Data-driven Digital Transformation for Uncertainty Reduction

Application of Satellite Imagery Analytics in Institutional Crop Credit Management

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ABSTRACT

Agriculture financing in developing countries is dominated by informal lending. One challenge in the expansion of institutional (formal) credit is the lack of reliable data on the historical performance of farmers. Due to the absence of data, financial institutions face uncertainties that obstruct the decision-making process, leading to sub-optimal credit disbursal. Based on the theoretical lens of uncertainty reduction, this study focuses on achieving two key research objectives: identifying uncertainties in institutional crop credit management processes and examining how a data-driven digital transformation for social innovation based on satellite imagery analytics could alleviate these hindrances. We longitudinally study a satellite imagery analytics firm and complement the case data with stakeholder interviews. The results capture state space, option, and ethical uncertainties institutional lenders face in expanding crop credit and explain how data-driven digital transformation can reduce these uncertainties. Adopting such a data-driven digital transformation promises to make different stakeholder groups interact and collaborate to achieve the common objective of financial inclusion of small-scale economic actors. Further, we show that satellite imagery in crop credit management can significantly reduce the uncertainties caused by the lack of independent data sources.

1. Introduction

Data-driven digital transformation is relied on to enhance performance, visibility, and resilience and eliminate risk, uncertainty, and redundancy (Ivanov and Dolgui, 2021; Papadopoulos et al., 2017; Wang et al., 2016). Several organisations have been embarking on the journey of data-driven digital transformation to reengineer their processes, business models, and supply chains by relying on technology that generates the necessary data (Bag et al., 2023; Papanagnou et al., 2022; Dubey et al., 2022). Technological developments have further fuelled the expansion of data-driven digital transformation for social innovation, which is defined as providing solutions to social challenges by improving access to resources, strengthening social capital and networked relationships, enhancing the outcomes, and enlarging the value to the whole society concerning speed, cost, and quality (Gupta et al., 2020; Nagendra et al., 2020a,b). Examples include using machine learning to improve disease detection (Devarajan et al., 2021) or providing more inclusive financial services (Kelley et al., 2022), using drones for reforestation initiatives, or using artificial intelligence in digital farming to improve crop yield and empower farmer communities.

Given that data-driven digital transformation is becoming more common in firms (Gölzer and Fritzsche, 2017), it is important and useful to delineate the impact of individual and novel digital technologies and get an in-depth understanding on how they each impact the pre-existing processes in an organisation when adopted. Since each digital technology is different in its characteristics, transformation pathway, and impact (Hanelt et al., 2021), it will be worthwhile to carry out separate

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Abbreviations

RBI	Reserve Bank of India
SIA	Satellite Imagery Analytics
NPA	Non-performing Assets
CSR	Corporate Social Responsibility
BOP	Base of the Pyramid
CIR	Credit Information Report
CIBIL	Credit Information Bureau India Ltd.
KYC	Know Your Customer
SOF	Scale of Finance
NABARD	National Bank for Agriculture and Rural Development
SLBC	State Level Banking Committee
PSL	Priority Sector Lending

in-depth investigation and discuss the findings by comparing with the learnings from preexisting research on a family of technologies such as Industry 4.0, disruptive, intelligent, smart, or advanced technologies. Aligned to this motivation, in this research, we focus on the adoption of a unique and novel big data analytics technology, namely satellite imagery analytics (SIA), for undergoing data-driven digital transformation in the context of institutional crop credit management.

Satellites have emerged as a source of big data and the imagery (real-time and archival) captured by them have supported the development of decision intelligence products. As examples, by relying on satellite imagery, Park and Stenstrom (2008) build classification models to provide inexpensive and timely urban land use information; Rapinel et al. (2014) identified and mapped natural vegetation on a coastal site; Chang et al. (2017) automated continuous water quality monitoring in environmentally sensitive regions; Karimi et al. (2020) developed a method to site and rank municipal landfill sites; and Nagendra et al. (2020c) conducted initial site assessments of solar photovoltaic projects. It can be noticed that the management research imbibing SIA has majorly focussed on data-driven digital transformation for fighting climate change and environment management, scope exists for a wider demonstration of the utility of such technology to deal with social challenges in the society such as financial inclusion.

Specifically in financial inclusion, we study the context of institutional crop credit management in developing economies where farmers widely experience the lack of access to institutional credit such as bank loans. The resulting dependence on informal sources of non-institutional credit such as loans from moneylenders contributes to farmers' low income and their relatively high suicide rates (Dongre and Deshmukh, 2012; Jeromi, 2007). For instance, over 35% of lending in Indian agriculture is dependent on informal sources or non-institutional credit, with 64% of them coming from professional moneylenders who are known to charge exorbitant interest rates (Kumar et al., 2017). Indian farmers are more prone to fall into a debt trap due to greater dependence on informal sources and overspending on non-income-generating activities (Rajeev and Vani, 2019).

One of the biggest roadblocks to the expansion of institutional credit in agriculture financing has been the lack of reliable data on the historical performance of the farmer and the corresponding agriculture field (D'Souza, 2020). Financial institutions face uncertainties due to a lack of documentation/information[1] that obstructs the decision-making process and leads to no or sub-optimal credit disbursal. Reducing uncertainties in institutional crop credit management offers several benefits to both agriculture and farmers. On agriculture front, it provides access to credit that aid in expanding operations and adopting new technologies (Aker et al., 2016). Similarly, it also provides access to credit for agriculture investments such as acquiring land, procuring machinery, and accommodating other capital expenditures (Kassie et al., 2011). For farmers, addressing uncertainties through filling the knowledge gap in the lending process enables financial inclusion. Through SIA, financial institutions get equipped to reach to more eligible farmers and provide higher financial support. It also helps bring farmers under formal banking systems, thereby aiding them to access other bouquets of services offered by financial institutions such as insurance. Simultaneously, this could provide an impetus for farmers to mobilise their savings into formal banking channels from the traditional savings modes. Finally, due to lower interest rates, operations and investment costs will be reduced, leading to better profits for the farmers.

For this research, we anchor to Galbraith's (1974) definition of uncertainty, which is a measure of difference between the amount of knowledge necessary to perform a task or make a decision and the amount of knowledge already available within the firm. Reducing this knowledge gap by accessing the necessary critical information through interventions by the firm is referred to as uncertainty reduction (Liu and Hart, 2011; Lee and Veloso, 2008). We use this uncertainty reduction frame to explain the impact of SIA intervention on institutional crop credit management in a developing economy content, and thereby achieve the following two research objectives.

(1) identify the uncertainties in institutional crop credit management processes
(2) examine how a data-driven digital transformation for social innovation based on satellite imagery analytics (SIA) could reduce those uncertainties

To achieve the objectives, we longitudinally study how an SIA firm, *Agri-Sat-Inno* (a pseudonym to maintain anonymity), reduce different categories of uncertainties related to institutional crop credit management with a data-driven digital transformation approach. We complement the case data with rich interviews from respondents belonging to different stakeholder groups.

Our results provide insights into the existing uncertainties in crop credit management processes and the impact of SIA in reducing them. First, the findings shed light on the financial institutions' existing creditworthiness assessment and monitoring processes. We find evidence that the agriculture loans are being disbursed below their potential and that their monitoring is negligible. The unviability of farming, coupled with the fear of increasing non-performing assets (NPAs), reduces the lending capacity of financial institutions. We find that lack of reliable data restricts banks from properly assessing farmers' needs, repayment capacity, the viability of farming, and commodity price trends. Second, our study shows how the barriers created by data uncertainties can be bridged with SIA-based data-driven digital transformation for social innovation. Data captured during the loan application process can be used for automated verification. Further benefits to the financial institutions include reducing NPAs, improved customer confidence, provision of new borrowing opportunities, better management of staff, reduction in wilful delinquency, and eased workflows. Finding new lending opportunities and additional lending possibilities to existing customers allows for increasing the amount of loans disbursed, leading to higher revenues. Additionally, reduction in wilful delinquency, better workflow, and better management of staff enable cost reductions and thereby lead to improvements in profits. The benefits of uncertainty reduction are transferred to overall agriculture development and to farmer's financial inclusion.

The rest of the paper is organised as follows. In the second section, we elaborate on the data-driven digital transformation for social innovation literature, followed by the specific case of SIA and institutional credit's demand and supply side constraints. In the third section, we present the theoretical underpinnings of this study regarding

[1] Exception are micro-credit systems, such as Grameen Bank in Bangladesh, who do not require formal documentation for gaining access to their financial services and obtaining loans (Khandker, 2005).

uncertainty and its relevance in agriculture lending. The fourth section describes the case's background and methodological aspects. In the fifth section, we present results in two parts, addressing each research question. In the sixth section, we identify the different types of uncertainties and explain how SIA can tackle them. In the final section, we conclude and present the study's implications for research, practice, society, and policy makers.

2. Literature review

2.1. Data-driven digital transformation for social innovation

Firms today must generate profits while managing stakeholders' expectations in addressing social and environmental issues. For the latter, firms often engage in corporate social responsibility (CSR) programs (Scandelius and Cohen, 2016). However, gap exists between stakeholders' expectations and the delivery of CSR programs (Ghanbarpour et al., 2024; Hawn and Ioannou, 2016; Kramer and Porter, 2011), as these activities are often detached from a firm's core business.

As an alternative, firms increasingly focus on social innovation to achieve business growth while meeting stakeholders' expectations. Social innovation, as defined by Phills et al. (2008, p. 11), is "a novel solution to a social problem that is more effective, efficient, sustainable or just than existing solution and for which the value created accrues primarily to society as a whole rather than private individuals". It differs from other forms of innovation due to its focus on solving social issues or needs (Barrett and Dooley, 2024; Babu et al., 2020; Gupta et al., 2020).

