Title: Understanding the Persistence of Rice Residue Burning in Northwestern India: A Mixed Methods Approach

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Abstract

Air pollution from rice residue burning in Northwest India remains an acute environmental and public health threat despite significant and sustained public investments in new technologies. This study uses a mixed methods approach to investigate why burning persists in Punjab State in Northwest India. Analysis of satellite-estimated fire count data suggests that trends in burning vary spatially, with some regions experiencing significant declines over time with little change in others. Based on this analysis, we conducted 90 semi-structured farmer interviews that account for sub-regional differences in burning and then build a heuristic model to characterize determinants of rice residue management (RRM) practices. A complete shift away from burning is associated with a combination of evolving community norms discouraging the practice, machinery access along with appropriate agronomic practices, and provision of technological support services. In regions where burning persists, agronomic practices including cultivation of long duration paddy and environmental factors such as as temperature and rainfall around rice harvest contribute to year-to-year variation in the choice of RRM method. Unexpectedly, an increase in 'partial' burning practices, where farmers burn loose straw was also documented and associated with the field use of machinery ostensibly designed to avoid burning. Using secondary and spatial data from the years 2018-22, we then assess the associations between RRM machinery distribution and rice varietal characteristics with patterns of burning. Results from this analysis suggest that the introduction of promising residue management technologies do not necessarily lead to reductions in burning. Based on our results, we identify short term interventions including residue monitoring along with deployment of residue collection to curb burning, medium term interventions focused on improving residue management options including developing value chains for residue, and improving the technology landscape and long term shifts toward more environmentally sustainable and resilient agricultural practices to permanently curb residue burning practices.

Keywords: Crop Residue Burning, Agicultural Technology, Mixed Methods

1. Introduction

Cereal production in Northwest India is vital for national and global food security. Punjab and Haryana account for over 70% of the total wheat and 30% of the total rice procured nationwide for the central food grain pool, which provides highly subsidized cereals for the most impoverished (GOI, 2025; Swaminathan & Bhavani, 2013). However, the intensive cultivation of rice-wheat has resulted in severe environmental issues, notably large-scale rice residue burning, affecting air quality and contributing significantly to greenhouse gas emissions (Dhanda et al., 2022). Annually, 23 million tons of rice residue are burned across 4 million hectares, contributing up to 40% of PM2.5 pollution in Northwest India during late fall and exacerbating respiratory diseases (Bhuvaneshwari et al., 2019; Lan et al., 2022; Shyamsundar et al., 2019). In addition to air pollution, residue burning depletes soil nutrients, disrupts microbial ecosystems, and affects local climate patterns through albedo changes and black carbon deposition, threatening long-term agricultural sustainability (Deshpande et al., 2023; Korav et al., 2024).

To curb this practice, the government of India banned residue burning in 2015. Additionally, government and non-governmental agencies have implemented various programs to increase awareness of the harmful effects of residue burning while developing and often subsidizing alternative *in situ* and *ex situ* rice residue management ('RRM') options (Downing et al., 2022). Although some progress has been made, farmers continue to burn a significant amount of rice residue with considerable year-to-year variability. During the peak burning intensity year of 2016, an estimated 32 million tons of residue were burnt with current levels exceeding more than half of this peak (Dipoppa & Gulzar, 2024; Dutta et al., 2022).

Importantly, studies suggest that transitions out of burning are uneven, signaling the complexity of shifting entrenched practices, even when alternative technologies are ostensibly available and profitable (T. Liu et al., 2020). Adoption constraints to *in situ* residue management technology have been identified, including financial and knowledge bottlenecks (Bhatt et al., 2023; Dutta et al., 2022). Further, while studies have considered the role of socio-economic heterogeneity between farmers in determining residue management practices, there is limited consideration of biophysical and farm management diversity (Erbaugh et al., 2024; Krishnapriya et al., 2024; Cordeiro et al., 2024). Finally, despite overwhelming evidence that residue burning is a spatially and temporally dynamic process, most studies fail to account for seasonal weather factors (Bahinipati, 2014).

We use a bottom-up systems approach to address these gaps, identifying structural and systemic drivers of rice residue management practices. Further, we unpack how farmers make short-term decisions to burn rice residue, focusing on the effects of *in* and *ex situ* residue management practices. The two key questions we seek to answer are: What are the main determinants of residue management practices and seasonal residue burning? What are the policy implications for efforts to arrest residue burning?

2. Region of focus: Punjab

We conduct our study in Punjab in Northwest India. We choose Punjab because the state accounts for nearly 70 percent of all crop residue burning in India (Dutta et al., 2022). It is a primary cause of hazardous air quality locally and contributes to poor air quality in the national capital region although recent studies show that proportion of contribution may be less than previously believed (Krishnapriya et al., 2024; Mangaraj et al., 2025). Punjab is one of India's most intensively cropped and productive agricultural regions. The crops grown in Punjab include maize, cotton, sugarcane, and horticultural crops, with rice and wheat as the primary crops cultivated. The area under food grains as a share of gross cropped area (GCA) constitutes nearly 83.4 percent of cultivable land and is growing (Table S1). Presently, Punjab is the third-largest producer of wheat and rice among all the states in India.

2.1 The Environmental, Institutional and Political Context of Residue Burning in Punjab

In Punjab, residue burning and poor air quality are closely linked to processes driven by agricultural intensification including the expansion of the rice-wheat cropping system. The rice-wheat cropping system rapidly expanded in Punjab during the Green Revolution with the introduction of modern crop varieties that were not photoperiod sensitive and often had shorter growing durations (Murgai, 2001). The rice-wheat rotation was adopted in areas that previously produced either wheat or maize as a single crop in the farming year (Kang, 2021). This intensive rice-wheat rotation has been further reinforced by assured irrigation at subsidized rates and price guarantees for these two crops through state procurement and minimum support prices (Ali et al., 2012). The area under rice has increased steeply over time with percentage of land under this crop went up from 6.9 per cent of the total area in 1970-71 to 60 per cent of the next cropped area in Kharif season in 2005- 06 (Panigrahy et al., 2010). During 2022-23, rice crop occupied 31.68 lakh hectares in Punjab with total paddy production of 205.24 lakh tons (137.51 lakh tons of rice) (Bhullar & Salaria, 2025).

