperature, rainfall.

o = Organisms, including plants and people, both directly and indirectly, as a result of land-use activities.

r = Relief/Topography, including elevation, slope, and curvature.

p = Parent material (geologic).

a = Age of the soil.

n = Location/Location coordinates.

Digital Soil Mapping (DSM) uses the SCORPAN model to analyze how soils interact with the environment so that statisticians can predict the soil properties from limited sample sizes. As part of the soil information process, DSM is also an iterative process, meaning it combines many different types of data.

4. Study Area: Punjab, India

Punjab is located in northwestern India and is located in a region characterized by an abundance of fertile soil called Indo-Gangetic Plain (IGP). The climate of the Punjab Region can be categorized as semi-arid/sub-humid with hot summers (April-June temperatures to 45 degrees Celsius / 113 degrees Fahrenheit) and cold winters (December-February temperatures between 0-4 degrees Celsius / 32-39 degrees Fahrenheit). The average total annual rainfall is generally between 400 to 700mm. Approximately 70% to 80% of the rainfall falls between July-September (monsoon season). The three primary soil orders found throughout the Punjab Region are Inceptisols, Alfisols and Aridisols with most of the parent materials being composed of alluvial deposits. The Punjab Region is comprised of three distinct Agro-Climate Zones; these are the Sub-Mountain Undulating Zone, the Central Plain Zone and the South-Western Arid Zone (Sidhu *et al.*, 2015) ^[16].

4.1 Dominant cropping systems (rice-wheat)

Punjab, an established centre of the Green Revolution in India, continues to be characterized by an extensive, irrigated rice-wheat cropping system (RWCS). Double cropping is practiced on more than 80% of the total area sown to crops in Punjab and has played a vital role in creating India's underground food security by making up a disproportionate amount of the national grain stocks. However, the RWCS relies heavily on external inputs through an extensive use of irrigation, chemical fertilizers, and pesticides. Consequently, the environmental impact of the RWCS is severe. (Chaudhary *et al.*, 2017) ^[15].

4.2 Key soil constraints: salinity, nutrient deficiencies, SOC depletion

Deficiencies and Balance in Nutrients: Many areas of the world are facing widespread deficiencies of essential nutrients due to decades of high input extraction and fertilizer use that lack potassium and micro-nutrients, while focusing on nitrogen and phosphorus. Soil tests show significant deficiencies of zinc, iron and potassium in many parts of the world, which inhibit crop yields and the nutritional quality of crops.

Depleted Soil Organic Matter (SOM)

Long-term tillage, crop residue removal, and minimizing organic matter inputs have caused significant declines in

SOM levels with stocks often falling below critical levels (0.5% in heavily cropped regions). This has negative effects on soil structure, water holding capacity and microbial activity (Benbi & Brar, 2009) ^[13].

Rising Salinity Levels and Alkaline Conditions

Increasingly excessive salt-depositing in less fit soils in the western arid region, based on poor drainage systems and a result of using non-potable / polluted surface groundwater. Consequently, substantial areas are becoming less productive as agriculture relies heavily on these resources.

Depletion of Groundwater

The extensive use of non-sustainable groundwater sources for ag production has resulted in extremely high levels of depletion; The consequence is twofold: the depletion of the resource, and the concentration of salts in the root zone due to the decreasing levels of the groundwater beneath the ice-free portion of the RWCS.

4.3 Overview of Soil Health Card Scheme and its limitations

The SHC Scheme was first introduced in 2015 and aims to provide farmers with a soil nutrient report card including fertilizer dosage advice. Millions of cards have been provided to Punjab farmers. The scheme is praiseworthy in raising the awareness of farmers but has serious limitations:

- The sampling is sparse and inconsistent (often one sample every 2-5 hectares), and therefore is unable to account for variability within the field
- The analyses conducted consist largely of macro-nutrients (N, P, K), pH, and other variables such as SOC, bulk density, and micro-nutrients are omitted from the analyses
- The recommendations that are provided are at the village or block level and not per field; and
- The recommendations are only provided on a static, printed report and do not allow dynamic updates or the ability to integrate with other types of geospatial data

The lack of spatial precision and completeness in the information limits the usefulness for true precision nutrient management, creating significant demand for the high-resolution, multi-attribute maps produced by DSM (Bhattacharyya *et al.*, 2015) ^[14].

