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ROLE OF PRECISION AGRICULTURE TECHNOLOGIES IN IMPROVING CROP PRODUCTIVITY AND FARM PROFITABILITY IN INDIA: A NARRATIVE-INTEGRATIVE REVIEW

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ABSTRACT:
Precision agriculture (PA) is a crop-management methodology that incorporates various tools at the intersection of time, space, and market intervention. Its importance in a country like India stems from the fact that fragmented holdings, coupled with labor and climatic challenges, entail the need for greater productivity and profitability of crops. The main issue is that most studies have approached PA from either the agronomics or the economics perspectives, while there exists very limited integrative evidence on smallholder Indian farm systems. This paper investigates the crop-science and economic elements of PA and devises structures aimed at enhancing the productivity of crops and profitability of farms among Indian smallholder farmers. A narrative-integrative review framework was employed for this study. The review was based on extensive research of literature published from 1997 to 2026, consisting of 60 documents of peer-reviewed articles, reviews, and formal institutional papers related to precision agriculture and its various subordinate fields on Scopus, Indian and ICAR sites, and other cited portals of research publications. The study outlines the functionalities of PA in managing nutrients and water, as well as the surveillance of crop health, yield prediction, and timely evaluation of crop stress. India's smallholder farmers benefit more from FPO and custom-hiring support models than from individual technology ownership. Among smallholder farmers, service-based Precision Agriculture (PA) adoption outperforms individual technology ownership. Profitability for smallholder farmers can be attributed to the value of services delivered, and custom hiring and Farming Producer Organization (FPO) support

KEYWORD: agribusiness management; crop productivity; digital agriculture; farm profitability; India; precision agriculture; remote sensing; resource-use efficiency.

1. INTRODUCTION

Precision agriculture (PA) involves the measurement and management of spatio-temporal fluctuations and patterns of precision within production systems of agricultural commodities. PA goes beyond the use of costly machinery and instead focuses on the collection and application of data to increase the accuracy of agronomic decisions. Traditionally, PA assumes that variations across different fields and different growing seasons in soil, water, nutrients, and plant vigor, as well as pest pressure and yield potential, require differential management (1,2). Foundational literature presents PA as a shift from generalized input application to site-specific crop management in which information, positioning, sensing, analytics and targeted intervention work together to improve both productivity (3,4) and sustainability (5).

The significance of Precision Agriculture (PA) in India is substantial. Although food production has increased significantly, challenges remain, including inconsistent fertilizer application, groundwater depletion, fragmented land, pest and disease crop losses, and increased exposure of crops to climate change. Indian farming has its special structural challenge. The majority of the holdings are small or marginal. This entails that the direct ownership model of expensive equipment cannot be the primary method for PA to be adopted and spread. India needs the model where low-cost sensors, mobile platforms, public data platforms, Farmer Producer Organization (FPO), custom hiring services, drones, and specific crop advisory services transform Precision Agriculture from an elite concept to an affordable agribusiness service.

PA should be evaluated in terms of two interconnected questions. First, how does this technology impact plant performance, crop establishment, nutrient uptake, water-use efficiency, pest monitoring, yield variability/consistency, and crop quality? Second, how does the impact translate into a financial gain when you consider the service fee, the capital investment, the cost of data, ongoing maintenance, the cost of training, the cost of labor, the risk, and the market value? A management decision made too late has little economic value, and therefore a drone images, a satellite's crop map, and soil sensors have little economic value if they don't help in sustaining crop yield, in lowering cost, and in increasing market accessibility. Because of this, Production Economics of the Agribusiness system will be used to further evaluate PA.

Evidence from the recent India-focused digital agriculture initiatives suggests that, in addition to the proliferation of new devices, data infrastructure, service provision, public policy, and trust, all influence the smallholders' digital adoption.

Remote sensing, UAVs, IoT sensors, decision support systems, AI, and new digital farm management platforms have increased PA literature beyond early yield mapping and GPS-guided equipment (6,7). Today, researchers and farm managers use remote sensing and vegetation indices (8,9) to measure crops and gauge their health and stress levels (10). UAVs extend this capability (11,12) by providing high-resolution and timely field observations (13) for crop scouting, stand assessment, spraying support (14) and within-field variability mapping (15). Thermal sensing, IoT devices and wireless sensor networks (16) add real-time or near-real-time data for irrigation, weather and crop-environment monitoring (17,18).

Recent studies have developed PA further, incorporating machine learning (19), computer vision (20), and plant phenotyping (21). These methods are applicable to India, as they can enhance disease detection (22) and yield prediction (23) as well as crop classification, irrigation scheduling and decision support (24,25) across different agro-ecological conditions (26). However, technology performance does not equate to adoption readiness. Adoption is influenced by various factors including costs, skills, trust, institutional delivery, crop prices, farm sizes, risk preferences, and the quality of related extension services. This review combines plant-science mechanisms, digital technologies, and agribusiness models to analyze the potential for the responsible scaling of PA in India.

Recent India-based precision farming reviews indicate that when considering local agronomy, farmer training, service delivery, and low-cost accessibility together, AI and IoT can be the most beneficial.

METHODOLOGY

A narrative-integrative design fits best for this review due to the multiple fields that precision agriculture in India spans. The goal was to outline the mechanisms by which precision agriculture influences crop productivity, resource-use efficiency, and profitability of the farm, not to determine a unified effect size.

Search Strategy and Keywords

The literature searches were conducted between May 30 and July 26, 2026. Searching the literature was done via Scopus, Web of Science, Google Scholar, ScienceDirect, SpringerLink, PubMed, ICAR repositories, portals of the Government of India, and relevant journals. The keywords used for the search were precision agriculture, smart farming, crop productivity, profitability of the farm, India, AI in agriculture, remote sensing, GPS, variable rate technology, IoT in agriculture, and drone technology. The searches were for literature published between the years 1997 and 2026. The complete Boolean query string used across the databases, modified only as necessary for syntax requirements for each database, was: ("precision agriculture" OR "precision farming" OR "smart farming" OR "digital agriculture") AND (India OR Indian) AND ("crop productivity" OR yield OR "resource-use efficiency" OR profitability OR economics OR adoption) AND (AI OR "artificial intelligence" OR "machine learning" OR IoT OR "Internet of Things" OR drone* OR UAV OR "remote sensing" OR GIS OR GNSS OR "variable rate technology" OR sensor*).