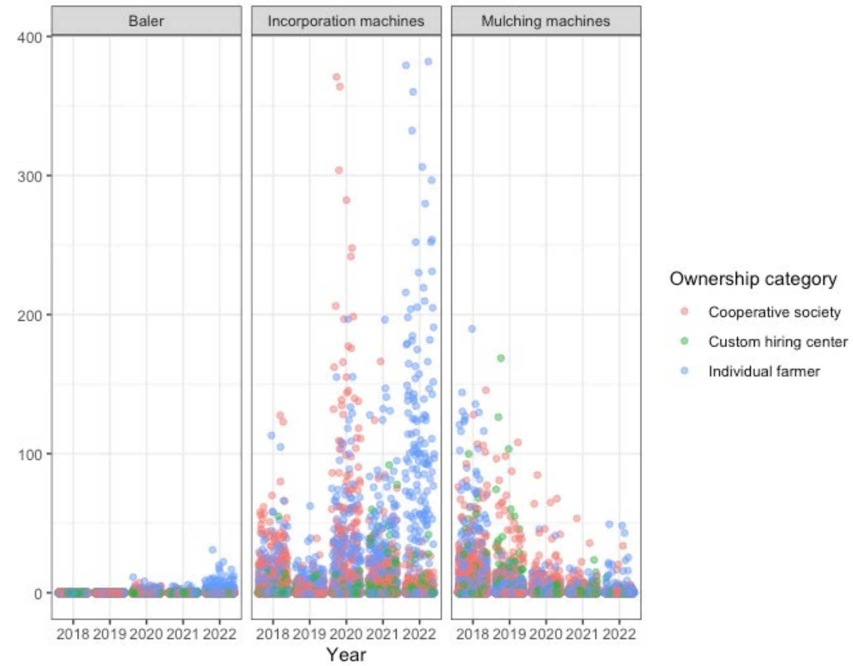
Farmers have a strong incentives to keep the turnaround time between the rice and wheat short to maintain productivity by ensuring wheat sowing occurs in early November. Accordingly, rice straw management and field preparation for wheat must typically take place within a two-week period constraining the time available for residue management (Coventry et al., 2011).

As a consequence of agricultural intensification the groundwater table in Punjab has faced severe depletion (Tripathi et al., 2016). In response to critical groundwater levels, policies were implemented to reduce groundwater overuse constraining farmers from establishing rice earlier, thereby shortening the window for rice residue management. Although in some areas these policies may have led farmers to adop shorter duration rice varieties, studies show that it may have had unintended consequence of concentrating agricultural burning in the late fall when meteorological conditions favour poor air quality (Balwinder-Singh et al., 2019).

Recognizing the serious implications of residue burning for human and environmental health, state and national authorities have instituted policies to combat this practice. In 2015, the National Green Tribunal of the Government of India banned the burning of crop residues and imposed fines for farmers who continued the practice, albeit with variable levels of enforcement. The lack of alternate residue management practices originally meant that punitive actions failed to appreciably reduce residue-burning practices in the region.

In 2018, the policy focus shifted to incentivizing alternatives to burning, particularly by subsidizing (up to 80% purchase cost) machinery for *in situ* rice residue management, which reduce time for residue management by cutting crop residue and either mulching residue on the field surface or incorporating it into the field and sowing wheat seeds in a single field operation. By 2023, Punjab State state had nearly 45,000 incorporation machines and 15,000 mulching machines. Nearly 60 per cent of them are owned by individual farmers, and the remaining are operated by CHCs and Cooperative societies (Figure 1). A major advantage of these technologies is that they save time compared to the alternatives of either collecting and bailing loose residues or incorporating residues with multiple tillage passes. Details of machinery are available in Table S3.

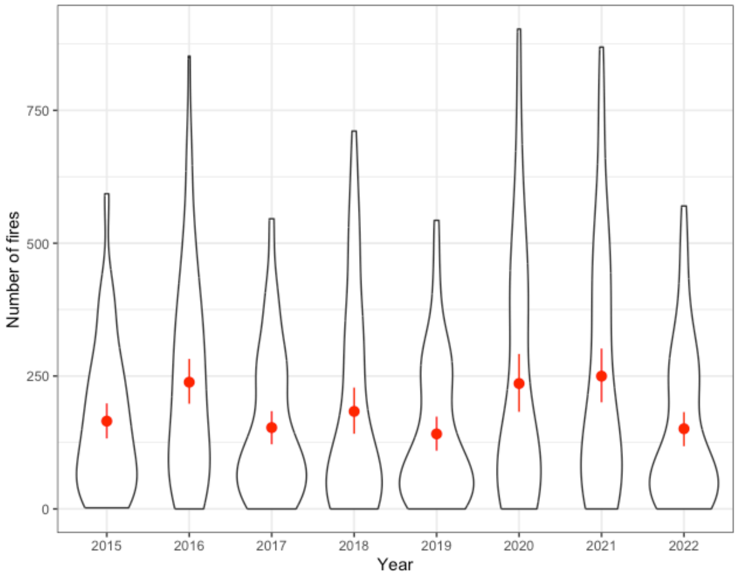
Figure 1. Number of residue management machinery subsidies by year and by ownership category



Source: Government of Punjab, Agriculture department

Ex situ crop residue management options have also been promoted. These options typically entail baling of loose residues for subsequent use as a raw material for energy generation, packaging material, mushroom cultivation, livestock fodder, or bedding beyond the fields where they were produced. However, the labor and infrastructure needed to gather, transport, and store significant quantities of rice straw are limiting, especially considering the low market value of the residue (Kurinji & Kumar, 2021). Additionally, during the harvest season, the high dew point of the atmosphere tends to raise the moisture level of rice residue. To improve quality and storability for some purposes requires drying which is typically not economical (Parihar et al., 2023). Even with substantial technical advances and policy support for both *in situ* and *ex situ* residue management options, progress to eliminate burning has been uneven (Khanna et al., 2024). Moreover, although certain years reflect a notable reduction in residue burning, these decreases are often reversed in subsequent years (Figure 2).

Figure 2. Fire burning occurrences by sub tehsil for Punjab from 2016-2022



Source: VIIRS Active Fire Products (Schroeder et al., 2014)

3. Materials and methods

We use a two-phase exploratory design that combines qualitative and quantitative analysis to identify multi-scalar social, economic, technological, and environmental factors that form the basis of crop residue management decisions and residue-burning practices in our study region. This approach permits us to understand emergent patterns that arise from the interaction of several factors (Creswell & Plano Clark, 2011; Greene et al., 2005).

The two-phase exploratory design is particularly useful in analyzing complex issues by first identifying key variables to study and then identifying critical aspects of the emergent theory to explore a phenomenon in depth (Creswell et al., 2003). This analysis consists of two steps: 1) qualitatively identifying important variables and relationships that shape residue management strategies at the regional and household level, and 2) quantitatively evaluating the effect of identified variables on short-term residue burning decisions using secondary data.