5. Materials and Methods

The research area for this study encompasses a region located in Punjab, North West India, and consists of land that lies within the geographical boundary range 29°30'N – 32°32'N latitude, 73°55'E - 76°50'E longitude. This area represents the northern most tip of the Indo-Gangetic alluvial plain and occupies an approximate area of 50,362 square kilometres. The area is bordered by Pakistan to the west, Jammu and Kashmir to the north, Himachal Pradesh to the north eastern direction, and Haryana and Rajasthan to the south. The upper boundary of the study area is defined by the Satluj River, which has had a major impact on how sediments have been deposited within this region. The physiography of the study area is characterized by a continuous expanse of old and new (Quaternary), alluvium, that have been reworked as a result of uplifting (orogenic)

processes, associated with river activity. The present landscape geomorphology has been created through a complex combination of local reworking of previously deposited sands in the form of sand bars and dunes, through aeolian processes, and subsequent flattening of sands, as well as continued transportation of sediment over long distances. The physiography of the study area has been divided into three physiographic units: the Satluj River floodplain, the older alluvial plain, and the stabilized sand dune area (southwest). Most of the parent material for soils in Punjab is alluvial and has come from either the Himalayan mountains through the Indus river system or Ganges river system (Bhattacharyya *et al.*, 2015) ^[14]. These soils contain mostly calcareous and medium-fine textured material that; were created under hyperthermic temperatures and ustic(arid) moisture conditions. According to USDA Soil Taxonomy, approximately 60% of the soils in Punjab are classified as Inceptisol, 15% Entisol, 12% Alfisol and 13% Aridisol. Soil textures vary from sandy loam to silty clay loam.

5.1 In Punjab, agro-ecological zones are divided into three distinct zones

- **Sub-Mountain Undulating Zone:** Located in the northeastern region of Gurdaspur, Hoshiarpur, Ropar, and parts of SBS Nagar characterized by its hilly landscape and receiving precipitation amounts significantly greater than any of the other two zones.
- **Central Plain Zone:** This is Punjab's most agriculturally productive area and the zone encompassing the following cities Jalandhar, Amritsar, Barnala, Fatehgarh Sahib, Sangrur, Patiala, Ludhiana, Kapurthala, and Tarn Taran.
- **South Western Arid Zone:** This zone includes Bathinda, Mansa, Faridkot, Muktsar, Fazilka, Sri Muktsar Sahib, and Ferozepur; characterised by lower rates of annual precipitation relative to the other two zones in Punjab, in addition to higher evaporation rates, salinization, alkalization (Sidhu *et al.*, 2015) ^[16].

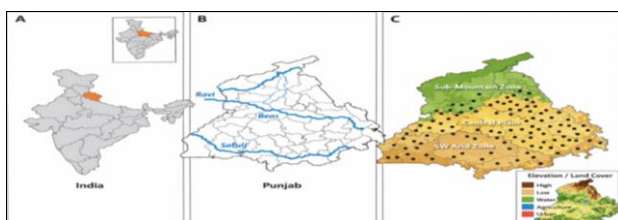


Fig: Location of Punjab in India, district map with major rivers, and distribution of sampling sites across agro-ecological zones with elevation/land-use inset.