Inclusion and Exclusion Criteria

Included in the study were peer-reviewed publications, reviews, and official documents from Indian institutions, provided that they described the impacts of precision agriculture technologies on crop production, resource-use, economics of the farm, barriers to adoption, and/or policy adjustment in Indian agriculture. Excluded were unrelated studies, duplicate publications, livestock studies, and non-evidence-based documents.

Screening Process

Three steps were involved in screening. The first consisted of title and abstract checks for crop-related precision agriculture. Productivity-related studies were included in the second step. Eliminated were livestock studies, non-evidence-based studies, and studies that provided only technical description of a farming prototype with no crop-related management. The last review had 60 studies. The following is a summary of the steps taken in the screening process.

As only one reviewer (the author) conducted the screening, there was no dual screening or assessment of inter-rater reliability. This absence of dual reviews and inter-rater reliability is in line with the narrative-integrative design of this review. For every source included, the assessor noted the bibliographic information along with the following: study location, crop or production system, type of precision-agriculture technology, study type, outcome type, effect type, and the economic viability, adoption barriers, and policy/service delivery implications. This was the data extraction process for the review. No custom data extraction format was applied. Instead, a reading protocol was applied to the 60 sources. The protocol documented bibliographic information, the location of the studies, crop systems, types of technology, types of outcomes, and the economic and policy implications of the sources. Sources were evaluated for their credibility and relevance considering their peer-review status or their affiliated institution, clarity of the methodology, direct relevance to crop production in the context of Indian smallholders, the publication date, and coherence of the claims with the evidence. In situations where the sources offered contradictory evidence, they looked at crop differences, region differences, differences in the size of the farm, the type of technology, the resolution of the images, the calibration of the sensors, and the conditions of service delivery. They reported the results as context-dependent and did not try to produce a single effect estimate.

Standardized tools such as CASP or AMSTAR (which are tailored for systematic reviews and meta-analyses) are not relevant for this type of appraisal, and as such, formal quality assessment for narrative-integrative reviews was not undertaken. Rather, the credibility of the consulted sources was judged based on the following four criteria: peer-review or institutional affiliation, transparency of research methods, direct relevance to crop production in the Indian smallholder context, and logical consistency between the claims made and the evidence provided. Sources meeting the criteria were included. Other sources were excluded at the full-text level. Where conflicting evidence was provided by the sources, we did not attempt to derive a single effect estimate. In such instances, contradictions, including variables like crop type, farm size, image resolution, sensor calibration, service delivery quality and regional agro-ecology, have been documented.

Literature Screening Summary

Literature screening was carried out in four stages. Our search across the noted databases and institutional repositories resulted in 112 records. After duplicates and irrelevant records were removed, we screened 96 titles and abstracts for relevance to crop-related precision agriculture. Relevant to the criteria for inclusion and exclusion, we assessed 72 full texts. Studies were excluded if they were limited to a livestock focus, were not evidence-based, were duplicates, or were of technical prototypes that did not relate to crop management or the economic decision-making context. Sixty sources were included in the final narrative-integrative synthesis.

Table 1. Review search strategy, screening logic and thematic organization

Review component	Operational detail	Purpose in the review
Review type	Narrative-integrative review with structured literature search	To combine agronomic, technological, economic and policy evidence (1,3,5,28,30)
Databases and sources	Scopus, Web of Science, Google Scholar, ScienceDirect, SpringerLink, PubMed, ICAR and Government of India portals	To include both peer-reviewed and official Indian evidence (21,47,48,50,51)
Core keywords	precision agriculture, remote sensing, UAV, IoT, VRT, crop productivity, profitability, India, digital agriculture, adoption	To capture technology, crop and agribusiness dimensions (6,11,16,19,23)
Time range	Around 1997-2026, with older foundational papers retained where essential	To cover both classic PA concepts and current digital agriculture (1,3,6,30,48,59)
Inclusion criteria	Relevant peer-reviewed articles, official reports, crop-production focus, clear technology or economic relevance	To ensure the paper remains within applied plant science and agribusiness scope (1,6,8,17,19)
Exclusion criteria	Non-agricultural ICT, livestock-only studies, duplicated papers, prototypes without crop decision relevance	To keep the synthesis focused on crop productivity and farm profitability (41,42,45,46)

Source: Literature search protocol prepared by author using review methods synthesized from PA, digital agriculture and review writing (28,30).

Precision agriculture technologies and their crop-management functions

PA consists of levels, the bottom of which consists of technologies that determine the locations of fields, sampling points, and operations (1,2). Global navigation satellite systems (GNSS) and geographic information systems (GIS) make it possible to map soil, irrigation, crops, pests, and yield in geo-referenced maps (4). GNSS is used for mapping the boundaries of fields, grid sampling, delivery of inputs, and mechanization of operations on the field, while GIS is used for the integration of separate observations into management zones (5). In India, where landholdings are generally fragmented, GNSS and GIS will likely be more valuable in enhancing service delivery via custom hiring, FPO-level mapping, crop insurance assessment, and more tailored extension services, rather than individual ownership of auto-steer technology.

At the core of contemporary Precision Agriculture is Remote Sensing which involves observation at a distance (6). Satellites, planes, UAVs and a range of proximal sensors can supply data on canopy reflectance and indices on vegetation, temperature, biomass, and crop stress, among many others (7,8). While crops can appear uniform to the naked eye, remote sensors can detect a variety of nutrient stresses (i.e. nutrient, water, etc) or crop diseases before they progress to the point of visible symptoms (9,10). This early warning feature is valuable to many crops including wheat, rice, cotton, sugarcane, vegetables, and other plantation crops. In India, satellite monitoring is most valuable when imagery is formatted into simple field advisories. Examples of these field advisories include identifying where to scout, where to irrigate, where nutrient deficiencies are likely to occur, and which plot needs the most immediate intervention.

Most recent assessments show that remote sensing, GIS, drones and field sensors help with monitoring crop stress and soil variation and there is general agreement. There is disagreement, however, on level of impact. Crop type, image resolution, cloud cover, and field validation timing, to name a few, strongly affect performance.