3.1 Qualitative methods

3.1.1 Sampling

We conducted semi-structured interviews with 90 farmers across Punjab to understand the intersection of factors that contribute to a farmer decision processes for RRM. We selected farmers across different fire-burning clusters that capture trends over time (Figure 3). Clusters were created using partitional time-series analysis of satellite-detected fire events from VIIRS (Schroeder et al. 2014) (i.e., active fire product at 375 m spatial resolution). First, annual fire count data was aggregated at the sub-teshil level; an administrative division of a district. To create groups with similar patterns of burning over time, we clustered each sub-tehsil based on fire events from 2018-22 to form four clusters with centroid values identified for each year across the time-series (Sardá-Espinosa, 2017) (Figure 3). We used the period 2018-22 as it was the main period during which subsidies for *in situ* residue management machinery was provided and subsequent increases in adoption of *in situ* residue management was observed. We used the dtwclust package in R to assign sub-tehsils into clusters. From each cluster, we interviewed approximately 20 farmers who cultivated kharif rice in combination with a rabi crop. We used random sampling to select an equal number of small, medium, and large farmers to interview. Names of villages and their general characteristics are provided in Table 1.

Figure 3. Panel A shows the location of sites and fire-burning clusters where interviews were conducted between March and May 2024. Panel B shows fire-burning trends by cluster between 2018-2022.

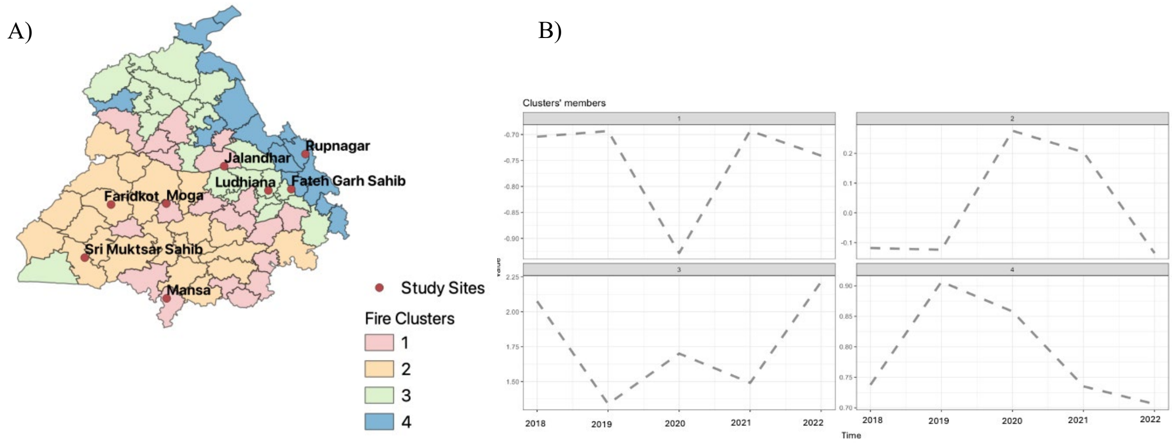


Table 1. Biophysical and cropping characteristics of selected districts where interviews were conducted

District	Sub-tehsil	Fire burning cluster	Village names	Number of farmers interviewed	Groundwater[1]	Soil	Main crop rotation
Jalandhar	Phillaur	1	Bakapur, Gill, Alewali, Burj Phuktar, Ladhram, Ramgarh	14	Over-exploited,	Light to medium textured soils	Rice-Wheat-Moong
Moga	Moga-1	2	Nidhanwala, Kalan Singhwala	10	Over-exploited,	Coarse loamy to fine loamy	Rice-Wheat +Diary
Faridkot	Faridkot	2	Doad, Jandwala	10	Critical, Saline	Sand clay to sandy loamy	Rice or Cotton - Wheat
Muktsar Sahib	Malout	2	Aulakh	12	Safe	Sand clay to sandy loamy, saline and alkaline soil	Rice or Cotton-Wheat
Mansa	Sardulgarh	3	Fatta Malukha, Churian, Janduke, Churian	12	Over-exploited, Saline	sandy loam to loamy sand saline and alkaline soil	Rice or Cotton-Wheat
Fateh Garh Sahib	Khamanon	3	Gaggarwala	12	Critical	Fine loamy soils	Rice - Wheat
Ludhiana	Samrala, Khernia	3,4	Balion, Dagalpur, Diwala, Powadh	10	Over-exploited	Medium to heavy textured soil	Rice-Potato-Wheat
Rupnagar / Roopar	Morinda Chamkaur Sahib	4,3	Mankheri, Kajouli	10	Critical	Sandy Loam to Loamy Sand	Rice or Maize-Wheat

[1]Ground water is classified as based on the stage of groundwater extraction by the Central Ground Water Board (CGWB) as Over-exploited: groundwater extraction exceeding 100%; Critical: groundwater extraction between 90% and 100%; Semi-critical: groundwater extraction between 70% and 90%; Safe: Blocks with a stage of groundwater extraction up to 70%

3.1.2 Interview design

Interviews were designed with the initial assumption that residue-burning decisions are complex, nested in characteristics of the place, farm management practices, and perceptions and preferences of farmers. Semi-structured interviews allowed us to collect detailed information on how farmers make these decisions. The interview was organized around a topic guide based on a detailed literature review (Table S2), which helped lead the conversation in a standardized way while allowing flexibility to identify relevant issues previously unknown to the researcher. In addition, semi-structured interviews were also used to obtain quantitative data regarding farm management practices. Importantly, these interviews allowed us to obtain information on participant residue burning, a sensitive issue that is challenging to capture accurately in a traditional structured survey (Kallio et al., 2016). Farmers who were hesitant to discuss their burning practices were asked about their perceptions of others' residue burning practices. All the interviews were carried out in the local language, Punjabi, and transcribed in English.

3.1.3 Thematic analysis

Thematic analysis was conducted on the interview transcripts using NVIVO software. We systematically identify, organized and explored insights into patterns of meaning (themes) across the responses from the semi-structured interviews. We conduct the thematic analysis in 4 phases, following Braun and Clark (2012). In the first phase, we familiarized ourselves with the data by reading the transcripts and highlighting items of particular interest. In phase two, we systematically coded the data by identifying 16 features potentially relevant to the research question (Table S4). In the third phase, we shift from codes to themes, looking for patterned responses and meaning to construct themes from the data. From the 16 codes, we identified three themes for each research question (Table S5). Finally, we reviewed the potential themes, recursively reviewing the developing themes in relation to the coded data and the entire dataset. In this stage, we evaluated the quality and evidence supporting the theme. Based on the themes and identified interconnections between variables, we constructed causal loop diagrams to provide a conceptual model of factors determining rice residue management decisions.

3.2 Quantitative methods

3.2.1 Drivers of burning using a Random Forest Model

We quantitatively assessed the drivers of residue burning emerging from our qualitative assessments using secondary data, including satellite data and government data on subsidies (Table 2) for the years 2018-2022 with machine learning (i.e., random forest – "RF") and also with an OLS regression model.