5.2 Legacy Soil Data and Field Sampling

The legacy soil data used for mapping in Punjab consisted of a number of data sources including: the soil maps from the National Bureau of Soil Survey and Land Use Planning (NBSS&LUP) at a 1:250,000 scale; reports from the soil surveys conducted by Punjab Agricultural University; and historical soil profile datasets containing a total of 1,247 geo-referenced soil profiles collected between 1985 and 2015. The Soil Health Card data base provided an additional 15,632 surface samples (0-15 cm depth) collected across all the districts of Punjab in the years 2015 to 2020. Field

sampling was done in late October and early November of 2021-2022 during the post-harvest period using a conditioned Latin hypercube sampling design for selecting 300 sampling locations that provide a representation of the entire range of environmental covariates (Wadoux *et al.*, 2020) ^[17]. Soil samples were collected using a soil core sampler from three depth intervals (0-15 cm, 15-30 cm, 30-60 cm) at each of the selected sampling locations, and 900 total soil samples were collected. Prior to laboratory analysis of soil samples were air-dried, powdered and passed through a 2.0-millimetre mesh. The following soil characteristics were assessed using standard analytical procedures: Soil Organic Carbon by the Walkley-Black Method; Particle Size Distribution by the Bouyoucos Hydrometer Method; Bulk Density by the Core Method; pH and Electrical Conductivity of 1:2 Soil:Water Suspension; Available Nitrogen by Alkaline Permanganate Method; Available Phosphorus by Olsen Method; and Available Potassium by Ammonium Acetate Extract. For quality assurance, 10% of the analysis was conducted in duplicate, and a standard reference material was included with every batch of analysis.

6. Modelling Framework

Machine build a predictive model, we used several machine learning algorithms to create quantitative relationships between information about soils and the environment. The Random Forest (RF) algorithm will be our main algorithm for this study because it is proven to provide reliable results for modeling high-dimensional data, is resilient to overfitting, and demonstrates the ability to successfully identify non-linear functions without requiring a distribution of the data to begin with (Wadoux *et al.*, 2020) ^[17]. The RF algorithm creates an ensemble of decision trees using bootstrap aggregation and random selection of features and makes final predictions on future data points by averaging the predictions made by each individual decision tree. For the final model, we tuned the model parameters using 10-fold cross-validation to determine the best number of trees (ntree = 500) and the best number of variables that will be randomly selected to split each decision tree (mtry). Variable importance was assessed by permuting each variable and calculating the relative increase in the mean squared error of the model when predicting on new data. This assessed the most influential environmental factors controlling each soil property. We also evaluated Support Vector Machines (SVM) with a radial basis function kernel and Gradient Boosting Machines (GBM) for comparison. The SVM method maps input data into high dimensional feature spaces to find optimal separating hyperplanes, thus allowing for accurate identification of complex relationships between the soil and the environment (Lamichhane *et al.*, 2019) ^[18]. While GBM can produce highly accurate predictive models through a sequential fitting of a new model to correct the errors of the previous model, it requires careful tuning in order to prevent overfitting. The algorithms employed were implemented in R version 4.2.1 using the caret and randomForest packages.

6.1 Pedotransfer functions

Utilizing Pedotransfer Functions (PTFs) allowed for the estimation of soil characteristics that are difficult to measure

directly using standard basic soil data, such as bulk density (BD). The PTF was validated based on previous research, and was used to estimate bulk density values at historical/legacy soil health point samples from Soil Health Cards, which requires a significant amount of time and effort for the user to obtain directly.(Martin *et al.*, 2009).

$$BD = 1.377 \times e^{(-0.0048 \times SOC)} + 0.185$$

Soil Organic Carbon (SOC) content in g/kg, and is the PTF relational database selected for the Punjab region was subsequently validated locally against 150 paired SOC and Bulk Density (BD) sites (R²=0.71, RMSE=0.12g/cm³) to establish an appropriate relationship between them. Mapped soils in the study area were estimated using water retentivity (through the use of Rosetta PTF model) at field capacity (FC) and wilting point (WP) from given sand, silt, clay, and bulk density (BD) data (Zhang & Schaap, 2017) ^[19]. The PTF of SOC and PAWC made it possible to develop functional soil maps and allow better irrigation scheduling and drought predictive analyses through using current data collected from SOC-BD relationships within the Punjab.