Social innovation is a highly dynamic process within which value creation occurs through the exploitation of opportunities and can be achieved by diagnosing opportunities and implementing practices for delivering superior value (Foroudi et al., 2020). Pursuing social innovation becomes even more relevant for firms that look to enhance their supply chains, cater to socially conscious consumers, and tap into base-of-the-pyramid (BOP) markets (De Silva et al., 2020; Khan et al., 2021; Nahi, 2016; Schaefers et al., 2018).

Social innovation is spread across political, economic, environmental, legal, and technological contexts (Foroudi et al., 2020). Regarding the latter, literature argues that technology can play a key role in diagnosing opportunities and implementing practices to achieve social welfare (e.g. Dubey et al., 2022; Nagendra et al., 2020a). Foroudi et al. (2020) argue that data and digital technologies have an immense opportunity to address emerging social problems in many developing and developed countries. We refer to such innovations as data-driven digital transformation for social innovation, which consists of integrating technology for finding opportunities, presenting a matching service, and implementing practices to address social issues.

The uncertainty faced by financial institutions in developing nations obstruct their agriculture credit lending. Here, data-driven digital transformation for social innovation may offer the potential to reduce uncertainties. Institutional lenders' existing process of assessing risk and creditworthiness is dysfunctional and hinders agricultural inputs (Möllmann et al., 2020; Muñoz-Cancino et al., 2023; Narayanan, 2016). Due to inadequate savings and the unviability of farming, farmers are forced to rely on credit for conducting their agricultural activities. Out of the two options available to farmers – approaching bankers or informal moneylenders – they rely heavily on the latter. This could be attributed to the convenience of borrowing, lack of collateral requirement, and leniency in repayment terms. However, unreasonable interest rates imposed by informal moneylenders push farmers into a severe debt trap. Alternatively, the interest rates for formal credit are more reasonable, and the financial leeway may aid farmers' agricultural growth. Hence, increasing formal credit penetration would represent an opportunity for improved livelihood. Although this need has been widely acknowledged, bankers face many uncertainties regarding providing agriculture credit. These uncertainties range from farmers and their farmland to climate, markets, and government policies. In these settings, social innovation has the potential to offer solutions that generate value for the stakeholders involved (De Silva et al., 2020). This study explores the potential of satellite imagery data-driven digital transformation in addressing this social issue.

2.2. Institutional crop credit

Developing countries ' literature on credit market segmentation divides rural credit markets into formal and informal segments (Ray, 2019; Zeller, 1994). Formal or institutional credit lending includes all the borrowings from financial institutions, such as banks, non-banking financial corporations, and registered unions. In addition to lending from family, friends or acquaintances carrying zero or lesser interest, informal or non-institutional credit lending includes private lending by unrelated individuals who charge relatively higher interest rates (Barslund and Tarp, 2008), which is being focused on in this study.

The uncertainties in establishing creditworthiness and risk management for institutional crop credit management have a deep socio-economic bearing. Each of these uncertainties further extenuates the problems from an agriculture supply chain perspective. These constraints can broadly be classified into supply and demand (Golait, 2007; Narayanan, 2016).

2.2.1. Demand-side constraints

Demand-side constraints restrict the farmers' demand for institutional credit. In this section, we elaborate on two major demand-side constraints of institutional credit: bureaucratic lapses and farmers' obstinacy in dealing with informal moneylenders.

2.2.1.1. Bureaucratic lapses. In the case of formal credit, though the borrowing interest rates are reasonable and fixed, farmers in developing nations are stifled with large bureaucratic procedures and are forced to pay bribes to officials. These constraints were confirmed in a study among Indian farm households by Kumar et al. (2013). It indicated that only 7% reported having obtained the desired loan amount, 92% indicated that the lending process required too much paperwork with long delays in loan processing, and 80% of the respondents claimed to have paid bribes. Credit markets have failed to reduce informal interest rates or improve formal credit intensity despite developmental policies instituted by governments (Atieno, 2001). On the demand side, this leads to higher transaction costs to access formal credit by small and marginal farmers who then shy away and resort to informal credit.

2.2.1.2. Farmers' obstinacy to deal with informal moneylenders. Farmers visit informal moneylenders to acquire credit for agricultural operations. The social ties between them compel the establishment of these relationships and the emergence of lending transactions (Bell, 1990; Majid, 2004). Karlan et al. (2009) show that close ties between people of similar communities in rural areas encouraged informal borrowing. Due to such conditions, the farmers might find it difficult to change existing borrowing habits and obtain credit from institutional lenders.

2.2.2. Supply-side constraints

The supply-side constraints restrict the financial institutions' lending capacities to the borrowers (i.e., farmers). In this section, we elaborate on four such constraints: gender, political affiliation, caste, and risk management and creditworthiness.

2.2.2.1. Gender. Studies in rural lending highlight that the absence of a reliable method for establishing creditworthiness leads to gender prejudices and increased loan rejection rates for women (Sandhu et al., 2012). This failed to augur well not only from a gender context but also from a societal and development context, given that over 80% of the rural Indian female labour force lists agriculture as their primary source of employment (Kadiyala et al., 2014). Literature clarifies that agricultural development goals would not meet their mark unless women are sufficiently considered in development programs (Tiwari, 2018).

2.2.2.2. Political affiliation. Policymakers across developing nations have frequently framed policies to expand institutional rural lending with microcredit programs. However, such top-down initiatives are prone to political patronage due to institutional weaknesses (Tsai, 2004). For instance, Cole (2009) found that political patronage in India during an election year leads to credit lending increases of 5–10 percentage points by government-owned banks. The Chinese government created subsidized credit policies intending to provide access to small and marginal farmers; Jia et al. (2010) found that indirect screening mechanisms employed due to such information asymmetries mostly benefitted local elites and did not reach farmers.

2.2.2.3. Caste. Evidence shows that the socio-economic structures in developing nations, consisting of different classes and ethnicities, tend to impact rural lending. For instance, Guérin et al. (2013) found that different castes and classes impact credit access among Indian farmers. This is not limited to informal lending but was found to affect formal lending. A study based on national data on household borrowings by Kumar et al. (2013) found that discrimination based on caste extends to agricultural credit provided by cooperative banks. Acknowledging the effect of caste in borrowing, Fisman et al. (2017) found that cultural proximity between lenders and borrowers increases the quantity of credit and reduces default.

2.2.2.4. Risk management and creditworthiness assessment. One challenge for financial institutions in assessing credit risk is establishing a creditworthiness measure based on the borrower's character, capital, capacity, collateral, and macroeconomic conditions (Allen et al., 2004; Rijanto, 2020). Such information can help create credit and behavioural scoring models for borrowers to forecast the risk of default, as discussed above. From an agri-credit supply perspective, this translates to the creditworthiness assessment that needs to be undertaken by financial institutions based on the historical productivity of the farm and the credit handling behaviour of the farmer. A study among marginal farmers in the region of Punjab in India indicates that the availability of reliable data is important at the stage of applying for a loan and during monitoring of the use of credit (Sandhu et al., 2012).

Hindrances in obtaining such information can have dire consequences for the political economy of agrarian change. For instance, irrational exuberance in microcredit lending to small and marginal farmers in the State of Andhra Pradesh had a boom-bust cycle over five years that eventually led to policymakers clamping down on the microfinance institutions due to debt-driven farmer suicides (Taylor, 2012). Therefore, a data-driven assessment of creditworthiness and risk management is critical for stakeholders who are enabled to support agricultural supply chains. In a recent attempt to solve the problem of establishing the creditworthiness of rural farmers in China, researchers focused on using fuzzy rough set and fuzzy C-means, which use correlation characteristics such as education, skills status, household spending, bank records, and agricultural production statistics (Bai et al., 2019). Their results are in alignment with several other research findings, which have established that having a single credit-scoring model may not be possible and the evolution of models is imminent over time, with new technologies making them more efficient (Limsombunchai et al., 2005; Möllmann et al., 2020; Simumba et al., 2021). Hence, it becomes pivotal to consider the risk management and creditworthiness assessment in addition to socio-economic supply-side constraints to understand institutional lenders' challenges. Here, we investigate how data-driven digital transformation, more specifically SIA, may offer solutions.

3. Theoretical background

At organisational level, Galbraith's (1974) define uncertainty as the difference between the amount of knowledge necessary to perform a task or make a decision and the amount of knowledge already available within the firm. Taking a futuristic focus, Beckman et al. (2004, p. 260) define uncertainty as "the difficulty firms have in predicting the future". Uncertainty exists when the information about decision outcomes and their probabilities of occurrences are not known to the decision-maker (Park and Shapira, 2017).

By relying on probabilities, Epstein (1999, p. 579) states that uncertainty is when the "information available to the decision-maker is too imprecise to be summarized as a probability measure". Hence, it can refer to situations where there is no information, or the information falls short of aiding objective decision-making. Reducing the gap in knowledge by gathering necessary critical information through interventions by the firm is referred to as uncertainty reduction (Liu and Hart, 2011; Lee and Veloso, 2008). Uncertainty in the institutional settings changes the relative costs of carrying out operations. If these costs are high, the firm would have no choice but to evade, alter, or exit the markets. Observing evading, altering, or exiting, these institutions generate adjustment and contribute to the dynamics of institutional change (Bylund and McCaffrey, 2017). Uncertainty presents unique challenges to firms and obliges them to act outside their areas of specialization (Bylund and McCaffrey, 2017). This is a frequent challenge faced by firms in their decision-making processes. Despite the advancement in the measurement and management of uncertainty, the accepted view is that it is a continuous to process to identify and reduce uncertainty.