Machine learning can outperform standard regression analysis in predictive ability, especially when studying non-linear problems that are hard to approximate with parametric models and when the underlying theory is unclear as is the case for rice residue burning (Best et al., 2022; Hindman, 2015). However, machine learning models are limited in their usability for hypothesis testing due to their limited interpretability. As the complexity of the model increases, interpretability decreases, representing a trade-off between model predictive performance and interpretability. Furthermore, the greater predictive power that complex models often possess may not transfer as well to other contexts as simpler theory-driven models would (Buolamwini & Gebru, 2018). To overcome these gaps while leveraging its advantages we use machine learning to complement a traditional regression approach.

We first used RF analysis to establish the strength of association and main interactions between features identified in farmer interviews as predictors of burning decisions measured as the number of fire incidences for each sub-tehsil normalized to the rice growing area in Punjab in October and November- the main harvest season .We then use a regression analysis to measure the effect of the variables on the residue burning outcome variable. We fit 10 models to the data; for each model, we divided the data, randomly assigning 80% of the household responses to a training set and the remaining 20% to a testing data set. We used the 'ranger' package (Wright & Ziegler, 2017) of the R Environment for Statistical Computing (Team, 2022) to fit a complete RF model to each of the ten training datasets. We also evaluated out-of-sample model performance (Cutler et al., 2018).

The outcome variable. i.e number of fire incidences are estimated based on remote-sensing burn data products, specifically VIIRS Active Fire Products (Schroeder et al., 2014) for regions identified as agricultural from the GlobCover 2009 land cover mask (Kalogirou, 2012) and normalized by the amount of land under rice cultivation in each sub-tehsil derived from the CROPGRIDS a global georeferenced dataset of 173 crops (Tang et al., 2024). Only dates during the rice residue burning season (i.e., October 1 to December 1) are considered. We identified predictor variables from the qualitative analysis. The variables were than derived from government data (subsidized machinery sales) or satellite data (i.e., weather, crop phenology and growth, and cultivar characteristics). Details on the variables considered are provided in Table 2. The RF model evaluated which predictor variables are associated with the intensity of residue burning. Variable importance and partial dependency plots were utilized to rank predictors and characterize the association between the most important predictors and rice residue burning. We also identified important interaction relationships between variables using interaction and two-way interaction strengths based on H-statistics.

Table 2. Variables Included in the Random Forest and regression analysis. All analysis were conducted for the year 2018-22

Dependent Variable	**Variable description**		**Regression specification**	**Source**[1]
Burn intensity	Remotely sensed derived value of the number of rice residue burning occurrence in October and November		F_{ty}	FIRMS
Independent Variables	**Variable description**	**Pathway to impact burning**		**Source**
Rainfall in harvest period	Total rainfall in the 2-week period before and after harvest in mm	Moisture in soil and residue	$Rainfall_{ty}$	CHIRPS
Rainfall intensity in harvest period	Average rainfall rate on “wet days” (R ≥ 1mm), measured in mm/day, in the 2-week period before and after harvest in mm	Efficacy and time to use *in situ* machinery	$SDII_{ty}$	CHIRPS
Monsoon start date	Rainfall start day defined as the first wet day (≥1 mm) from April 1st that receives at least the climatological 5-day wet spell amount in April–October, without being followed by a 10-day dry spell (receiving < 5 mm) in the following 30 days from the onset (Moron and Robertson, 2014).	Rice planting and time available for harvesting	$\beta_5 Monsoon_{ty}$	CHIRPS
Growing length of rice	Total number of days from rice green up to harvest	Period for field preparation, residue amount	Pl_{ty}	MODIS Vegetation Index Products (NDVI and EVI)
Maximum temperature in harvest period	Mean maximum temperature in the 2-week period before and after harvest in °C	Time available to prepare field	$Temp_{ty}$	CPC
Soil water index	Mean moisture condition at various depths in the soil in November	Soil type and estimate of soil water content	SWI_{ty}	CLMS
Incorporation machines[2]	Cumulative number of subsidies availed for super seeders, mb ploughs and	Availability of machinery	$Incorp_{ty}$	Government of Punjab,

	rotavators by that sub-tehsil upto that year			Department of agriculture
Mulching machines	Cumulative number of subsidies availed for happy seeders by that sub-tehsil upto that year	Availability of machinery	Mul_{ty}	Government of Punjab, Department of agriculture
Balers	Cumulative number of subsidies availed for balers upto that year	Availability of machinery	$Baler_{ty}$	Government of Punjab, Department of agriculture
1 Details on satellite data sources are provided in Supplementary Table S6 2 Details on machinery are provided in Supplementary Table S3				

3.2.2 Drivers of Burning using Regression Analysis

To assess the effect of key variables on the burn intensity of rice residue, F_{ty}we estimated the ordinary least squares (OLS) regression:

$$F_{ty} = \beta_0 + \beta_1 Mul_{ty} + \beta_2 Pl_{ty} + \beta_3 Incorp_{ty} + \beta_4 Baler_{ty} + \beta_4 Temp_{ty} + \beta_5 Monsoon_{ty} + \beta_6 SDII_{ty} + \beta_7 Rainfall_{ty} + \beta_8 SWI_{ty} + Tehsil_t + Year_y + \varepsilon_{ty} \quad (1)$$

Table 2 describes the variables in the regression. We include time and region fixed effects to account for unobserved location- or time-specific characteristics that might correlate with the independent variables of interest. We report robust standard errors to control for the effects of serial correlation of fixed order (Stock & Watson, 2008).