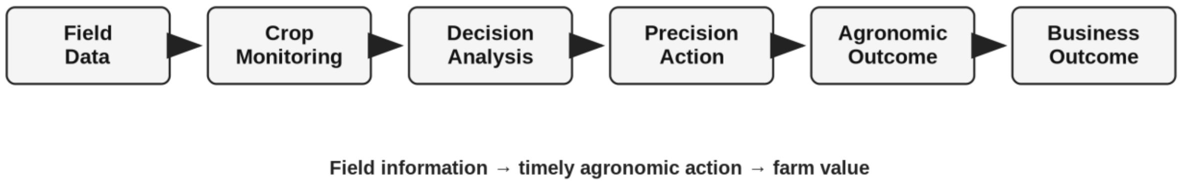

Fig. 1. Conceptual schematic of the pathway through which precision agriculture converts field data into crop productivity and farm profitability.

Source: Synthesized by author from foundational PA, remote sensing, farm information systems and profitability literature (1,2,3,4,5).

Drones (UAVs) - increasingly referred to as agricultural drones - are positioned between satellite imagery and traditional field scouting (11,12). Drones can gain high resolution imagery (13) at specific crop stages and can also facilitate spraying (14), mapping and damage assessment (15). Their value is enhanced in situations where satellite imaging may be too coarse or insufficient due to cloud cover; in situations requiring fine spatial resolution; or when damage to crops is localized. Unlike satellites, drone imagery can spot changes in canopy vigor and signs of water stress and early onset diseases. So farmers can use it to apply fungicides or herbicides or water only to the affected parts of the field.

However, UAVs do not inherently provide profitability. The business case for UAVs relates to a whole range of factors such as field size, value of the crops, price of the service, operator's expertise, time taken to process the images, chemicals used, compliance to the regulation, and most importantly, the farmer's capability of making the required decision on the provided information.

Drone use likely improves speed and precision for scouting and spraying. However, the cost-effectiveness and the challenges of adopting drones for farm operations show a diverse pattern according to the farm scale and the crop’s value.

The IoT and sensors offer the temporal PA layer (16). Soil moisture sensors, weather stations, water flow meters, humidity, temperature and nutrient sensors can all provide field data to assist in the scheduling of irrigation and fertigation, as well as in the generation of disease-risk messages (17,18). These readings are important for agronomy because they indicate when soil moisture diminishes to the threshold for beginning crop yield loss, which is the deciding factor for commencing irrigation. For regions stressed by a shortage of water, the benefits of pump-based irrigation are not limited to yield enhancement. They also include reduced energy costs, reduced pumping, and a lower risk of leaching nutrients or waterlogging. Nevertheless, the success of a sensor system hinges on a number of factors, including calibration, maintenance, constant connectivity, and interpretation. A sensor that is placed in a poorly representative location or is left uncalibrated is likely to provide more of a hindrance to farmers than help.

Smart sensor studies agree that real-time monitoring increases the efficiency of water and resource management. However, differences in placement, calibration, power supply, connectivity and farmer advisory support affect the field value of different sensors.

AI, machine learning, computer vision, and decision support systems comprise the analytical layer (19,20). These systems allow for crop classification (21), yield prediction (22), disease detection (24,25), weed identification, biomass estimation, and the transformation of multi-source data into decision rules (23). For plant science, this indicates that stress responses of crops and their physiology can be measured on a larger scale (26). For agribusiness management, this indicates that services and planning including advisory, input, procurement, crop insurance and credit services can be based on more data. Nonetheless, data representative of the domain is essential for algorithms. If models are trained on one crop, one region, one soil, or one variety, they may not perform well in other cases. In the case of the heterogeneous agro-ecologies of India, validation is not optional; it is a requirement for the trust of farmers and the economic viability of the model.

Farm management information systems and digital agriculture platforms combine many features (27). They capture and link information at the field level, from machines, farmers and advisors (28) and combine this with the weather and market data (29,30). The platform perspective holds significance for India as PA will expand through services rather than through the singular ownership of expensive technologies. A farmer may not invest in a drone, a subscription to satellites, a soil sensor network, or a variable-rate applicator. However, they may pay for services like field mapping, drone spraying, crop health reports, irrigation advisories, or a digitally managed dashboard by FPOs.

Table 2. Precision agriculture technologies and their agronomic and economic functions in Indian agriculture

Technology	Main crop-production function	Economic logic for farmers or service providers	References
GNSS and GIS	Field boundary mapping, soil sampling grids, operation tracking and management zones	Improves accuracy of custom services, reduces overlap and supports crop insurance and advisory records	(1,2,4,5)
Satellite remote sensing	Monitoring crop vigour, canopy cover, moisture stress and seasonal variability	Provides low-cost scalable surveillance for large areas and supports early intervention	(6,7,8,9,10)
UAVs or drones	High-resolution crop scouting, stand assessment, spraying support and damage mapping	Works well as a paid service for high-value crops, FPOs, custom hiring and time-sensitive operations	(11,12,13,14,15)
IoT sensors	Soil moisture, weather, irrigation and crop-environment monitoring	Saves water, energy and labour when advisory and maintenance systems are reliable	(16,17,18)
AI and DSS	Disease detection, yield prediction, irrigation scheduling and input recommendations	Converts raw data into decision support, but requires local validation and trust	(19,23,24,26,29)
Variable-rate technology	Site-specific application of seed, fertilizer, water or chemicals	Reduces input waste but requires machinery access, prescription maps and sufficient serviced area	(1,2,31,33)

Source: Synthesized from precision agriculture, remote sensing, UAV, IoT, machine-learning and farm information-system literature (1,2,6,11,19).

Role of precision agriculture in improving crop productivity

Site-specific nutrient management

Crop productivity gains depend on the accurate and timely identification and correction of agronomic constraints (6). In the context of nutrient management, PA deals with the problem of uniformly applied fertilizers to fields with varying levels of soil fertility, organic matter, moisture, slope, and yield potential. Site-specific nutrient management integrates soil testing, crop sensing, chlorophyll assessment, remote sensing, and yield records (7) to determine where nutrients are low or in excess and where yield response is expected (10). Agronomic value derives from optimally aligning the supply of nutrients with crop demand. Economic value derives from preventing waste in areas with no additional fertilizer demand and protecting yield in areas with nutrient deficiency that constrains growth.

In India, managing nutrients is very important in a PA pathway because fertilizer is used imbalanced in the regions and in the crops. The Soil Health Card program is a starting point for soil-test-based recommendations. However, further steps must be taken to include the local yield response, geo-referenced maps and timely monitoring of the crops in the stage that they are in. The usefulness of soil data is greatly reduced when treated as a static report. As a layer in a decision system, they can help generate dynamic nutrient management plans, optimize inputs, facilitate FPO-level procurement of fertilizers, and enhance extension services.