One of the widely accepted studies by Savage (1972) proposed what is often viewed as the standard approach to tackling uncertainty. It consists of five stages: (1) figuring out the possible states, (2) enumerating the possible actions, (3) figuring out the consequences of actions of all the states, (4) attaching value to each consequence, and (5) selecting the value-maximizing action. Bradley and Drechsler (2014) contend that the standard approach prescribed by Savage (1972) would work only where all the states, actions, and consequences are well known. They extend and propose the following three categories of uncertainties: state space uncertainty, option uncertainty, and ethical uncertainty. Approaching uncertainties in categories will guide in understanding how decisions are made in uncertainty and what strategies can be employed to address them. By anchoring around these three different categories, we explain the uncertainties prevalent in institutional crop credit management. We opine that it is very relevant in the case of the current phenomenon, as it aids in both understanding existing uncertainties and addressing them by adopting SIA.

State space uncertainty refers to the uncertainty that stems from the lack of knowledge about the complete set of potential scenarios that might occur and conditions that can affect the outcome of a decision. In decision theory, the state space represents all possible states or outcomes affecting the decision-making process. In the case of agriculture institutional lending, this occurs in two ways. Firstly, there could be uncertainty regarding the economic viability of a farmer (or borrower). The economic viability of farming could be ascertained if comprehensive information on the investments, expenses and returns were available (Sidhu and Vatta, 2012). Given the informal nature of agriculture activities carried out and the lack of record keeping by the farmers in developing countries, calculating economic viability is a very tedious task and hence engenders uncertainty (Spicka et al., 2019). Due to a lack of proper information, the lenders would fail to understand if a particular borrower's farming activities are economically viable. Secondly, there could be uncertainty in commodity price after the harvest (Ghadim et al., 2005). Due to the lack of time series data of agricultural commodities price and their trends, the lenders would be unaware of the possible returns to the farmers.

Option uncertainty refers to the uncertainty about the available choices or actions that a decision-maker in a firm can take. This includes uncertainty about the outcomes of different options, the feasibility of options, or the availability of options. In this category, farmers' repayment behaviour uncertainty can be taken an example. Information regarding the farmers' previous borrowings (agricultural and non-agricultural), repayment behaviour, and financial delinquency is necessary (Papias and Ganesan, 2009). Lack of this information could create uncertainty regarding the repayment capabilities of a particular borrower. This could also hinder the lenders' capacity to determine the allowable credit and the chargeable interest rate (Bai et al., 2019).

Finally, ethical uncertainty occurs when the valuation of consequences is not known. Ethical uncertainty involves uncertainty related to moral or ethical considerations in decision-making. It arises when there is ambiguity about the morally right or wrong course of action, often due to conflicting ethical principles or values. This pertains to the uncertainty around farmers' needs in the current context. Lenders should possess comprehensive information about the farmland and their household characteristics to assess these. In developing nations, there is a high chance that the funds obtained for farming activities are diverted to non-agri purposes (Khandker and Faruqee, 2003).

SIA can potentially address uncertainties in industries such as infrastructure, aviation, space, national security, telecom, and agriculture. Many stakeholders can leverage their offerings, including banks, insurance companies, and governments (e.g., Nagendra et al., 2020a). Specifically, SIA could address all three types of uncertainties. In case of state space uncertainties, SIA could provide additional information in the pre and post-disbursal inspection stages. In pre-disbursal inspection, SIA essentially integrates into established assessment processes by using the data captured during the farm loan application process for automated verification of underlying assets, borrower capability to farm, and the borrower's historical farming practice. For post-disbursal inspection, SIA derives a farm-specific health index to assess the cultivation's effectiveness and quality. This is based on localised parameters such as weather variance, groundwater level, and the farmer's performance in utilising fertiliser inputs, which can be detected from satellite imagery.

Targeting option uncertainty, SIA captures personal and relevant details of the land of the interested borrower, including their location (village, survey number), the area under cultivation, the crop being cultivated, and the source of irrigation. To reduce ethical uncertainty, SIA can verify the farm's historical use to authenticate its farming history. This is performed using archived satellite imagery for the past years to conduct a time-series farm performance analysis. This provides the basis to reject applications without a reasonable cultivation history.

SIA is capable of reducing different categories of uncertainties faced by financial institutions in extending agriculture credit. This would challenge the incumbent practices at the financial institutions, closing the gap between unbanked, underbanked and developed societies (Salampasis and Mention, 2018).

4. Data and analysis

4.1. Research approach

We conducted a longitudinal case study analysis (covering multiple stakeholders), as discussed by Eisenhardt (1989) and Yin (1994), that followed interpretivism as opposed to a positivist approach. The main considerations that gave us an impetus to adopt this research approach are the phenomenon's lengthy causal pathway, novel technology adoption, and focus on the qualitative process (operational and managerial) rather than the quantifying impact.

The research objectives were focusing on addressing 'how' aspect, qualifying the investigation for interpretive approach. To comprehensively tease out the uncertainties in institutional crop credit management processes (objective 1) and explain the role played by data-driven digital transformation for social innovation in reducing those uncertainties (objective 2), a lengthy causal pathway was required so that we can study over a continuous period (as opposed to cross-sectional or period data) and obtain information on several unknown aspects. Second, given the nature of SIA based data-driven digital transformation, which was not prevalent in the industry earlier, holistic information was not obtainable from set of stakeholders.

Third, we had to holistically understand the operational and managerial processes at the firm and how it was impacted by data-driven digital transformation to appropriately map to different categories of uncertainties. Longitudinal case study methodology allowed us to analyse the operational and managerial changes (rather than from a technical perspective) in expanding formal institutional credit in the agriculture supply chain. The technicalities of building algorithms that ingest satellite big data are very important. However, we believe that the operational and managerial vantage points provide a more holistic basis for contrasting the legacy process against the advantage of using SIA. This allows us to shed light on the overall structure and the potential improvements in operations to ease the transaction between small and marginal farmers and the lending institutions.

4.2. Sampling – case study and interview respondents

We explain the sampling strategy for two aspects of the study: the selection of case organisation and the selection of sample respondents. The selection of case organisation *Agri Sat Inno* was not random but was through purposive sampling based on how the case contributes towards achieving the research objectives (Siggelkow, 2007). Specifically, the firm leverages advances in SIA, machine learning, and big data analytics to implement large-area analytics. It is renowned for pioneering in SIA for offering decision intelligence in India. Second, *Agri-Sat-Inno* is one of the forerunners in India in using SIA for agriculture operations, insurance, and credit management. Third, the staff of *Agri-Sat-Inno* is experienced in interacting with multiple stakeholders at the ground level, which includes policymakers, financial institutions, and farmers. This enabled us to obtain rich insights into the role played by SIA in tackling uncertainties and also enabled us to reach out to wide range of respondents through snowballing approach.

For the semi-structured interviews, by conducting a detailed review of the empirical phenomenon (i.e. institutional crop credit management), we listed different relevant stakeholder groups. We also cross-verified the stakeholder groups by presenting it to *Agri-Sat-Inno*. We then reached out to respondents through convenience sampling ensuring that they mapped definitely to a stakeholder group. By adopting snowballing approach with the initial respondents and by checking with *Agri-Sat-Inno for referrals*, we were able to reach out to more respondents.

4.3. Data collection

In the first stage, we interacted with the case organisation multiple times by attending meetings and discussing with the employee. Several rounds of discussions were conducted to identify the deeply rooted issues at the ground level on SIA implementation. We also formally interviewed three employees, namely product manager, head of remote sensing division, and co-founder and global product head; conducted participant observations by taking part in the meetings and discussions; informally interacted with executives and employees across functions including the chief executive officer, the global head of product and management, the assistant vice president for business development, and the assistant vice president for products. Relevant documents from the company and their SIA platform were reviewed. This enabled us to understand the technology and the nuances behind its implementation.

In the second stage, we conducted in-depth semi-structured interviews (refer to Appendix 1 for the interview questionnaire) with respondents belonging to different stakeholder groups. We continuously evaluated if new insight from the interviews were emerging from a specific stakeholder category. We stopped conducting interviews on reaching theoretical saturation in line with the understanding from

Morse (1995), Strauss and Corbin (1990) and Bowen (2008). The stakeholder groups were direct and indirect beneficiaries, including farmers, informal moneylenders, policymakers (i.e., government officials), businesses (i.e., potential clients of SIA analytics – financial institutions), technical experts (i.e., satellite imagery experts), and agriculture academics/think tanks. *Appendix 2* provides detailed information on these respondents.

The interviewer explained to farmers about SIA based data-driven digital transformation in simple terms. In the research context, since the farmers are beneficiaries of the digital transformation and are not the users of the digital technology, it was not necessary for them to be aware of the digital technology. If farmers were interested in understanding the technical aspects, they were elaborated in the regional language. Also, all the questions were asked in their regional language, which enabled them to understand and respond conveniently.

Specifically, for farmer stakeholder group, we addressed two key considerations under method bias: instrument and administration bias. We first formulated the questions among the researchers and finalised them in consultation with the experts in the respective field. The first few interviews among various stakeholders allowed us to revise and improvise on the questions. Further, before beginning the interviews, we obtained the review from a local agriculture officer and a local farmer to cross-check the comprehensibility of the questionnaire. After incorporating suggested changes/improvements, we conducted the farmers' interview. We attempted to minimise administration bias by implementing uniform interview conditions for all the respondents. All the interviews were conducted by two researchers/authors who were aware of the study/phenomenon and the vernacular language.