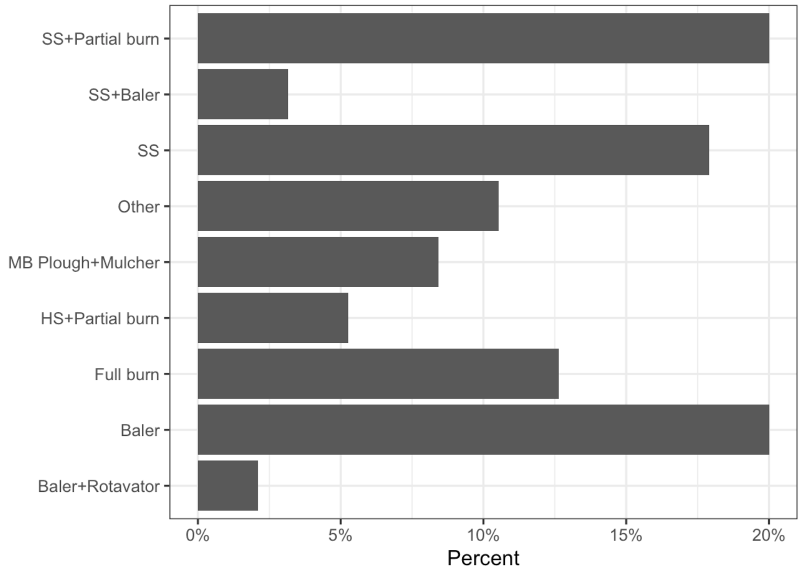
4. Qualitative Results

4.1 Residue Management and Burning Landscape

Our cluster analysis identified four unique trends of fire burning across the landscape; 90 farmers were interviewed from 10 sub-tehsils representing these four clusters (Figure 3). Participants were all male, aged 24 to 80 (mean = 42), and had landholding sizes ranging from 0.8 to 16 hectares (mean = 4 hectares). All farmers in the study cultivated rice as the primary crop in the Kharif season (the rainy season in the Indian subcontinent, also known as the monsoon season. It typically lasts from June to November) in 2024. Farmers cultivated different rice varieties, including short-duration PR-126, medium-duration PR 131, PR 128, PR 114 and HKR 47, and longer-duration, mainly PUSA-44 and reported switching varieties between years. Thirty-two percent of farmers also cultivated basmati rice. While almost all the harvesting was done by combines, 18% of farmers who cultivated basmati harvested manually. All the farmers selected for our interviews cultivated wheat in the Rabi season (the winter season in the Indian subcontinent it typically lasts from October to March), and 40% also cultivated vegetables, primarily potatoes. 25% of farmers also cultivated a third crop, primarily summer maize, mainly for livestock feed.

Farmers used diverse RRM practices. The most frequently used RRM practices included balers, happy seeders (HS), and super seeders (SS) (Figure 4). For individual farmers, RRM tended to vary by year with more than 80% of respondents reporting that they have a palette of options that they choose from, depending on factors such as weather, straw load, pests and labor availability. Sixy percent of farmers reported making decisions on RRM right before rice harvesting, while 40% reported deciding on the RRM method before they planted rice.

Figure 4. Residue management practices of farmers of the last three years reported in the semi-structured interviews (n=90)

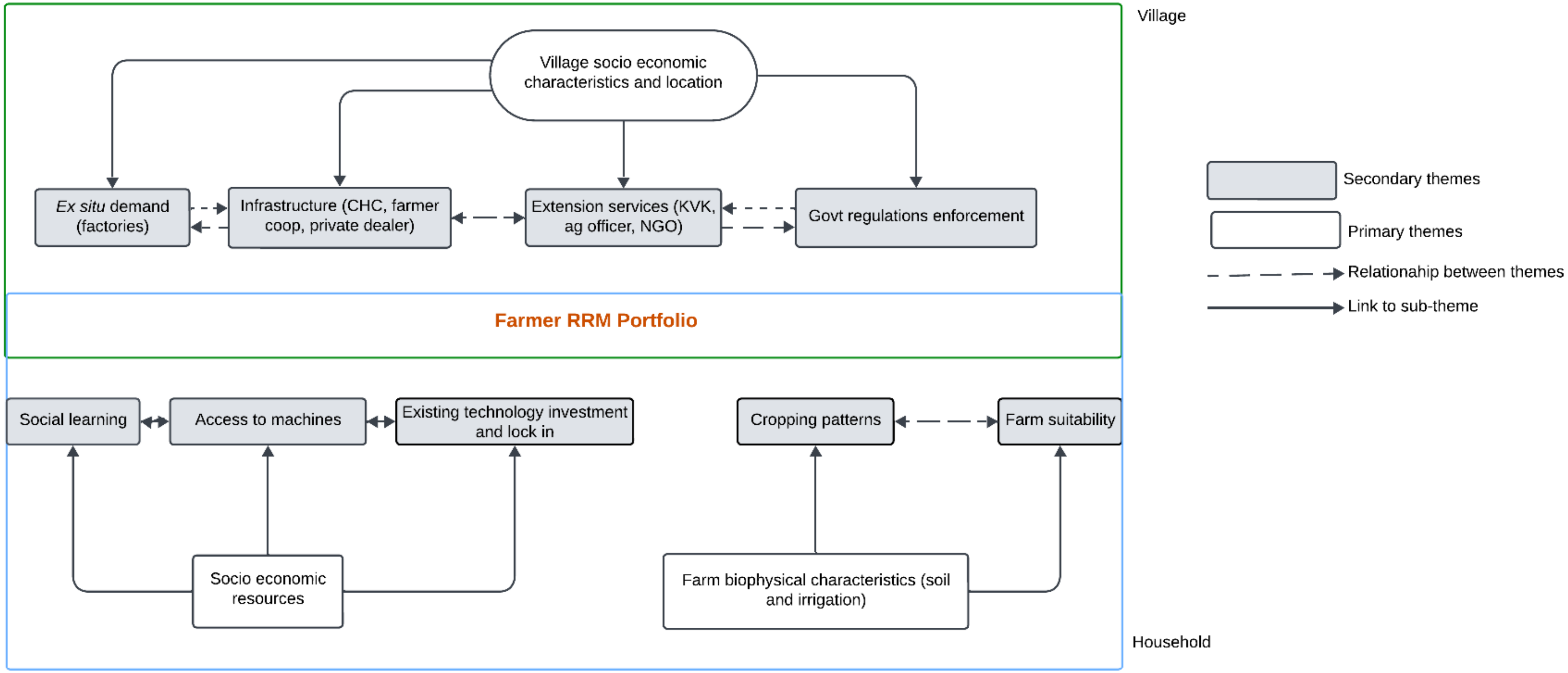


While less than one-quarter of the surveyed farmers reported full residue burning at least once in the last three years, 25% reported practicing partial burning before using *in situ* RRM machines. Partial burning entails burning the loose straw, estimated to be between 30-70% of the rice residue biomass accumulated in the narrow swathes of combine-harvested fields. Given the ban on burning, it is also possible that farmers under-reported their use of the practice. In our interviews, however, they did not hesitate to report partial burning practices, perhaps because they felt that it was much less harmful than full burning and hence should not be banned. Almost all farmers in our interviews (94%) were aware of the negative effects of burning on soil health (82%), human health (92%), and the environment (72%).

4.2 Multi-Scalar Influences on Adoption of RRM Practices

Using a thematic analysis of the in-depth interviews, we identified central factors associated with the adoption of different RRM practices (Tables S4 and S5). We mapped the themes associated with RRM adoption in Figure 5. Overall, the portfolios of practices adopted by farmers were similar within a village, particularly for farmers from a similar socio-economic class. Practices were generally determined by the regional availability of local infrastructure for the collection and transportation of residue and markets and the availability of machinery. Community knowledge of the practice, which influenced acceptance and trust in the technology, was also important in the local uptake of RRM practices.