Water management and irrigation scheduling

One of the most important factors for PA's effect on productivity and profitability is water (16). Relying on farmer experience when making irrigation decisions often results in sensitive crop stages being under-irrigated and other instances of over-irrigation when soil has enough moisture. The use of thermal imaging, soil moisture sensors, weather stations and crop models can refine the irrigation schedule by correlating water application according to crop demand (17,18). The mechanism behind crop science is managing watering schedules during critical growth periods. This enhances the process of photosynthesis, uptakes of nutrients, flowering and grain filling, and ultimately improves yield in the market. The mechanism of the business is just as crucial. Improved irrigation minimizes risks associated with water, energy, and labor costs.

Although sensor-based irrigation can be applied to a multitude of crops, such as wheat, rice, and sugarcane, it does need to be customized to each location. For example, a sensor embedded in sandy soil cannot be calibrated in the same way as a sensor embedded in clay soil. In addition, a moisture threshold for one crop stage may be totally different for another crop stage. However, in protected cultivation, orchards, and high-value crops, the return on sensor-based irrigation investment may be even greater, since water stress impacts product quality and ultimately how much you can sell it for. For cereals, energy savings and yield stabilization may be more important than the price you sell it for.

Crop health surveillance and pest management

Another major productivity pathway is assessing crop health (21). Tools like remote sensing, drone imagery, mobile images, and computer vision (22,23) have the capacity to detect a variety of issues including abnormal crop patches, diseases, pests, weeds, nutrient deficiencies, and lodging (24,25). The benefit is not simply the ability to detect, but to

detect at an early stage. If a disease/insect outbreak were detected after causing extensive damage, the technology would have slight economic value. If the technology is able to detect a hotspot early enough for targeted scouting and intervention, it would lead to lower crop losses and eliminate the over-application of pesticides to the entire field.
Imaging sensors and computer vision have great potential for plant disease management but can be problematic if not used correctly. Some symptoms can be visually quite similar. For example: early signs of disease, water stress and nitrogen deficiency may all lead to a reduction of canopy reflectance or leaf greenness (24,25). As a result, sensor signals should be integrated with field scouting, agronomic diagnosis, and local knowledge. In the case of India, this is critical since cultivar, climate, soil composition, phenological crop stage and mixed pest incidence vary greatly across the Indian subcontinent. A solid PA system should not supplant the agronomist, but should escort the agronomist or extension worker to the appropriate section of the field.

Yield estimation and crop quality

Estimating yield and monitoring crop quality affects both production and marketing decisions. Remote sensing, coupled with crop models, aids in the estimation of biomass and canopy development as well as yield variation (8,29). For farmers, this aids in planning for harvests, adjusting inputs, and managing risk. For agribusiness firms, it aids in planning for procurement, allocation for storage, contract farming and assessing risks for credit. For government agencies, it aids in estimating crops, insurance and disaster response. The direction this takes is completely in line with the Digital Agriculture Mission which focuses on farmers, geo-referenced maps, crop sown registries and crop estimation.

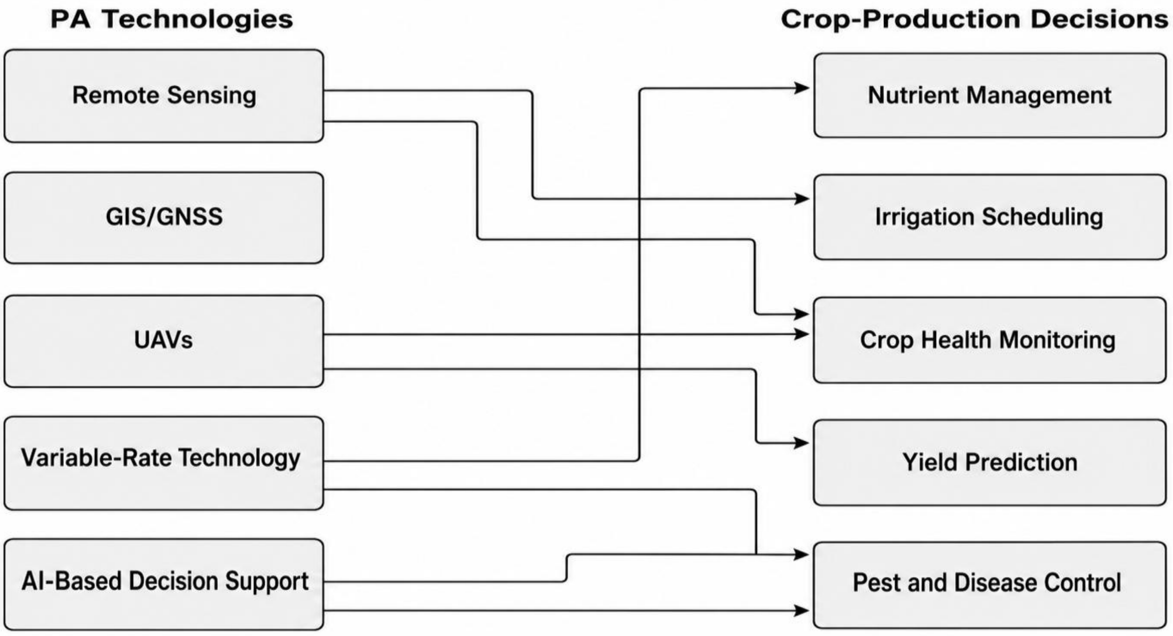

Fig. 2. Conceptual schematic showing how major precision agriculture technologies support crop-production decisions.

Source: Synthesis of PA technology reviews and decision support studies (6,8,11,19,20)

Resource-use efficiency and environmental implications

One strength of Precision Agriculture (PA) is that it increases efficiency related to resource use. Regarding crops, efficiency is producing more yield with less water, nutrients, pesticides, energy, labor, and land. From a business standpoint, it is less spending while still accounting for income or perhaps even increasing it. Precision Agriculture increases use efficiency by determining the WHEN and WHERE of resource inputs. This is what separates Precision Management from Blanket Management. Where Precision Management provides for the variability of a resource, Blanket Management treats a resource uniformly.
Using irrigation based upon recorded soil moisture, crop growth stage, and the weather, increases water-use efficiency (16,17). In areas where groundwater extraction is expensive, more precise irrigation practices can conserve energy. In systems that rely on irrigation canals, it can minimize waterlogging and nutrient leaching. For high-value crops, it can enhance quality consistency and reduce the stress associated with water deficits. For India, this is especially relevant given the concurrent environmental and economic problems of water scarcity and groundwater depletion. Farmers are negatively impacted financially due to the increasing energy costs associated with pumping water, even if their crop yields are unaffected.
Nutrient-use efficiency benefits from having fertilizer tailored according to crop response and spatial variability (1,2). In some fields, areas with shallow soil, poor drainage and high salinity have low potential. These areas are less likely to benefit from additional fertilizer. Areas with low nutrients may respond to fertilization. PA differentiates between the areas (31). The same can be said for pesticides. Some sensors and scouting drones may indicate localized pest pressure.