We conducted the interviews based on a questionnaire developed against the backdrop of the relevant literature, our theoretical lens, and the initial interactions at the firm. Wherever possible, we conducted the interviews physically; the remaining ones were conducted through virtual meetings. All interviews except those with farmers and informal moneylenders were conducted in English. The interviews of farmers and informal moneylenders were conducted in the regional language 'Telugu'. All the interviews were recorded, translated (wherever necessary), and then transcribed.

The visits to the firm began in February 2020, and the interviews were conducted from March to July 2020. The interviews ranged from 16 to 98 min (average = 47 min). We interviewed several categories of respondents. We chose farmers and informal money lenders from Andhra Pradesh and Telangana state for convenience and comfort in the regional language. We obtained first-hand information on how farmers would evaluate the impact of such digital transformation, the hurdles they would face, and the associated benefits. In the case of money lenders, we probed how they will perceive SIA, will it be seen as affecting their business prospects. Respondents were easily approachable and provided accurate responses due to the comfort in the regional language. Similar experience was observed with the employees of financial institutions and government officials from Andhra Pradesh, Tamil Nadu, and Karnataka. The underlying borrowing/lending dynamics were explained by critically evaluating how the financial ecosystem could perceive, implement, and evaluate SIA.

However, the rest of the stakeholders, including experts across the industries (satellite data and agriculture), had thorough knowledge about the field and decades of experience in the respective industries. Their insights helped us uncover new dimensions of the phenomenon. The remaining interviewees were spread across different states in India. The diversity of the interview respondents helped us understand stakeholders' multiple perspectives on challenges and opportunities associated with institutional crop credit management in India.

4.4. Data analysis

We analyzed the uncertainty related to the phenomenon by mapping to state space, options, and ethical uncertainty categories. Our analysis aimed to explain the role SIA's adoption can play in improving creditworthiness assessment by financial institutions by addressing state space, option and ethical uncertainty.

The obtained data was first condensed into manageable forms using the narratives method (Guba and Lincoln, 1994). The phenomenon at hand and the data collected warranted us to follow two methods of analysis: relying on theoretical framework and addressing rivalling explanations (Lindgreen et al., 2020). We continuously matched the empirical observations with the emerging theoretical framework as we collected interview data. Further, we defined and tested rival explanations. Accordingly, consideration of societal rivals' effect and direct rival explanations was taken. Direct rival explanations are prominent when an intervention other than the target intervention accounts for the results. We addressed this by probing multiple stakeholders about the actual/expected impact of the SIA and cross-verifying any contesting explanations through iterative interviews. Societal rival explanations are societal trends that account for the results, not the intervention in the question (Yin, 2003). For instance, we wanted to understand if a particular socio-political issue influenced the farmers' behaviour on loan repayment. We addressed this by following up with experts, referring to secondary data sources, and confirming those results with additional interviews.

4.5. Validity and reliability concerns

In this section, we describe the approach to address and ensure this study's construct validity, internal validity, external validity, and reliability (Lindgreen et al., 2020). We used triangulation for convergence and triangulation for complementarity in the current case study as one of the major approaches to address validity concerns. Convergence seeks to establish traditional rigour and corroborates multiple data sources or interpretations; complementarity can explain differing perceptions of the research phenomenon arising from various data sources (Farquhar et al., 2020).

Regarding construct validity, the researcher should ensure that the phenomenon was studied using correct operational measures. The first objective sheds light on existing uncertainties in crop credit management. We undertook triangulation by conducting interviews with multiple stakeholders and considering secondary data to establish appropriate measures. In the presence of a research objective that establishes a causal relationship in a case study, it becomes necessary to ensure internal validity. In answering the second research objective, we attempted to establish a causal relation between implementing SIA and eliminating uncertainties in institutional lending. Here, we used rival explanations and triangulation methods. Further, to ensure external validity, we included interviewees with diverse experiences across space and time. The insights obtained from employees in financial institutions, government employees, and agriculture academics/think tank members enabled us to assess the generalizability of our findings. Finally, this study places importance on reliability. This being a longitudinal case study, we took time to establish the interview protocols, conduct pilot tests, and build an exhaustive case study database. This is also evident from the approach described in the methodology section, in which we began with groundwork and interaction with *Agri-Sat-Inno* employees and only later conducted the interviews. The research design is presented in Table 1.

5. Results

The results provide insights into existing uncertainties and explain SIA's impact on institutional crop credit management.

5.1. The current process of crop credit management

In general, farmers' savings and capital formation rate was found to be low and abysmal in the case of small and marginal farmers, who

Table 1
Research design.

Serial No.	Step	Summary
1	Getting started	Framed the two research objectives: (1) identify the uncertainties in institutional crop credit management processes (2) examine how a data-driven digital transformation for social innovation based on satellite imagery analytics (SIA) could reduce those uncertainties
2	2.1. Selecting case 2.2. Forming stakeholder groups	2.1. Best-fit case study for this study was selected. *Agri-Sat-Inno* was not random but was through purposive sampling based on how the case contributes towards achieving the research objectives 2.2. Different stakeholder groups were listed by conducting a detailed review of the empirical phenomenon (i.e. institutional crop credit management) and cross-verified it by presenting to Agri-Sat-Inno
3	3.1. Crafting instruments and protocols 3.2. Collecting data from the case organisation 3.2. Identifying and interviewing respondents belonging to different stakeholder groups	3.1. Developed semi-structured interview protocols for *Agri-Sat-Inno and other* stakeholder groups (appendix 1) 3.2. Data was collected from the case organisation through formal interviews, informal interactions, observations by participating in the meetings, and reviewing relevant company documents and their SIA platform 3.3. In-depth semi-structured interviews were conducted with 26 respondents across the stakeholder groups (appendix 2)
4	Analysing data	Data gathered through semi-structured interviews, participant observation and company documents were analyzed by relying on theoretical framework and addressing rivalling explanations.
6	Shaping findings	Data analysis was performed to identify the different uncertainties and role played by SIA in reducing those uncertainties. Findings can be used to build or strengthen theoretical framework on SIA based data-driven digital transformation for social innovation
7	Enfolding literature	Findings were compared and triangulated with data-driven digital transformation, institutional crop credit management, and uncertainty reduction literature streams.

Source: Adapted structure from Eisenhardt (1989).

constituted 50% of the interviewed farmers. They all reported that obtaining credit was necessary to purchase agricultural inputs (e.g., seeds, fertilisers, pesticides, and rental machinery). Therefore, the farmers reportedly approach either banks or informal moneylenders.

When approaching banks, they apply either for a fresh loan or a renewal. For the former, a farmer must prove that the owned land is non-encumbered. Documents to prove the same need to be submitted in addition to no-dues clearance certificates from all banks in the service area. A farmer must document land ownership and the loan application form for a loan renewal. Hence, to obtain the loan, the farmer must be the land owner and possess legal documentation to prove it. This might be discriminatory and a considerable demand-side bottleneck, as India has a huge population of landless agriculture labour/farmers. According to the latest census data from India, out of the 263 million people involved in agriculture, only 119 million own land (Dogra, 2020). In the loan application form, farmers must provide information on household characteristics (e.g., details of household members, caste, religion, incomes, assets, liabilities) and farm-level variables (e.g., type of crop, acreage). Additionally, farmers must provide a guarantor, ideally a fellow farmer who obtained credit from the same bank and has a good repayment record.

With these initial documents, the bankers proceed to determine the creditworthiness. According to the interviews, there are three main sources for assessing farmers' creditworthiness: past performance on loan repayment, inputs received from the informal network of the bank field officer/manager, and a Credit Information Report (CIR) score issued by Credit Information Bureau India Ltd. (CIBIL). In the case of a loan renewal, obtaining the past performance of a farmer is straightforward. Furthermore, bankers confirmed an active communication among themselves to understand the farmers' repayment discipline in a particular service area.

> "Before beginning the loan processing, we have certain requirements. Number one in India, there is CIBIL (i.e., Credit Information Bureau of India Limited). It is similar to the diagnosis before anyone gets medical treatment. CIBIL score is equivalent to this in terms of banking. If anyone has to be given credit, we must undertake certain procedures. The first is to obtain the KYC (Know Your Customer) documents. And the second one is CIBIL. We bankers can log into the CIBIL and check each farmer's IDs and scores. If a farmer takes a loan from any bank, it gets reflected in the CIBIL score." (R1, Ex-Deputy General Manager, Agriculture credit, Nationalised bank)

For a fresh loan, this assessment is more difficult, and bankers must rely on inputs from field officers and locally recruited bank employees who are well versed in field-level agro-climatic conditions, farmers' backgrounds, behaviour, and capabilities. Bankers reported this to be crucial, as field officers tend to have insights into the personal dealings of farmers that could affect loan utilisation or farming performance. Farmers utilising the crop loan for offspring's marriage or sponsoring education is a classic example. CIR score is a three-digit numeric issued by CIBIL ranging from 300 to 900. All the bankers have access to the same, and it depicts an individual's credit payment history across loan types and credit institutions.

In addition to the above information, the bankers reported relying on the "Scale of Finance" (SOF) to determine individual farmers' loan eligibility. SOF is a document prepared by the National Bank for Agriculture and Rural Development's (NABARD) State Level Banking Committee (SLBC), determining the rules and limits of agriculture lending. NABARD is a government development finance institution which oversees the policy, planning, and operations of agriculture and allied activities in rural India. SLBC is a NABARD-set-up committee that determines guidelines regarding crop lending at the micro level. One of the pieces of information spelt out in SLBC's report is the allowable credit to be disbursed. Financial institutions' employees must adhere to it when making lending decisions.