Figure 5. Thematic Map derived from qualitative analysis (Tables S4 and S5) displaying themes and relationships between themes related to farmers' adoption of rice residue management methods. The map displays the main themes at the household and landscape level.



Ex situ residue management was common in regions close to major urban areas with good roads and proximate bioenergy plants, leading to a higher demand for rice residue from factories. In some regions, farmers sell residue to tribes known as Gujjars, who feed their cattle rice residue; however, the demand is limited. Farmers in areas with a greater concentration of government agricultural extension agencies, called Krishi Vigyan Kendra's, generally had improved access to knowledge and RRM machinery. Farms closer to major urban centers also reported being more closely monitored and frequently fined for residue burning, which is a deterrent.

In addition to regional factors, household factors such as financial resources were identified as important in determining farmers' RRM portfolios (Figure 5). Although the state heavily subsidizes RRM machinery, farmers have to make an upfront payment, restricting access to relatively poorer farmers. Furthermore, certain RRM machinery, such as super seeder, are heavy and require more powerful tractors. A 55-horsepower (HP) tractor costs upwards of 5,000,000 INR ($6,000 USD) and purchase subsidies on these are not provided by the government.

Most farmers who did not own a machine preferred to hire machines. While state-supported rental agencies called custom hiring centers (CHCs) provide government-subsidized machine rentals, these machines are reportedly often poorly maintained and unavailable. For this reason, most farmers who do not own RRM machinery prefer to hire machinery or machinery services directly from other farmers. More than 80% of farmers in our interviews who owned *in situ* RRM machines rented them out to fellow farmers. There was generally high demand for a limited number of machines during harvest, with priority given to wealthier farmers with more social leverage in the village.

Wealthier farmers with larger landholdings and connections to agricultural extension officers were also more likely to be the early adopters of new technologies, testing new machinery first in one part of their field before fully adopting it across all fields. These "progressive" farmers were often the first to become aware of new technologies, availability of subsidies and test machines, best practices, and nuances of technology usage. Further, these farmers had financial resources to afford complementary technology and associated fuel costs. Additionally, smaller farmers reported learning new residue management practices primarily from other farmers rather than government or university sources.

For example, out of 90 farmers interviewed only four farmers in our interviews who had larger land holdings and self-identified as progressive farmers used a combine harvester equipped with a Super Straw Management System (SMS). The SMS machine which is recommended for usage before the operation of *in situ* residue management machinery cuts and spreads straw uniformly across the field, increasing the efficacy of *in situ* residue management technology and reducing the need to burn residue partially. Farmers with smaller landholdings were unaware of the benefits of the SMS as an enabler for other *in situ* management technologies. Furthermore, the SMS machinery has been shown to be unsuitable for small landholdings (N. Kumar et al., 2023).

Farmer preferences and perceptions of field aesthetics played an important role in determining their choices of RRM techniques. Some farmers strongly preferred cleared fields and perceived fields with surface residue mulching as "dirty" and associated with increased diseases, rodents, and weeds. Farmers also perceived that residue incorporation increased pests, particularly pink stem borer, and more than half of the farmers who used *in situ* RRM felt that they had to use more pesticides. Of course, that also implies added out-of-pocket costs, as pesticides are expensive.

Existing cropping patterns also impacted farmer preferences for RRM. For example, farmers who cultivated potatoes and other vegetables as a third crop between Rabi and Kharif or as a Rabi crop removed residue through baling rather than managing it *in situ* using machinery such as SS and HS, which do not accommodate direct vegetable planting.

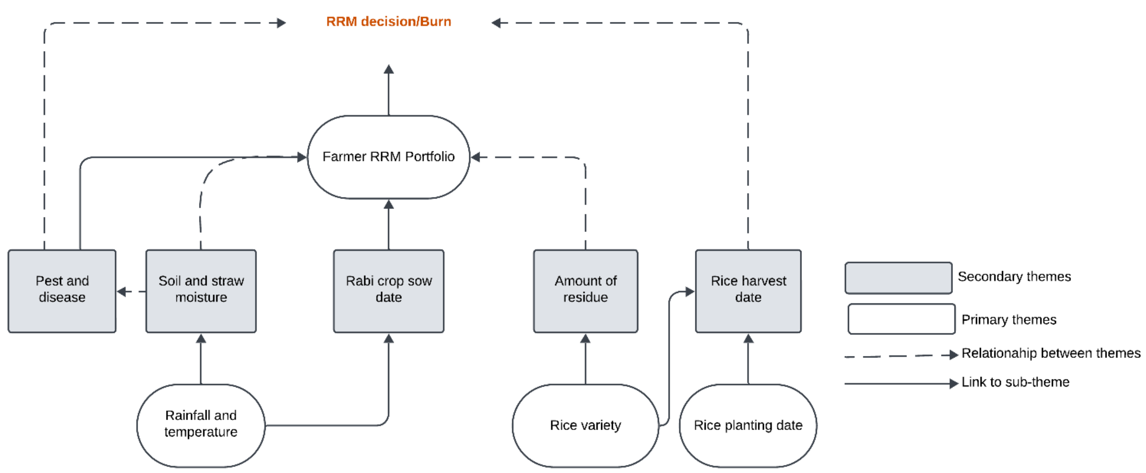
Field biophysical characteristics, such as soil texture, influenced farmers' RRM preferences. Farmers with heavier-textured loamy soil preferred *in situ* residue incorporation (e.g., with Super Seeder) to accelerate drying, while farmers with sandy soil preferred mulching (e.g., with Happy Seeder), which they reported helped maintain moisture in the soil for longer.

Existing technological investments impacted the RRM choices available to farmers, especially in regions with large individual ownership of RRM machines. Farmers were reluctant to shift quickly to newer technologies despite the evident shortcomings of existing technologies. For example, long-term usage of SS has been reported to increase sub-soil compaction; Punjab Agricultural University, the main agricultural university, and state knowledge partner, has recommended that farmers shift to the smart seeder, a newer technology that uses strip tillage and has proven benefits over HS and SS (Manpreet-Singh et al., 2024). However, farmers reported that they had already invested in super seeders and could not shift easily.

4.3 Seasonal Residue-Burning Decisions

Most farmers reported a flexible approach to residue management that changes by the production year. Only 15% of farmers in our sample reported completely stopping all burning practices for the last three years, whereas 40% of farmers reported practicing some form of burning along with other residue management practices in the same period. This suggests that access to RRM alternatives is insufficient to ensure farmers won't burn rice residues.