In these scenarios, creating a target may greatly reduce pesticide usage without compromising protection for the crops. This can eliminate costs, improve residue, and environmental issues.

Technologies of precision agriculture can have important positive and negative impacts on climate and sustainability. To some extent, precision technologies help limit greenhouse gases by minimizing the use of surplus fertilizers, consuming less fuel and reducing the pumped water and field operations (31). Environmental benefits are not guaranteed. For example, since efficiency could worsen, a technology could increase inputs used without boosting crop response. Also, a drone service that is used at the wrong time and/or is poorly calibrated may not reduce the need for pesticides. The environmental benefit of Precision Agriculture (PA) depends on the correct use of an agronomic practice rather than the application of technology.

Table 3. Resource-use efficiency pathways created by precision agriculture

Resource	PA intervention	Expected efficiency pathway	Agribusiness implication
Water	Soil moisture sensors, thermal sensing, weather-based irrigation advisories	Reduces under- and over-irrigation and protects critical crop stages	Lower pumping cost, improved yield stability and better service potential in irrigated clusters (16,17,18)
Fertilizer	Geo-referenced soil tests, canopy sensing, management zones and VRT	Matches nutrient application to crop demand and field variability	Input optimization, FPO procurement planning and potential reduction in waste (1,2,31,50,55)
Pesticides	Drone scouting, image-based disease detection and targeted spraying	Improves early diagnosis and limits blanket chemical use	Lower chemical cost and residue risk; useful for export and premium value chains (21,22,23,24,25)
Labour	Digital scouting, GPS-enabled operations and drone services	Reduces time spent in manual monitoring and improves operational timeliness	Supports rural entrepreneurship and custom-hiring service models (11,13,15,27)
Information	Farm records, GIS layers and decision support systems	Converts raw observations into repeatable decisions	Improves credit, insurance, procurement and advisory products (27,28,29,30,57)

Source: Synthesized from remote sensing, IoT, machine learning, farm management and environmental PA literature (16,19,23,27,30).

Farm profitability and economic returns

PA profitability differs from PA productivity (32,33). A technology that boosts yield may still be unprofitable if it's too costly, has inconsistent service, or the crop price is low (34,35). Another technology that has a small yield increase may be considered profitable if it lowers the cost and risk of irrigation, fertilizer, and pesticides (36,37). Economic theories state that when appraising PA, you have to look at whole farm profitability (38,39) instead of just technical productivity (40).

Five primary routes to profitability exist. The first is input-saving. Variable cost is reduced when fertilizers, pesticides, and water are applied to fields only where needed. Yield improvement is the second pathway. Optimization of irrigation and improved pest detection can lead to reduced losses and greater crop growth. The third pathway is quality improvement. In many crops, including fruits and vegetables, quality improvement can be more beneficial than yield improvement. Risk reduction is the fourth pathway. If stress signs, pests, and drought are detected early, losses can be mitigated. The fifth is market and finance linkage. Digital record keeping, geo-tagging and crop monitoring can facilitate traceability, crop insurance, credit scoring, and contract farming.

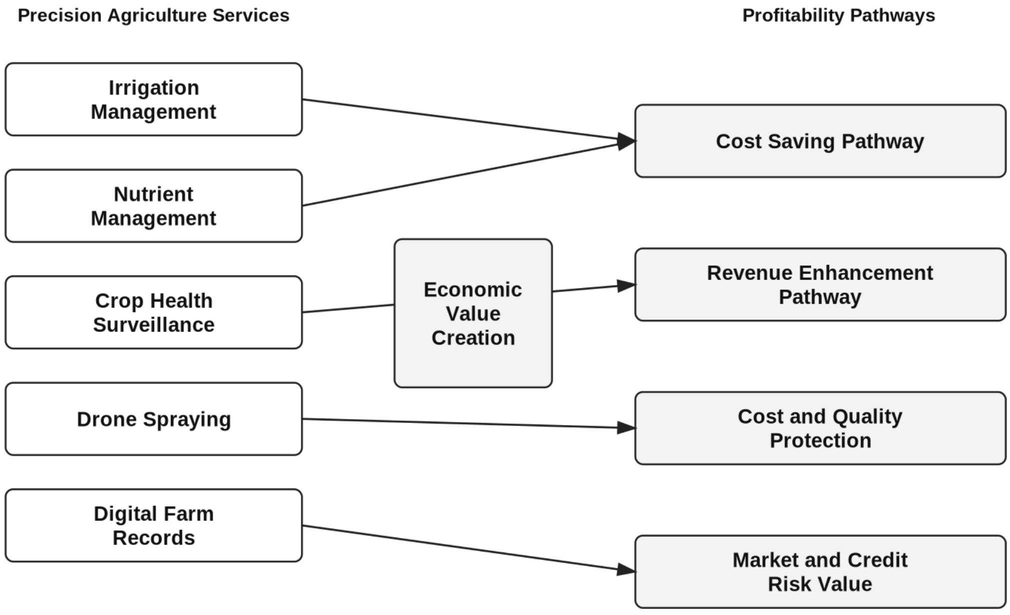

Fig. 3. Conceptual schematic of the profitability pathways associated with selected precision agriculture services.

Source: Studies conducted on the economics of public goods, profitability of farming, and provision of public services (31,33,36,39,40).

For Indian farmers, an important economic question is whether precision agriculture technology can be adopted more sustainably through an ownership model or through a service-based model. Most farms are small, so individual ownership of drones, networks, variable rate applicators, or advanced analytics may be infeasible. A more appropriate model is service-based access through farmer producer organizations (FPOs), cooperatives, custom hiring centers, agritech startups, input supply companies, rural enterprises, and public extension. This changes a fixed capital cost to a variable service cost. This model also improves asset utilization because a drone, sensor suite, or GIS service can serve multiple farms rather than a single one.