Once the above process was completed, the bankers reportedly were able to determine the farmers' loan eligibility. However, at this stage, respondents from financing institutions reported that their relationship with the farmer might come into play. The manager in charge of the credit disbursal can exercise their discretion on the approval and amount of the loan. At this stage, respondents admitted that there could be a scope for human intervention. The manager would either deny loans to eligible farmers or approve loans to ineligible farmers based on personal relationships. Upon completion, the bank communicated its decision to accept or reject the crop loan application. At this stage, the bankers reported that field officers are supposed to conduct a pre-disbursal inspection to verify the authenticity of the details submitted by the farmer based on field visits and leveraging their village-level social networks. Subject to satisfying the conditions and based on the bank managers' discretion, the eligible candidates are disbursed crop loans. Post disbursement, interest was charged.

At this stage, the role of field officers becomes important again, as they need to perform post-disbursal inspections. This entails regular field visits to monitor the usage of crop loans following the loan application. At this stage, the farmer receives the loan and utilises it to conduct farming activities. Making timely repayments was also found to be necessary to improve their creditworthiness and for being able to renew their subsequent credit. We have visualised the complete process in Fig. 1.

5.2. Uncertainties in the current state

5.2.1. Lack of data & discrimination

The interviews reveal how the current system of assessing creditworthiness is sub-optimal due to two major obstacles, namely data gaps and discrimination. In step 2 of Fig. 1, bankers must verify loan applications and supporting documents to determine creditworthiness. Although guided by SLBC's scale of finance and a farmer's CIR score, the available documents likely fail to throw light on a farmer's performance and income-generating capacity. This depicted a need for more micro-level farmer data, including farmers' past performance, harvest trends, weather forecasts, and existing market conditions of crop prices. The lack of all these leads to state space uncertainties in determining farmers' creditworthiness, disbursal decisions, and inspection of loan utilisation. Additionally, if a bank manager wishes to discriminate against borrowers based on caste, gender, or religion, it could lead to ethical uncertainty.

> "The role of caste will be there in a few cases of credit evaluation and disbursement. Because it is a rural area, the bank manager may have a negative opinion of farmers from a specific caste or based on some other factors. There might be a preconceived notion that maybe the farmers from a particular community/caste will not repay the loan."(R3, Employee at the Financing Institution, In charge of agriculture credit, Branch Manager, Nationalised bank)

5.2.2. Negligible monitoring

Once the loan is sanctioned, the banks are supposed to conduct pre- and post-disbursal inspections. Based on the interviews, we found inefficiencies in both steps. Banks' official norms require that field officers visit every farm before loan disbursal (of fresh loans as well as renewals) to check up on a farmer's whereabouts, land, mortgages (if any), and any additional information contained in the loan application form (Step - 4). However, we found that field officers seldom perform this task. The loan is granted upon application for loan renewals. We identified three reasons: the bank employees' laxity, improper staff allocation, and limited workforce. Given the limited workforce employed at the bank and the wide area coverage for farmers, completing background checks and pre-disbursal inspections becomes difficult.

Another issue is the lack of post-disbursal inspection (Step 6). Most farmers stated that they divert loan amounts repeatedly for other purposes. Frequently cited examples include marriage, education of kids and construction of capital assets. Few farmers also reported using these funds to provide informal credit to others and earn profit from the differential interest.

> "We use the loan proceeds for farming and other personal needs. We don't indulge in any bad habits like alcohol or gambling. When I say personal needs, I mean for children's education or marriage or medical needs" (R7, Farmer, Cultivates Bengal Gram, holds 25 acres in Andhra Pradesh, India)

> "There are a lot of farmers who do not conduct agriculture and still take crop loans and earn by rotating the proceeds. They would take the money from the bank for low interest and then lend it to someone else, make a profit interest, and return it to the bank by the end of the year. There is no checking from the bank staff" (R11, Farmer, Cultivates Bengal Gram, holds 5 acres in Andhra Pradesh, India)

It should be noted that a farmer's ownership of land and its proof is sufficient to get him/her the credit. If post-disbursal monitoring is skipped, the actual conduct of farming activities might be absent, and the funds could be diverted for other purposes. Surprisingly, the interviews also showed that several bankers acknowledged the diversion of funds but were nonchalant about it as long as the repayment was on time. This inefficiency could be the by-product of considering crop loans as a statutory burden rather than a thriving business opportunity. There are two key implications of this finding. Firstly, policymakers could introduce other convenient credit options that demarcate the farm and non-farm requirements. Secondly, this phenomenon restricts farmers who intend to expand their operations but cannot due to borrowing restrictions. Based on the interviews, it was found that per acre credit is given around Rs. 20,000 (~US$ 240) to Rs. 30,000 (~US$ 360) based on

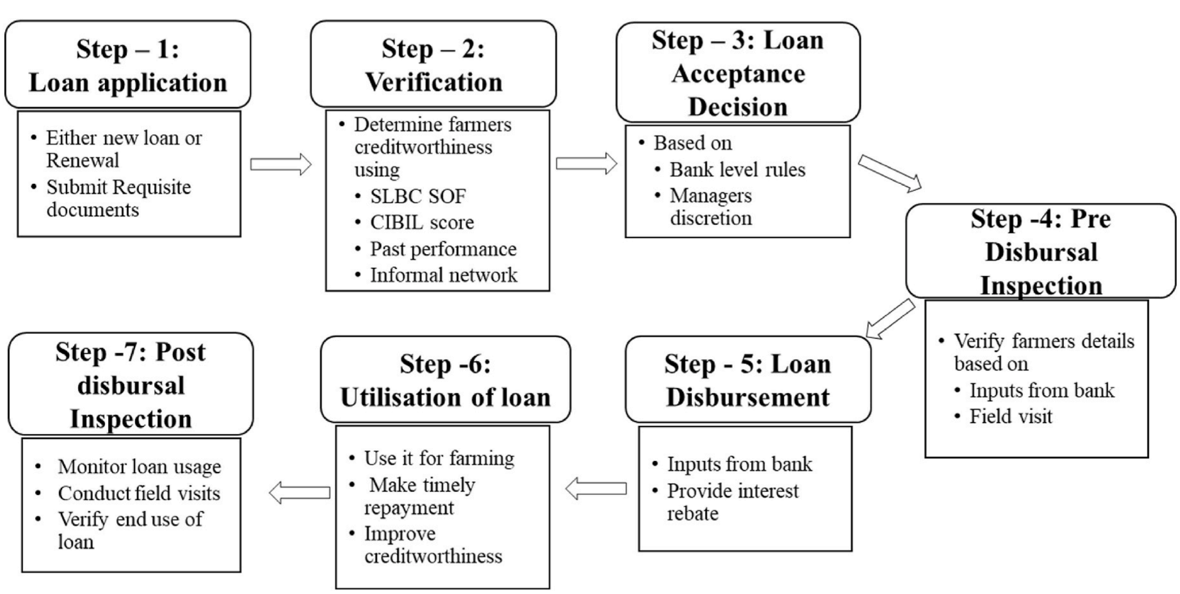

Fig. 1. Existing crop loan process.

the crop the farmer sows and the bank manager's discretion. The total loan per farmer is capped at Rs. 150,000 (~US$ 1807). It was found that despite most farmers availing of crop loan facilities, they still borrow from informal moneylenders to bridge a gap in fund requirements. Therefore, more crop loans could be given to deserving farmers with proper monitoring.

> "We are giving the crop loan for farming purposes. But we cannot assess it; they could divert it to other activities. The diversion will be there to some extent (for marriage or kids' education). A minimum of 20–30 per cent would be diverted for their purposes" (R3, Employee at the financing institution, In charge of agriculture credit, Branch Manager, Nationalised bank)

5.2.3. *Complex socio-economic environment*

One contributing factor to the dismal disbursement and monitoring of crop loans is the complex socio-political environment surrounding agriculture in India. Based on the interviews, we identified three key issues: bankers' fear of non-performing assets (NPA), Priority Sector Lending (PSL) requirements, and politicization of credit. Firstly, banks in India faced substantial risks of loans and advances in default or arrears, termed NPA (Paul, 2018; Bawa et al., 2019). Every generic loan given carries with it a risk of evasion and non-payment. However, in certain cases like agriculture, this is even more aggravated due to the underlying dynamics. Challenges such as fragmented landholdings, dependence on monsoons, climate change, and lack of remunerative prices make farming highly unviable (Ranade, 2018). Agriculture loans pose larger risks than other segments, so bankers tend to be more wary. The risk of NPA likely leads to state space uncertainty because the possible farmers' repayment states are unknown.

Secondly, an important feature of agriculture credit in India is the PSL. This is a key regulation mandated by RBI, which specifies that a minimum portion of the bank's lending should be made to certain priority sectors such as agriculture. The PSL regulations aim at addressing development challenges (RBI, 2019). Under the latest guidelines issued by the Reserve Bank of India, the domestic, commercial banks, regional rural banks, and small finance banks in India are required to provide at least 18% of the adjusted net bank credit for agriculture purposes (out of which 10% is earmarked for small and marginal farmers) (RBI, 2020). The bankers must struggle to balance the PSL requirements and the fear of NPAs.

Thirdly, an interesting aspect peculiar to India is the politicization of agriculture credit. Respondents stated that politicians contesting in elections at the state and national level government in India regularly promise to waive outstanding crop loans. Although this is costly for the state exchequer and provides visible relief to the farmers, it has a side effect of engendering indiscipline among farmers. This could lead to option uncertainty wherein the consequences of politicians' announcements are unknown. Several interviewed farmers revealed that in anticipation of upcoming elections and based on politicians' promises, they tend to withhold the repayment of the outstanding crop loans.