Figure 6. Thematic Map derived from qualitative analysis (Tables S4 and S5) displaying themes and relationships between themes influencing farmers' seasonal RRM practices and residue-burning practices



Farmers reported that seasonal weather factors impacted decisions to burn both directly and indirectly (Figure 6). Rains during the rice harvesting period can delay operations, reducing the time available to prepare fields for wheat. Untimely rainfall can also affect *ex situ* management. Factories do not accept residues with high moisture content. Intense rainfall also influences the *in situ* management of rice residue; SS and HS do not function well with wet residue and wet conditions can prevent field access for machinery Particularly in fields with clayey soil more prone to water logging. Temperature was also identified as an important seasonal factor affecting RRM decisions. Farmers associated increased temperatures during early winter with increased odds of higher temperatures during the grain-filling period, and therefore often prioritized burning in these situations to ensure timely wheat establishment. Farmers regarded residue burning as vital to controlling diseases and pests, especially the pink stem borer. Many who retained residue and experienced a rise in pests opted to burn residue to tackle these issues in subsequent years. Additionally, farmers reported that higher temperatures in early winter increased the occurrence of pests, prompting residue-burning practices.

Rice varieties also play a significant role in shaping residue management strategies. Shorter-duration hybrid rice cultivars such as PR-126 produce less crop residue and matures in 90 to 95 days after transplanting, attributes that decrease incentives to burn residues. However, farmers perceived lower overall yields, difficulties in accessing seed, and lower recovery fractions during milling. On the other hand, longer-duration rice varieties, like Pusa 44, yield higher amounts of grain and are favored by local rice mills, yet they generate more crop residue. Many farmers growing these longer-duration varieties have reported engaging in partial residue burning in combination with RRM machinery. This is necessary because these machines struggle to handle the large volumes of straw produced particularly without the use of SMS during harvesting and must operate within a narrower timeframe to ensure timely wheat planting.

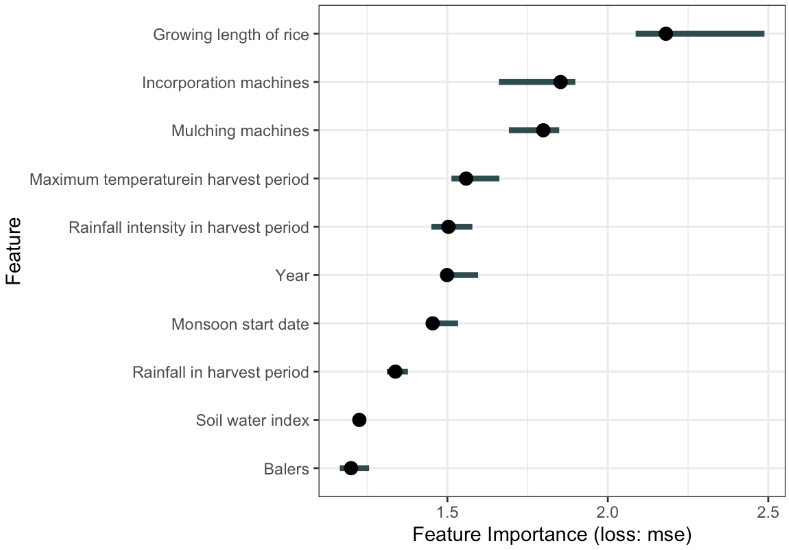
5. Quantitative results

5.1 Testing burning decision variables with random forest

Using our qualitative analysis to identify main variables (Figure 6 and Table 2), we then quantify their influence on residue burning using an RF model. About 70% of the variance in cumulative burning intensity at the sub-tehsil level was explained by this model (out-of-bag prediction (OOB) R^2) with an average OOB prediction error (root mean squared error, RMSE), i.e., of 0.01, about 60% of the mean fire intensity per area of rice cultivation. The linear fit (R^2) of the observed values versus the predicted values was 79 % (Figure S5).

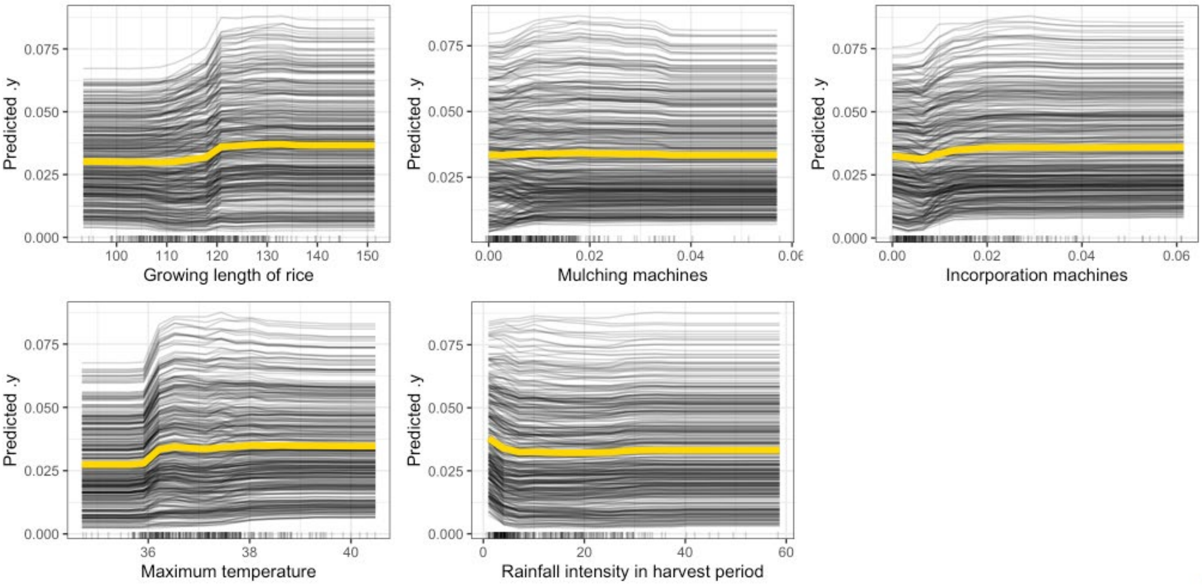
The variable importance plot (Figure 7) shows that rice growth duration, is the most important variable contributing to the overall prediction of the intensity of burning measured by the mean decrease in the Gini coefficient followed by mulching machines, incorporation machines and maximum temperature in harvest period. The mean decrease in the Gini coefficient measures how each variable contributes to the homogeneity of the nodes and leaves in the resulting random forest (Martinez-Taboada & Redondo, 2020).

Figure 7. Variable importance plot of random forest model to predict burn intensity. Units are the increase in mean square error (MSE) if the predictor were randomized.