Economic returns are crop dependent. Certain crops are high-value due to the returns on quality due to the crops' direct market value for uniformity. A few examples of high-value crops include vegetables, spices, fruits, floriculture, seed crops, and plantation crops. For cereals, PA could help depending on reduced risk services, input savings and policies concerning market prices and their premiums. For cotton and sugarcane, PA could help and be implemented for pest and irrigation monitoring, as well as yield estimations. Pulses and oilseeds don't need pay-as-you-go systems but could benefit from low-cost advisories. This means that the models from PA need to be region and crop specific.

Adoption barriers in India

There are a multitude of economic, technical, institutional, and behavioral barriers that limit the implementation of PA in India (41,42). Cost is the most apparent of the barriers. Investment in advanced sensors, drones, software, images, machinery, and advisory systems is required and the returns may not be seen for multiple seasons (43,44). Smallholders often cannot absorb the risk associated with adopting new technologies (45,46).

The second barrier is farm fragmentation. Small and scattered plots lower the economic viability of machinery-based PA (47). Fragmentation raises the expense for mapping, data analysis, field operations and service delivery. Furthermore, it implies that the models which are assumed to be viable for large farms will not be applicable to the Indian context. As a result, PA in India needs to focus on mobile-based advisories, cluster-level services, small sensor packages, shared machinery and FPO-led platforms.

The third barrier is digital and agronomic literacy. Data can be delivered to farmers in the form of a map, index or alert, but farmers can be left puzzled about what to do next. An aerial image can identify a weak crop patch, but that can be caused by so many factors (Nutrient deficiency? Water/vapor stress? Salinity? Pest damage? Poor germination?). Without an understanding of basic agronomy, data can be more perplexing to farmers than helpful. Additionally, staff in extension services need training in remote sensing, dashboard sensors, and their economic implications. Thus, the adoption of PA is not just a farming community problem, but a capacity problem in the extension service.

The fourth barrier is infrastructure. IoT systems require electrical power, a reliable mobile network, stable cloud services, and an array of other maintenance and support services. UAV (drone) systems need trained personnel for battery management, calibration, safe chemical transport, and a host of regulatory issues. Even data systems require a level of inter-operability with a focus on privacy.

Trust and data governance makes up the fifth barrier (41). PA requires data from farms: where they are, what crops they grow, farm inputs, yields, soil status, irrigation, pest occurrences and sometimes financial information (42). Farmers must know who owns the data, who has the authority to use it, how it relates to credit or insurance, and whether it may limit their ability to negotiate in contract farming (43). Digital agriculture researchers state that unequal data governance may result in exclusion from the benefits of productivity-enhancing technologies (44). This is particularly relevant for smallholder agriculture, where farmers often provide data but do not control the value created from it.

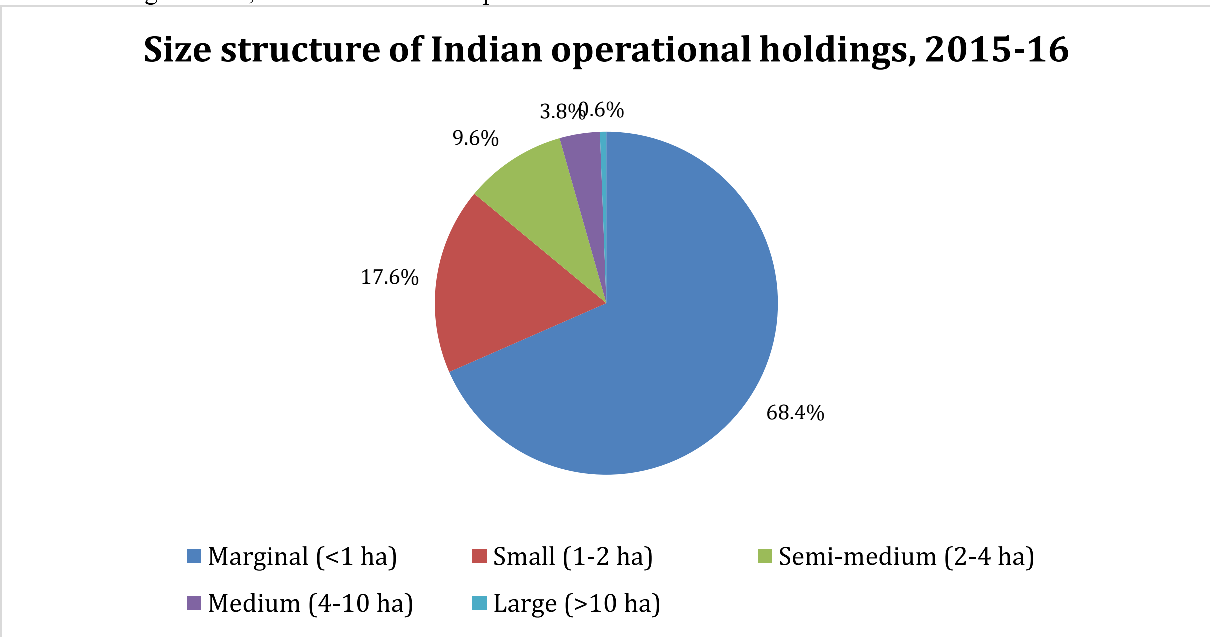

Fig. 4. Size structure of Indian operational holdings in the Agriculture Census 2015-16.
Source: Prepared using Agriculture Census 2015-16 data reported by the Government of India (47).4

Table 4. Major adoption barriers and agribusiness responses for scaling PA in India

Barrier	Effect on adoption	Agribusiness or policy response
High capital cost	Limits individual ownership of drones, sensors and VRT machinery	Provide service-based access through FPOs, custom hiring, leasing and pay-per-use models (33,34,36,39,46)
Small and fragmented holdings	Reduces machine utilization and raises per-hectare service cost	Cluster villages, crop belts and irrigation commands as service units (33,46,47)
Low digital literacy	Limits interpretation of dashboards, maps and alerts	Train extension workers and farmers in decision-focused digital agronomy (41,42,45)
Weak connectivity and maintenance	Reduces reliability of IoT and platform services	Develop offline-first tools, local technicians and maintenance contracts (17,18,29,44)
Data ownership concerns	Reduces trust in digital platforms and crop records	Use transparent consent, public standards and farmer-controlled data governance (41,42,43,44,56)
Uncertain economic returns	Makes farmers reluctant to pay for PA services	Demonstrate cost-benefit results by crop, region and farm-size category (32,34,35,39,40)

Source: Synthesized from PA adoption, digital agriculture and smallholder evidence (33,36,39,42,46).