6.2 Three-dimensional soil property modelling

Traditional methods of mapping soil in two dimensions do not take into account the vertical variability important to the understanding of root zone processes, nutrient cycling and carbon storage. To correct for this deficiency, a 3D modelling approach based on the method was used. For each soil property, continuous depth functions using mass-preserving equal-area splines were fitted to the measured depth intervals, which allows for the interpolation between the measured depth intervals while maintaining mass integrity. This interpolation method allows for the estimation of soil properties to any depth interval (e.g., 0-5cm, 5-15cm, 15-30cm, 30-60cm) over the entire study area. The spline parameters were also spatially modelled using the hybrid RK model and a separate model was calibrated for each standardized depth layer. The resulting 3D soil property maps represent both lateral and vertical variability in soil, which enables the assessment of carbon stocks by depth, management of nutrients in the root zone, and hydrologic modelling.(Minasny *et al.*, 2017)

7. Results and Validation

Table 2: Key Soil Properties and Model Performance Metrics

Soil Property	Depth	R ²	RMSE	Lin's CCC	Key Covariates (from Variable Importance)
Soil Organic Carbon (%)	0-15 cm	0.73	0.11	0.81	Rainfall, NDVI, DEM
	15-30 cm	0.64	0.09	0.74	DEM, Rainfall, ECa (EMI)
Bulk Density (g cm ⁻³)	0-15 cm	0.68	0.08	0.75	SOC, Gamma-K, Sand
	15-30 cm	0.61	0.11	0.68	Gamma-K, SOC, DEM
Clay Content (%)	0-15 cm	0.81	4.2	0.86	Gamma-K, Gamma-Th, DEM
	15-30 cm	0.76	5.1	0.80	Gamma-Th, Gamma-K, ECa (EMI)

8. Discussion

8.1 Improvements over conventional soil maps

The digital soil maps derived from this research are an important development in the availability of soil information for Punjab compared to past sources of soil information. Previous mapping systems, which used 1:250,000 scale NBSS&LUP reports to determine soil mappings, were based on about 47 different mapping types according to soil classification and relied on average values for select physical soil properties to represent those mappings. Traditional maps assume homogeneity within each polygon, a false assumption given the heterogeneous alluvial landforms in Punjab(McBratney *et al.*, 2003). The digital soil maps, on the other hand, provide continuous and high resolution (100 m) estimates of soil properties, thus capturing the full range of variability for relevant decision-making at the farm level. So for example, within the same mapping unit (Typic Ustochrepts) within a portion of the Ludhiana District, traditional mapping indicated soil organic carbon (SOC) was between 0.38% and 0.92%, but with DSM the realized variability was 2.4 times greater than indicated by traditional mapping methods.

8.2 Identification of degradation-prone zones

Spatial overlay analysis of projected soil property maps has revealed areas experiencing multiple, interrelated degradation processes. Four separate degradation-prone zones were defined:

Zone 1 (Southwest Arid District)

Zone 1 has been determined to face a complex level of degradation as a result of the simultaneous occurrence of low SOC (< 0.3%), high BD (> 1.65 g cm⁻³), very high EC (> 4 dS m⁻¹) and sandy soils. The resulting conditions indicate that Zone 1 is under severe stress with respect to a lack of water, lack of nutrients and excessive salt concentration. Approximately 280,000 hectares (8% of the study area) are located within this high-priority intervention zone.

Zone 2 (Crystal Plain-Rice/Wheat Heartland)

Zone 2 has moderate SOC (0.4–0.6%) and evidence of declining trends, as well as initial indications of micronutrients (especially Zn and Fe) deficiency. This zone also has areas of localized structural degradation (due to intensive mechanization). This zone requires preventive interventions in order to prevent further degradation.

Zone 3 (Floodplain Zone)

Zone 3 consists of sandy soil over clayey soil, demonstrating increased BD in the subsurface soil and recurrent waterlogging conditions during the monsoon. Approximately 175,000 hectares are located within these problematic soil conditions.

Zone 4 (Sub-Mountainous Hilly Zone)

Although Zone 4 has low fertility levels and is less severely

degraded due to low cropping densities, it does have an increased risk of erosion on sloping land, resulting in soil loss and sedimentation downstream.