> "The government had announced loan waiver 2–3 times. Some farmers would delay the payment or not pay the loan, hoping that a loan waiver would come into effect. They might later pay more interest if the loan waiver is not implemented. So it is a very risky thing to do." (R8, Farmer, Cultivates Cotton in 20 acres in Andhra Pradesh, India)

5.3. *Data-driven social innovation for uncertainty reduction*

5.3.1. *The direct impact of SIA on uncertainty reduction*

This section discusses how SIA-based social innovation may reduce identified uncertainties. The interviews highlight SIA's ability to shorten existing loan processes and drastically improve its efficiency. Stage 1 remains unchanged as farmers submit applications for either a fresh loan or a renewal. In Stage 2, which involves verification, the bankers – in addition to using the CIR score, informal networks, and the past performance of the farmers – can rely on insights from satellite data. Such insights include aspects that map the entire crop life cycle in conjunction with the loan life cycle. Key insights include soil moisture, cropped acreage, availability of ground and surface water, weather data (historical and forecasted), yield predictions, and price movements. Using this information, bankers could make a better-informed decision. Thus, the banker in Stage 3 would be better positioned to assess farmers' creditworthiness and make an objective decision. This also directly aids bankers in tackling the discrimination in the loan disbursement process. Further, in Stage 4, although field officers would still need to visit the farms for pre-disbursal inspection, SIA would make the workload distribution more efficient and targeted. For instance, the SIA could identify farmers who could be potential risk points and hence prioritize inspections.

> "SIA would be a very good intervention for us. It heavily depends on what variables are picked up by the model and the accuracy provided. If the variables are comprehensive and accuracy is high, then it is a very good thing. Most of the time, the topographic data picked from satellites is very relevant and accurate to the reality of the ground. This might be the next big thing happening in agriculture finance and banking." (R2, In charge of agriculture credit, Branch Manager, Private bank)

> "The services of SIA reached the financial institution and benefit the farmer as they are now being assessed. It replaces arbitrariness (in lending). If the farmer has the potential, the analytics will pick it up. The banks will have their data and process that needs to be shared. The remote sensing companies will have to share their assessment of the farmer with the company or the financial institutions. So I don't think it's a symmetric two-way process." (R 20, Director of a National Institute on Space Science and Technology, India)

After loan disbursement, SIA can play an important role in post-disbursal inspections. This benefits bankers, as they could reduce their monitoring field visits and receive assurance that loans are used for farming purposes without diversion. Any deviations can immediately be captured and used to educate the farmers. Further, constant monitoring could help understand market price trends, aiding loan recovery. Alternatively, a better understanding of the ground realities can be achieved if farmers experience a rough year due to bad market conditions, untimely monsoons, or similar externalities. This allows bankers to be more empathetic with farmers and gives rise to an individualized treatment of each farmer based on specific conditions. The data provided by SIA, in combination with the farm loan application and other existing data, can thus be used to carry out automated verification of underlying assets, assess the borrower's capability to farm better, and better understand real-time farming practices. We have captured the re-engineered crop loan process in Fig. 2 below.

5.3.2. *Indirect impact of SIA on uncertainty reduction*

In addition to the direct benefits, the interviews allowed us to identify indirect benefits for the financial institutions. The most important is expanding bankers' portfolios while reducing or better managing risk. Due to better usage and prioritization of data, the resultant process rewards farmers who work hard and apply better land management practices. Other indirect benefits include reducing NPAs, improved customer confidence, provision of new borrowing opportunities, better management of staff, reduction in wilful delinquency and eased workflows.

Bankers are confident in providing loans to better-performing farmers while keeping up with the target of PSL. The risk of default can be reduced, therefore giving rise to reduced NPAs. Another benefit is improved customer confidence, as farmers can understand that their disciplined borrowing behaviour is rewarded. Bankers expressed that a

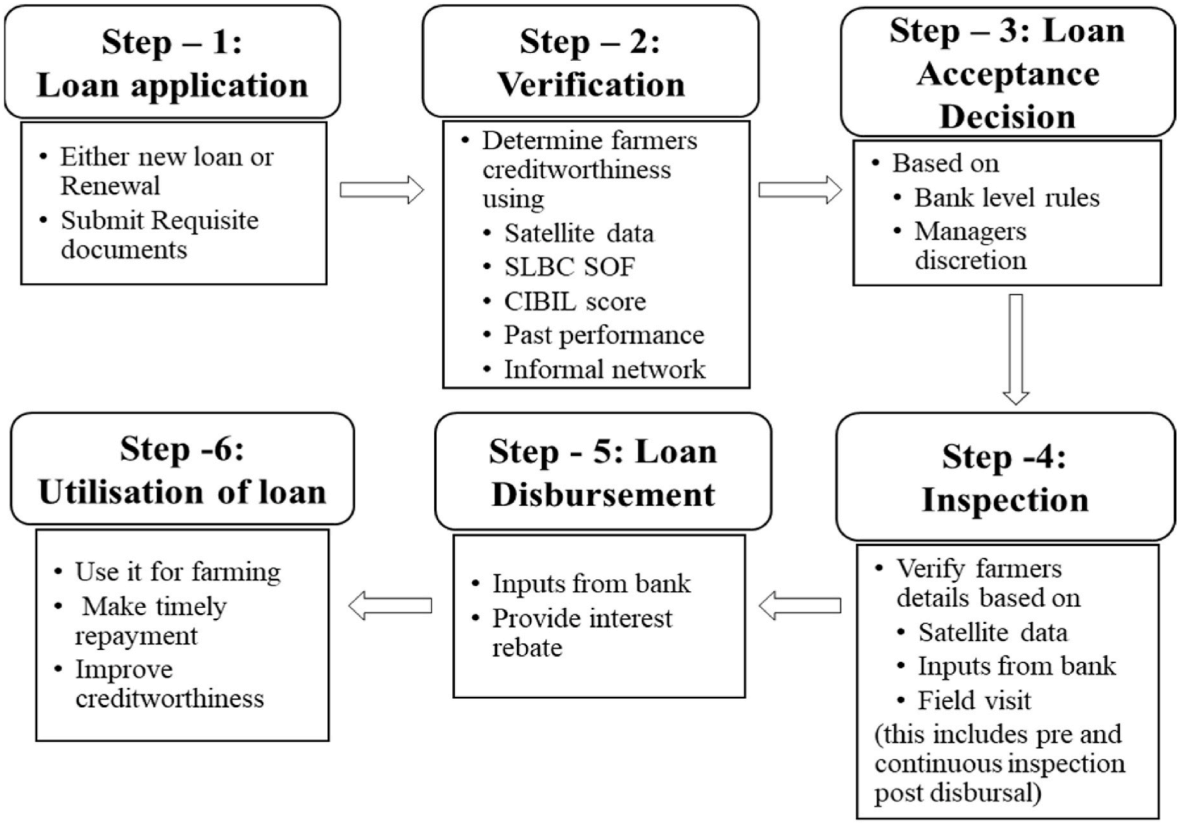

Fig. 2. Reengineered crop loan process.

gradual increase in credit limits for eligible borrowers could achieve this. Additionally, bankers believed that this would lead to a reduction in wilful delinquency. Further, using SIA can generate new leads and open up new borrowing opportunities. Finally, existing customers can be better monitored, as priorities can be made regarding the number of visits and the inspection time, leading to eased workflows.

"It is a bit unfortunate because there may be a big chunk of potential customers who may be better candidates to get a loan but cannot participate in the process. Simply because they are not in the process. This is where SIA helps in that it at least gives them a direction on where to look. Because of this database, some of the farmers who also deserve loans have a higher chance of getting loans. So, one benefit is that it eases their workload. And second is that it can give more potential farmers and make them their potential customers." (R4, Employee at the SIA firm, Product manager)

These benefits can likely increase financial institutions' top and bottom lines. Finding new lending opportunities and additional lending possibilities to existing customers can increase the loan amount, leading to higher revenues (i.e., top line). At the same time, reduction in wilful delinquency, better workflow, and better staff management can enable cost reductions and thereby lead to profit improvement (i.e., bottom line).

5.3.3. Concerns related to SIA technology adoption

Our findings illustrate various ways in which technology could have positive impacts on the crop credit ecosystem. However, the interviews also point out three major areas of concern. Firstly, organisations should consider the aspects of change management regarding employees and the organisation. Interviewees pointed out that implementing SIA could disrupt the status quo of day-to-day activities, giving rise to principal-agent problems. Appropriate communication, upskilling, and training activities are needed to tackle such challenges. Secondly, organisations should also consider the possibility of resistance to change by other actors in the supply chain. This includes the farmers, fellow financial institutions, and government agencies. Farmers might feel exploited, fellow financial institutions might grow over-competitive, and government agencies might be clueless about the prospects of introducing new technology. Therefore, financial institutions must work collaboratively and implement this technology in ways that reduce resistance. Finally, the implementing organisation should consider the policy environment. Government bodies (both at the high and low levels) in developing countries are notorious for complicated bureaucratic setups, corruption, lack of ease of business, and red-tapism (Dhaliwal and Hanna, 2017).

"Let's say you've been using one system for the last ten years, and suddenly, you will shift from one to another and face many problems. If you want to shift from one existing system to another system, then you have to make a balance. Whenever we deploy the solution from our side, it is a collective process for the banking firm." (R5, Employee at the SIA firm, Head of remote sensing division)

6. Discussion and conclusion

This study identifies the uncertainties in the current state of institutional crop credit management and reveals how SIA-based social innovation could reduce these uncertainties. We positioned our study under the broad area of "Data-Driven Digital Transformation for Social Innovation". Within this area, we specifically delve into the role of satellites. There is a great opportunity to increase the use of satellite services in agriculture (Loncaric et al., 2023), and several studies have explored their role. Several studies investigated the role of technologies in fuelling social innovation. Among these, studies have explored the role of satellites in providing real-time and archival imagery (Srinivasan, 2008), site assessments of solar photovoltaic projects (Nagendra et al., 2020c), and aiding in disaster management (Nagendra et al., 2020a).