Government policies and institutional support

Though there is no sole dedicated legislation for Precision Agriculture (PA) in India, supporting policies are scattered across different domains. These include initiatives on digital public infrastructure, soil health, mechanization, Irrigation and Agricultural Extension, crop estimation, drones, and PA. The Agriculture Census is a critical data source in establishing a PA model in India, as it highlights the prominence of smallholder farmers (47). The Digital Agriculture Mission gives institutional direction by focusing on AgriStack, the Krishi Decision Support System, geospatial village maps, farmer registries, crop-sown registries, and soil profile mapping (48,51).

The Soil Health Card Program is essential as it takes soil testing and translates it into direct advice for farmers (50). PA value rises when soil testing is geo-referenced and integrated with crop history, remote-sensing analysis, yield response,

and nutrient recommendations. Soil testing, input optimization, and fertilizer consultancy could create new agribusiness opportunities along with FPO-based nutrient planning and crop-specific consultancy packages.
Drone promotion is an emerging policy pathway. Government backing for Kisan Drones and showcases via organizations such as ICAR, Krishi Vigyan Kendras, state agricultural universities, FPOs, and custom hiring systems implies that the service model is acknowledged in the policy (49,52). Drones are useful for crop surveys, spraying, land records, disaster surveying, and field assessment. However, drone policy should go beyond hardware subsidies. It should encompass safety, training, and environmental concerns; quality and price transparency certifications; and chemical application protocols.
If they are open, interoperable, and trusted, Digital Public Infrastructures can decrease the costs of PA services (53). When secure standardized systems provide farm boundaries, crop-sown data, weather data, soil data, and advisory outputs, both private and public actors can develop crop-specific services much easier (48,51). However, data governance must ensure that farmers have a stake in the value their data generates. Public policy must safeguard farmer agency and promote innovation.

Table 5. Indian policy instruments relevant to precision agriculture

Policy or initiative	**PA-relevant component**	**Potential contribution to productivity and profitability**
Agriculture Census 2015-16	Documents dominance of small and marginal holdings	Guides service-based and cluster-based PA design (47)
Soil Health Card	Soil testing and nutrient recommendations	Supports site-specific nutrient management and input optimization (50,60)
Digital Agriculture Mission	AgriStack, Krishi DSS, crop registries and soil profile mapping	Creates digital infrastructure for advisories, crop estimation and service delivery (48,51)
Kisan Drone promotion	Drone demonstrations, FPO support and custom hiring pathways	Expands access to scouting, spraying and mapping services (49,52,54)
ICAR and KVK initiatives	Farmer training, demonstration and technology validation	Builds trust and translates technology into field-level action (49,52)

Source: Synthesized from official Government of India, Press Information Bureau, Soil Health Card and ICAR sources (47,48,49,50).

Crop-specific opportunities and agribusiness models

Cereals and rice-wheat systems

Cereal grains and rice-wheat systems have numerous pitfalls for precision agriculture as they entail large production systems dealing with problems such as fertilizer usage, inefficient scheduling of irrigation, management of residue, incidence of pests, and variability of yield. In rice-wheat systems, PA could assist with the management of nutrients, the implementation of irrigation techniques that conserve water, and the monitoring of crop growth and yield. Decision-support systems and remote sensing techniques could be utilized to determine the presence and effect of uneven stands, growth and moisture stresses, and nutrient deficiencies in crops. Given the vast size of cereal production related to agribusiness, the PA systems based on provision of services could be implemented in a more effective manner through farmer producer organizations, cooperatives, hiring centers, and public extension systems.

Cotton, sugarcane and plantation crops

Pest monitoring, canopy monitoring, and variable nutrient management and spraying are some of the benefits of PA for cotton. PA for sugarcane includes the benefits of scheduling irrigation, managing ratoons, estimating yields, and planning harvesting. Canopy health monitoring, disease monitoring, and management focused on quality are PA benefits for plantation crops. Services-based PA is more appropriate for these crops since they are mainly cultivated in well-defined crop belts, and service providers can achieve scale in that context.

Horticulture, vegetables and protected cultivation

One of the largest potential growth sectors for Precision Agriculture in India may be Horticulture. Horticultural crops are highly susceptible to quality, consistency, pest, water, and time challenges. Sensor-based fertigation, early warning systems for disease, and digital traceability will likely improve marketable yields. For high-value crops, farmers are more likely to pay for PA services as the benefits of better quality and less rejection are more easily realized in income.

Pulses and oilseeds

A different PA approach is required for pulses and oilseeds. Most of these crops are grown by smallholders using rainfed or resource-limited practices. The best suited interventions are likely to be low-cost advisories relating to the sowing window, soil moisture, pest risk, crop health and localized weather. Costly hardware intensive solutions are likely to be unviable. For these pulses and oilseeds, the PA should focus on mobile advisories, remote sensing, FPO-level aggregation and public extension.

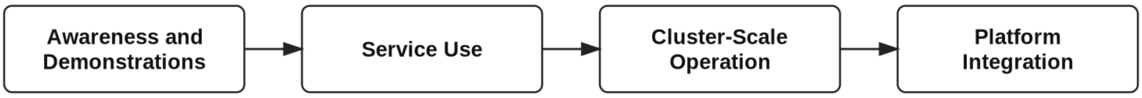

Fig. 5. Conceptual schematic of a service-led adoption pathway for precision agriculture in Indian smallholder farming.
Source: Synthesized by author from PA adoption, smallholder digital agriculture, government policy and service-delivery literature (33,36,41,47,48).

Four service models are of interest from an agribusiness perspective. Pay-per-use drone services that scout, spray and map are the first. The second is the sensor-as-a-service model that applies to irrigation and protected cultivation. The third is the FPO-based advisory model. Here, soil, crop and market data are analyzed for a group of farmers rather than an individual farmer. The fourth is the platform service model. Here, crop monitoring is used in conjunction with procurement, traceability, insurance and credit services. Each of these models will require a well-defined revenue mechanism. Farmers will be reluctant to pay for services unless the service will reduce their costs, enhance their yield, reduce their risk or create an opportunity in the marketplace.