9. Policy and Management Implications

The change from generalized or anecdotal evidence on soils to quantifying soil data in a spatially explicit methodology will create significant changes to the development and implementation of agricultural policy. In India, these agricultural development programs include the National Food Security Mission, the National Mission for Sustainable Agriculture, and many state-level Agricultural Development programs. Historically, these programs have used coarse-resolution soil data, which has limited their ability to effectively target resources to those areas in need of intervention, and ultimately to create the most cost-effective interventions (Bhattacharyya *et al.*, 2015) ^[14]. Processed DSM products that were developed as part of this study will allow for the implementation of policies in geospatially targeted areas. As India provides the second most significant agricultural subsidy after food through fertilizer subsidies (fertilizer support), DSM outputs can help reduce costs and increase effectiveness of subsidies. At present, all fertilizers are subsidized equally throughout India creating an imbalance of application of fertilizer and generating environmental issues associated with excess nitrogen used in agriculture. Therefore, developing a differential subsidy in a spatially distributed way based upon nutrient maps created from DSM would lead to increased subsidies for potash and micronutrients in areas that are deficient in these nutrients, while reducing the subsidies on nitrogen in the high-fertility regions at the same time, will lead to improved efficiency of nutrient utilization, less environmental pollution from excess nitrogen, and help to address the issues of ongoing and increasing multi-nutrient deficiency. (Gulati & Banerjee, 2015) ^[21] Watershed Development Programs, Soil Conservation Programs and Climate Adaptation Investments (all above) could potentially be prioritized according to degradation risk mapping methods. Degradation risk mapping was used to determine that Zone One (southwestern arid) is experiencing extreme competitive degradation on multiple levels.

10. Global Relevance and Transferability

The iSOIL study's integration methodology is a framework that can be applied across different agro-ecological contexts around the world, and it is not limited to a specific region. Its principles, including: integrating legacy data; targeted sampling; assembling multiple-source covariates; machine learning modeling; 3D prediction; and quantifying uncertainty, can be used universally across all regions; however, their specific implementation should account for local conditions.

In Southeast Asia, intensive rice production systems experience similar issues to Punjab in terms of nutrient depletion, soil structural decline, and the development of salinity in delta regions. Therefore, the 3D mapping and depth-specific predictions associated with the iSOIL framework are important tools for understanding root zone processes within the puddled rice culture system, as well as for informing sustainable intensification of food production in the region.

In Latin America, the recent trend towards the expansion of agriculture into marginal land and the growth of precision agriculture are driving a need for more accurate and detailed soil information. The experience gained from Brazil with the development of carbon maps using DSM for agricultural planning validates the scalability of these technologies, as they are now being used to inform policies and decisions at both the national and farm levels. (Adhikari & Hartemink, 2016) ^[1].

The iSOIL framework (developed for temperate farming areas of North America and Europe) will modernize national soil information systems by harmonizing and integrating legacy datasets into iSOIL. The Global Soil Map project works towards the same outcome (consistent, 100 m-resolution maps of soils around the world). (Arrouays *et al.*, 2014) ^[5].

11. Conclusion

The chapter provided a detailed case study on the use of digital soil mapping and soil informatics and how they can be applied to meet urgent soil information gaps in Punjab, India – a location that is at the centre of the inflection point of intensifying agricultural pressure and addressing sustainability challenges, which are common to most of the world's agriculture

The iSOIL Punjab case study shows how digital soil mapping and soil informatics have developed from being only a research concept to now two well-developed operational tools that directly address soil-based information needs of the real world. The next major challenge is not only to refine the methodologies further, but also to scale these methodologies on a global basis, and to integrate them into institutional structures, so that the totality of the information generated can ultimately lead to improved soil management, increased agricultural productivity, and increased resilience for hundreds of millions of smallholder farmers that rely on healthy soils for their livelihoods and food security. Addressing this challenge requires continued commitment from researchers, policy-makers, developers, and farmers; all of whom must work together to develop the soil information systems necessary to support sustainable agriculture in the 21st century.

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