Previous works have also focused on SIA technology's technical feasibility and applicability in agriculture (Yang et al., 2012). investigated how satellite imagery could assess crop growth and yield variability for precision agriculture (North et al., 2018), examined the case of boundary delineation of agricultural fields in multitemporal satellite imagery (Victor et al., 2022), reviewed works on how deep learning embedded on satellite imagery for agriculture. These studies are in addition to crop identification (Schmedtmann and Campagnolo, 2015), agricultural drought forecasting (Marj and Meijerink, 2011) and estimating agricultural plastic waste (Lanorte et al., 2017) among others.

However, assessing the role of SIA, especially in agriculture crop credit management, is underexplored, and we have found only two studies in this regard. Möllmann et al. (2020) examined whether remotely sensed vegetation health indices could explain the credit risk of the agriculture loan portfolio of microfinance institutions (MF) in Madagascar. They found that utilising remotely sensed data for index insurance designs helps MF institutions better hedge their portfolio risk of agriculture credit. On the other hand, Simumba et al. (2021) investigate how satellite data combined with mobile and public geospatial data could improve the credit evaluation of financially excluded persons in rural Cambodia. Taking this argument ahead, our study examines how satellite imagery could help in the creditworthiness assessment of farmers in rural south India, wherein the results throw light on the critical phenomenon for emerging countries where economies are still agriculture-dependent.

Following Bradley and Drechsler (2014), we explored how the existing crop loan process suffers from three types of uncertainties: state space, option, and ethical. To address state space uncertainty, SIA needs to assist in determining the economic viability of a borrower's farming activities and provide a reliable harvest price prediction. To determine economic viability, SIA can deploy outcome prediction models at the individual farm level. This, in combination with ancillary data sets (e.g., data obtained from drones), can be used to create multiple farm-level prediction models. With these predictions, the possible outcome scenarios become transparent, which helps financial institutions create an ideal risk portfolio and identify new lending opportunities. SIA can provide trend analyses of harvest prices to eliminate uncertainty regarding harvest prices. Based on time series data that identify trends and seasonality, SIA can produce forecasts that contribute to managing the portfolio more efficiently and effectively.

To tackle option uncertainty, SIA would need to provide a better understanding of farmers' repayment capacity. This can be addressed by building repayment prediction models that estimate various scenarios of payments to be made by farmers based on past performance. As financial institutions would be better positioned to empathize with the farmers during the disbursing and monitoring of the loan, this could lead to higher customer satisfaction and better loan collection processes.

Finally, to address ethical uncertainty, SIA forms the basis of monitoring systems due to its ability to perform real-time monitoring throughout the farmers' crop and loan cycles. Deviations in cropping activities or weather conditions can be quickly captured. This would enable a better understanding of the farmers' creditworthiness and could result in better management of financial institution resources. Table 2 maps different types of uncertainties to the capabilities of SIA.

6.1. Research implications

Our study adds to the literature on using sophisticated technologies such as SIA for social innovation. By leveraging state-of-the-art technology, institutions can generate economic value (Pisano, 2010; Stuart et al., 2007). Adding to extant findings (Block and Sandner, 2011; Greenhalgh and Rogers, 2006), our study shows that technology can assist firms in enhancing their economic and social value delivery. This opens up the research to examine social innovations based on similar sophisticated technologies, such as machine learning (Bazarbash, 2019), artificial intelligence (Leminen et al., 2020), blockchain (Salampasis and Mention, 2018), or the Internet of Things (Paiola and Gebauer, 2020; Pardo et al., 2020).

Furthermore, we demonstrate the potential of SIA-based social innovation in the agriculture supply chain. Our findings indicate the potential to extend the application and support capacity building for adopting SIA into other agricultural processes, such as farm inputs, water management, agriculture disaster management, or policymaking for food security. This adds to the growing literature on satellite data usage in solving agriculture issues.

6.2. Practice implications

Institutional lenders in developing economies face challenges in identifying credit opportunities, as well as in disbursing and monitoring loans (Golait, 2007; Yadav and Sharma, 2015), leading to sub-optimal loan disbursement (Garikipati et al., 2017). Here, SIA can help scale the overall efficiency and efficacy of the transactions in agriculture financing, thereby enabling an expansion of institutional lending for small and marginal farmers. Our study presents preliminary evidence of reducing transaction costs between the borrowers and lenders against the legacy processes. Adopting SIA may provide a competitive advantage to stakeholders in the financial industry (e.g., commercial banks) as well as advantages such as increased transparency of the creditworthiness assessment, digitization of onboarding processes of borrowers, reduced transaction costs in assessment, and oversight of the underlying asset. Therefore, stakeholders in the financial sector should consider investing in internal capacity building by reviewing legacy processes, performing trial runs, training staff in implementing such technology towards plausible adoption, and scaling.

6.3. Social implications

Although farmers do not directly benefit from a SIA intervention, they are the indirect and ultimate beneficiaries. Agriculture in developing countries has been unviable for several decades (Gulati et al., 2019; Nadkarni, 2018). This can be attributed to many reasons, such as haphazard policies, lack of market linkages, or low productivity (Bathla et al., 2017; Gulati et al., 2019; Landes and Burfisher, 2009). All these have pushed farmers into a vicious debt cycle, creating a poverty trap (Carter and Barrett, 2006). This has dissuaded policymakers from

Table 2
Mapping uncertainties to capabilities offered by SIA.

Uncertainty category	Uncertainties	Capabilities of SIA	Impact
Ethical Uncertainty	Lack of proper monitoring system	Real-time monitoring	Reduction in wilful delinquency
Ethical Uncertainty	Inadequate/substandard information sources system	Integration of multiple data sources	Understand creditworthiness and better staff management
Option Uncertainty	Understanding farmers' repayment capacity	Calculation of repayment prediction models	Higher customer satisfaction and better loan collection
State Space Uncertainty	Understanding the viability of farming	Farming outcome prediction models	Creation of new lending opportunities
State Space Uncertainty	Understanding commodity price trends	Trend analysis of prices	Efficient management of lending portfolio

attending to their woes and financial institutions from considering them as potential markets. The results from our study could be used to leverage and promote using sophisticated technologies such as SIA to overcome these challenges. For instance, upon identification of disciplined farmers by the SIA, additional/customized loans could be provided. This could lead to improvements in farm-level outcomes and the socio-economic conditions of farmers. Collective development of such data-driven social innovation could improve the farming ecosystem in developing nations.

6.4. Policy implications

Integrating SIA into established services may improve information and advisory services for farmers and the agriculture value chain. At the same time, established services such as agro-meteorological advisory can be improved using SIA (Chattopadhyay and Chandras, 2008). This would ensure the adoption of insights generated through SIA and allow them to be integrated into the overall array of activities that support agriculture and contribute to the sustainability of small and marginal farms (Skakun et al., 2016).

6.5. Limitations and avenues for future research

As with any qualitative research, our work also has some limitations. First, we did not consider the challenges within the start-up company *Agro-Sat-Inno*. Although the conditions within the firm could be organisational and entrepreneurial, they may still affect how they deal with financial institutions and address the uncertainties existing in crop credit management. Second, we did not consider the dynamics and the challenges of technology adoption within financial institutions. Its adoption could give rise to intra-organisational complications and conflicts. The third limitation is the issue of generalizability, given the nature of the methodology (i.e., case study). Our results are based on the analysis of a single firm that has incorporated, conducting its operation with farmers and dealing with financial institutions in India. The data-driven social innovation is also restricted to SIA. While we expect the current findings to apply to other financial institutions and their interaction with similar firms across developing nations, replication studies are needed. While the results can widely be applied in several regions of India, the replication of results geographically might not be feasible. In considering the results for other geographical settings, we must consider the role of socio-cultural contexts and norms/practices. Another limitation arises from the nature of the case study methodology, which involved cross-sectional interviews done at specific stages of the innovation adoption. Due to the nature of these interviews, we could only examine SIAs' impact until the point at which the interviews were conducted rather than throughout. A few other limitations include a shorter period, which might limit the generalizability of our findings but does not diminish its value. Also, given the nature of qualitative methodology, we could not establish causality. We have proposed a few potential future research areas to overcome these limitations.

We find several opportunities for future research in the three areas – technologies, countries, and social issues. Future research could study the above model for other emergent technologies, such as machine learning, artificial intelligence, and deep learning. Studying similar technological interventions in other countries becomes pertinent, as this would shed light on the differential impact on institutional effectiveness and its relevance in addressing social issues. In developing countries, it would be important to examine the specific factors that influence the usage of data-driven social innovation in addressing institutional credit management. Finally, it is also important that future research explores the impact of SIA and the technologies mentioned above on other pressing social issues, such as addressing sustainable development goals (e.g., zero hunger, providing quality education, promoting gender equality, providing affordable and clean energy, and reducing inequalities).

CRediT authorship contribution statement

Gopalakrishnan Narayanamurthy: Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **R Sai Shiva Jayanth:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **Roger Moser:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Investigation, Conceptualization. **Tobias Schaefers:** Writing – review & editing, Validation, Supervision, Investigation. **Narayan Prasad Nagendra:** Writing – review & editing, Validation, Resources, Conceptualization.

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Appendix 1. Questionnaire used for interview

Stakeholder: Employees at financing institutions.
Questions regarding adoption.