Findings

The reviewed foundational studies showed that PA makes crop management shift to site-specific decisions considering the factors of position, of sense and of management of information. PA illustrates the connection to the sustainability and food-security goals. The connection is best made when the technology is applied and integrated with agronomic decision-making, and is not viewed solely as the adoption of farm technology (1,2,3,4,5).

Remote-sensing studies demonstrated the ability of image-based monitoring to capture canopy condition and to detect the variations in the moisture stress and the biomass, and changes in the vegetation index, which are difficult to identify with the traditional inspection of the field. Furthermore, reviews of remote-sensing and vegetation studies illustrated that satellite and proximal sensing are applicable for the assessment of crop health, detection of stress and yield-related studies and interpretations, although there are unresolved issues on spatial resolution, cloud cover, and timing of sensing and local validations (6,7,8,9,10).

UAV studies demonstrated that drones can enhance PA by offering timely detailed observations for crop scouting, stand assessment, spraying and damage mapping. The reviewed UAV literature further suggested that the benefits of drones are highly dependent on the operational framework, value of the crop, quality of images, compliance with regulations and the farmer’s capability to make crop-management decisions based on the derived images (11,12,13,14,15).

The studies of Thermal sensing, IoT and sensor networks showed that near real-time information has potential to take advantage of the assessment of the crop and the environment for scheduling irrigation and monitoring climate. This study suggests that systems of sensors can improve decision-making significantly, provided calibration, connection, maintenance, and interpretation are sustained reliably in the field (16,17, 18).

Research integrating machine learning, computer vision, and decision support systems, has indicated that the adoption of digital technology promotes crop classification, irrigation scheduling, yield estimation, identification of diseases and weeds, and the optimization of pesticide use, etc. (19,23,24). Additional research on plant diseases and phenotyping showed that the image-based diagnosis must be verified locally since the symptoms of disease, nutrient deficiency, and water stress may be confusion in agro-ecological zones (25,26).

Studies of farm management and digital agriculture showed that precision agriculture (PA) systems become more valuable with the integration of field data, machine data, and weather data coupled with advisory systems in decision support systems (27,28). Reviews of Agriculture 4.0 and big data found that digital systems may be designed to support sustainable agriculture; however, they must first offer the farmer, the service provider, and the institutional actor real and actionable recommendations (29,30).

Research in economics and the environment showed that PA systems may reduce the over-application of fertilizers, pesticides, and water improve greenhouse gas emissions, and improve the productivity of the farm as a whole if an economically just and viable intervention is made (31,32). Evidence of viability showed that PA systems need to be evaluated for financial cost and benefit to the farm and risk as well as the cost of services gained in comparison to the value of the crops and the outcome of all farming activities and not only the increase in crop yields (33,39,40).

Studies in the adoption of PA systems found that farm cost, size, and the risk of farming; skills and service quality; and the perceived benefit of farming services affect the adoption of Precision Agriculture (PA) systems. Evidence also showed that smallholder farmers in particular need a digital agriculture framework that is based on shared services, builds trust, practices responsible and innovative technologies, and has transparent data practices and legal frameworks that prevent discrimination.

According to policy documents and institutional practices, small and marginal landholdings dominate the structure of Indian agriculture. This makes service-led Precision Agriculture (PA) initiatives more applicable than the privatization and ownership of costly machinery (47,48). Evidence related to specific projects, namely the Digital Agriculture Mission, Soil Health Card, Kisan Drones, and certain ICAR/KVK initiatives, suggest publicly available resources in India, such as public digital resources, soil-based recommendations, drones, extension services, and the economic validation of farmers will help create the foundation for scalable Precision Agriculture (49,50,52).

Future recommendations

In PA promotion, crop and regional specificity needs more attention than general offerings. In the rice-wheat model, nutrients and pest precision play a role. In cotton PA, pest and spray precision are featured. Sugarcane PA introduces precision for irrigation and ratoon monitoring. Precision for horticultural PA includes fertigation, pests, and diseases, especially with respect to quality. Low-cost weather and stress and pest advisories go into pulses and oilseeds. Packages of these elements should improve net farm income, lower service costs and input costs, and reduce risk, while also having a positive farmer acceptance factor. Technology novelty should not be the justification for crop and region PA packages.

Digital capacity for precision agronomy combined with access-based service models and open data frameworks is needed to scale PA in India. FPOs, cooperatives, custom hiring centers, rural enterprise, and extension systems should drive the provision of drone services, soil mapping, and crop scouting as well as irrigation and sensor support and yield estimation services. Public and private projects should focus on farmer engagement and data governance as well as calibration and quality control. Claims for climate-resilience should address measurement frameworks for water and stability of income and yields along with reduced use of nutrients and pesticides.

CONCLUSION

In India, precision agriculture (PA) technologies have the potential to enhance both the productivity of crops and the profitability of farms; however, this potential can only be unlocked through the successful integration of technology with meaningful agronomic and business solutions. PA technologies including, but not limited to, GNSS, GIS, remote sensing, UAVs, IoT sensors, AI-based decision support, and variable-rate systems, can help in the management of crops and better facilitate the management of nutrients, irrigation, pests, and even the efficiency of resources. The plant-science value centers on the earlier identification of crop stress and the more precise application of inputs to aid crop development. The value of the agribusiness extends to cost savings, yield protection, quality and risk improvements, and enhanced connections to better markets, credit, and insurance.

In the Indian context, the most plausible path to PA is not small-holder farmers purchasing highly expensive equipment. Instead, it is a model trusted by evidence-based public institutions and customers, built around Farmer Producer Organizations (FPOs), custom hiring centers, rural entrepreneurs, public extension services, and digital public infrastructure. The soil health, digital agriculture, and government drone initiatives form a vital base; however, they require integration with economic validity, real-world evidence, digital literacy, and data governance frameworks centered around the farmer. The sophistication of sensors should be of secondary concern when gauging the applicability of PA. Rather, the primary focus should be centered around the caliber of crop-related decisions and the quantitative improvement of net farm income.

In India, the future of PA should reflect specificity to crops and regions, be service-oriented and economically demonstrative. It should aim to strike a balance the improvement of technology with agronomic and economic validation to the farmer. If this is attainable, PA technologies will support the resource conservative methodologies of farming while increasing the profitability of farming in India.

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