1. Explain the loan application appraisal process for farmer loans (without satellite big data analytics (SBDA)).
2. What is the new loan application appraisal process (with SBDA)?
3. What are the various challenges you face with the new process?
4. What training process did you undergo while implementing this new process?
   Questions regarding Human/Non-human elements while implementation
5. What are the various benefits of the new process?
6. How have people within your organisation responded to this new technology?
7. What could be done to improve the adoption of this new technology?
8. Are there any complaints from the customers (Farmers) after implementing the new process?
9. Are there any problems in acquiring data/reports under the new system?

Questions regarding drivers and barriers of the Analytics.

10. What are the drivers for implementing analytics to expand institutional credit?
11. What are the barriers for implementing analytics to expand institutional credit?

Questions regarding assessing success/failure of the Analytics.

12. Do you think this new process increased the loan disbursement to the farmers? How?
13. Do you think the new technology would benefit farmers?
14. Do you think the new technology is good/bad? Why/Why not?
15. Has the new technology added/reduced your workload?
16. Do you feel the discrimination in loan disbursement has reduced?

Stakeholder: Employees at the Satellite Imagery firm

Questions regarding adoption.

1. What are the various challenges you face with the new process?
2. What training process did you undergo while implementing this new process?
3. What training process do you impart to the employees at financial institutions for the new process?
4. Please describe the process of acquiring a new client for your product.
5. What difficulties did you face in convincing clients to take up this product?

Questions regarding Human/Non-human elements while implementation.

6. What are the various benefits of this process?
7. What are the risks/challenges with this process?
8. What could be done to improve the adoption of this new technology?
9. Are there any complaints from the financial institutions after implementing the new process?
10. Are there any problems in acquiring data/reports under the new system?
11. What support are you obtaining from the government in adoption of this system?
12. What obstacles are you facing from the government in adoption of this system?

Questions regarding drivers and barriers of the Analytics.

13. What are the drivers for implementing analytics to expand institutional credit?
14. What are the barriers for implementing analytics to expand institutional credit?

Questions regarding assessing success/failure of the Analytics.

15. Do you think this new process increased the loan disbursement to the farmers? How?
16. Do you think the new technology would benefit farmers?
17. Do you think the new technology is good/bad? Why/Why not?
18. Do you feel the discrimination in loan disbursement has reduced?

Stakeholder: Farmers

Questions regarding adoption.

1. Are you aware of the new process for credit disbursal?
2. How do you think this new analytics driven process is going to affect your agri-value chain?
3. What are the advantages in the new credit disbursal system?
4. What are the drawbacks in the new credit disbursal system?

Questions regarding Human/Non-human elements while implementation.

5. Is there any resistance from the farmers towards the new system?
6. What improvement are required for this new system?

Questions regarding drivers and barriers of the Analytics.

7. What are the drivers for implementing analytics to expand institutional credit?
8. What are the barriers for implementing analytics to expand institutional credit?

Questions regarding assessing success/failure of the Analytics.

9. Do you think the new system has benefited the farmers?

10. Do you feel that the amount of loans disbursed to the deserving farmers has increased?
11. Do you feel the discrimination in loan disbursement has reduced?

Stakeholder: Government officials

Questions regarding adoption.

1. What are the various challenges with the new process?
2. Is government providing any kind of support/incentives to these organisations?
3. What could be done to improve the adoption of this new technology?

Questions regarding Human/Non-human elements while implementation.

4. What are the various benefits of the new process?
5. How have users/beneficiaries (bankers, farmers etc.) responded to this new technology?
6. Are there any complaints from users/beneficiaries (bankers, farmers etc.) after implementing the new process?

Questions regarding drivers and barriers of the Analytics.

7. What are the drivers for implementing analytics to expand institutional credit?
8. What are the barriers for implementing analytics to expand institutional credit?

Questions regarding assessing success/failure of the Analytics.

9. Do you think this new process increased the loan disbursement to the farmers? How?
10. Do you think the new technology would benefit farmers?
11. Do you think the new technology is good/bad? Why?
12. Do you feel the discrimination in loan disbursement has reduced?

Stakeholder: Satellite data experts

Questions regarding adoption.

1. What would be the various challenges with the new process?
2. What training process do you recommend while implementing this new process?

Questions regarding Human/Non-human elements while implementation.

19. What are the various benefits of this process?
20. What are the risks/challenges with this process?
21. What could be done to improve the adoption of this new technology?
22. Are there any complaints from the financial institutions after implementing the new process?
23. Are there any problems in acquiring data/reports under the new system?
24. What support are you obtaining from the government in adoption of this system?
25. What obstacles are you facing from the government in adoption of this system?

Questions regarding drivers and barriers of the Analytics.

26. What are the drivers for implementing analytics to expand institutional credit?
27. What are the barriers for implementing analytics to expand institutional credit?

Questions regarding assessing success/failure of the Analytics.

28. Do you think this new process increased the loan disbursement to the farmers? How?
29. Do you think the new technology would benefit farmers?
30. Do you think the new technology is good/bad? Why/Why not?
31. Do you feel the discrimination in loan disbursement has reduced?

Stakeholders: Agriculture academics/Think tanks

Questions regarding adoption.

1. What would be the various challenges with the new process?
2. What training process do you recommend while implementing this new process?

Questions regarding Human/Non-human elements while implementation.

3. What might be the various benefits of the new process?
4. How would people within organisation responded to this new technology?
5. What could be done to improve the adoption of this new technology?
6. Would there be any problems in acquiring data under the new system?

Questions regarding drivers and barriers of the Analytics.

7. What are the drivers for implementing analytics to expand institutional credit?
8. What are the barriers for implementing analytics to expand institutional credit?

Questions regarding assessing success/failure of the Analytics.

9. Do you think this new process would increase the loan disbursement to the farmers? How?
10. Do you think the new technology would benefit farmers?
11. Do you think the new technology is good/bad? Why/Why not?
12. Do you feel the discrimination in loan disbursement would reduce?
13. What might be the benefits of informal money lending compared to the financial institutions lending (with SBDA)?
14. What might be the benefits of financial institutions lending (with SBDA) compared to the informal money lending?

Stakeholder: Informal lenders

Opening questions.
How do they assess the creditworthiness of farmers who request credit from them?

1. To whom will you give money?
2. To whom will you not give money?

Questions regarding adoption.

1. Are you aware of a new satellite based credit evaluation system?
2. Do you think financial institutions will have trouble adopting this system?

Questions regarding Human/Non-human elements while implementation.

3. What are the various benefits of this process?
4. What are the risks/challenges with this process?
5. Would the new system affect your business of money lending?
6. Would farmers turn towards the financial institutions due to the new system?

Questions regarding drivers and barriers of the Analytics.

7. What are the drivers for implementing analytics to expand institutional credit?
8. What are the barriers for implementing analytics to expand institutional credit?

Questions regarding assessing success/failure of the Analytics.

9. Do you think this new process would increase the loan disbursement to the farmers? How?
10. Do you think the new technology would benefit farmers?
11. Do you think the new technology is good/bad? Why/Why not?
12. Do you feel the discrimination in loan disbursement has reduced?
13. What are the benefits of informal money lending compared to the financial institutions lending (with SBDA)?
14. What are the benefits of financial institutions lending (with SBDA) compared to the informal money lending?

Other questions

1. If bank takes care of all the financial requirements, will farmers still come to you for extra money? Why?
2. Is your interest rate higher than bank interest rate?
3. Why do you lend money? Is it for extra money that you earn or to help people from your locality?
4. When do you think farmers will stop coming for informal money lending from you?
5. Have farmers not returned the money in the past? What you do in those cases?
6. In comparison to ten years before, has informal lending increased or decreased now? Why?

Appendix 2. List of Interview Respondents

	Role/Position	Stakeholder classification	Length (minutes)
R1	Ex Deputy General Manager, Agriculture credit, Nationalised bank	Employees at the financing institutions	98:08
R2	In charge of agriculture credit, Branch Manager, Private bank		52:32
R3	In charge of agriculture credit, Branch Manager, Nationalised bank		98:56
R4	Product manager, Case company	Employees at the SIA firm	62:53
R5	Head, Remote sensing division, Case company		49:20
R6	Co-founder and global product head, Case company		21:57
R7	Cultivates Bengal gram - 25 acres - Andhra Pradesh, India	Farmers	31:50
R8	Cultivates Cotton - 20 acres - Andhra Pradesh, India		16:33
R9	Cultivates Paddy - 60 acres - Andhra Pradesh, India		22:02
R10	Cultivates Mosambi - 3 acres - Andhra Pradesh, India		22:05
R11	Cultivates Bengal gram - 5 acres - Andhra Pradesh, India		21:06
R12	Cultivates Vegetables - 2 acres - Andhra Pradesh, India		18:17
R13	Assistant Director of Agriculture, Kalligudi, Tamil Nadu. Coverage - 25,000 ha	Government officials	72:58
R14	Agriculture Extension officer, RR District, Hyderabad.		41:55
R15	District Development Officer, NABARD. Tiruvannamalai, Tamil Nadu		76:78
R16	Agriculture Technology Management Agency (ATMA) Block Technology Manager, Kalligudi, Tamil Nadu		
R17	Professor at National Institute of Advanced Studies, former Indian Space Research Organisation (ISRO) employee	Satellite data experts	61:27
R18	Former professor at a premier Institute for Space Applications and Geo informatics		61:51
R19	Technical expert in SIA and works for new age start-up which uses SIA in agriculture		72:37
R20	Director of Indian Institute of Space Science and Technology, Thiruvananthapuram.		46:16
R21	Agricultural Economist at premier economic research organisation	Agriculture academics/Think tanks	74:25
R22	Informal moneylenders		23:19
R23			25:06
R24			24:28
R25			21:23
R26			20:28

Data availability

The data that has been used is confidential.

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