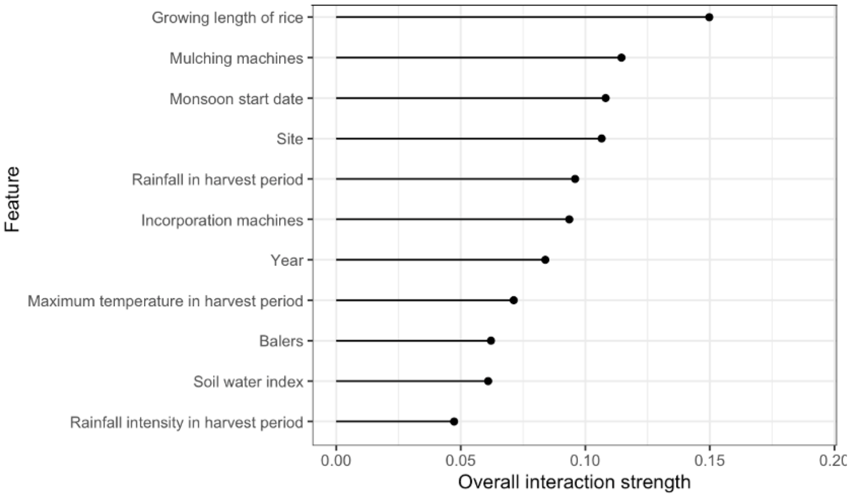
In Figure 8, we present partial dependency plots to describe the relationship between fire intensity by rice cultivated area and the five most important predictor variables, holding all other predictors at their median values. Figures 8 panel A and D show an increase in burning associated with rice growing lengths greater than 115 days and temperatures greater than 36 degrees Celsius during the harvesting period. We also find a non parametric relationship between mulching machines and incorporation machines on burn intensity, although this effect is not pronounced.

Figure 8. Partial dependency plots of the top 5 variables in the random forest model to predict burn intensity. Note that "Predicted .y" indicates the number of predicted fires normalized to rice cultivated area (burn intensity based on the values of the predictor variable model)



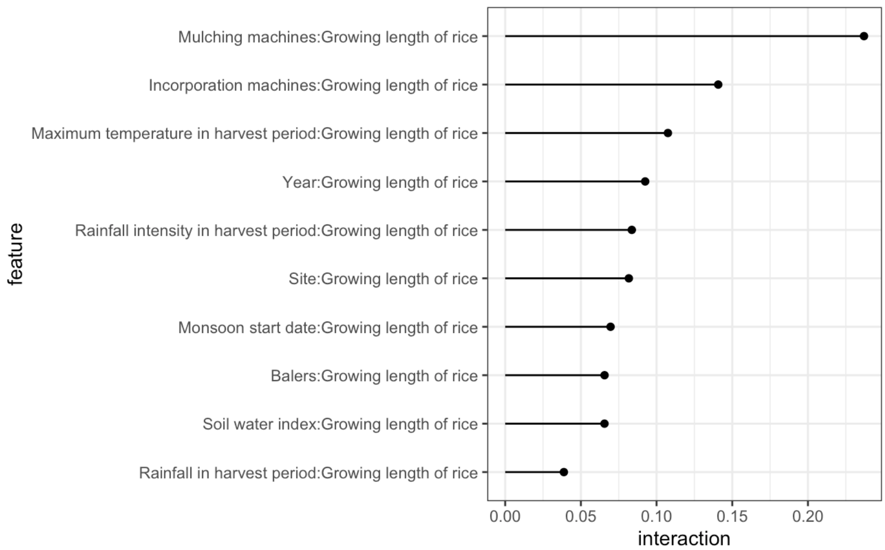
Our qualitative results indicate that bio-physical conditions and crop management strategies in the region moderate the effects of *in situ* residue management machinery. We capture these interactions in our RF model, using the feature interaction strength measured by the H-statistic, which tells us whether and to what extent a feature interacts in the model with all the other features (Figure 9). Overall, we find that rice growing season duration explains more than 20% of the variance in the model, indicating a strong interaction effect.

Figure 9. The interaction strength (H-statistic) for each feature with all other features for the RF model predicting residue burn intensity. The growing length of has the highest relative interaction effect with all other feature



We further explore the nature of these interactions by calculating the two-way interactions between the growth duration of rice and all other variables in the model (Figure 10). Two-way interaction measure that tells us whether and to what extent two features in the model interact with each other. Figure 10 shows strong interactions between the growing length of rice and mulching machines (greater than 20% of the variance).

Figure 10. 2-way interaction strengths (H-statistic) between the growing length of the rice and each other feature.



Following indications of strong interactions between rice growing length and *in situ* residue management machines, we use two-way interaction plots to describe the relationship between key interaction terms identified. Figure 11 shows that the positive impact of *in situ* machinery on burning intensity is more pronounced for rice with a growing length greater than 115 days.

Figure 11. Two-way interaction plot showing the change of burn intensity (y hat) of in situ residue management machines A) Mulching and B) Incorporation with change in growing length of rice.

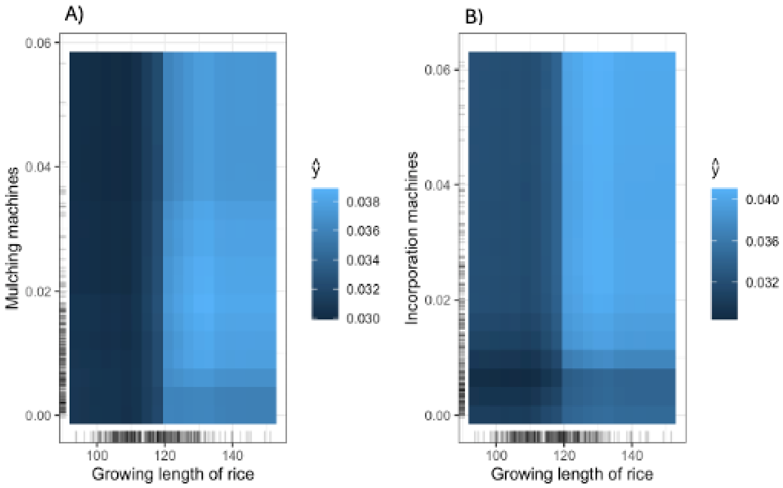


Table 3. OLS estimates of factors associated with residue burning intensity. We report beta coefficients and standard errors clustered by sub-tehsil for each variable. Diagnostic statistics appear at the bottom of the table.

	(A)	**(B)**
Mulching machines	0.518*	−0.240
	(0.213)	(2.732)
Incorporation machines	0.00132	-0.2396
	(0.978)	(0.686)
Balers	−3.728	-3.758
	(0.287)	(2.417)
Total rain during harvest period	1.0440**	1.0940**
	(0.002)	(0.002)
Rainfall intensity in harvest period	-9.0498***	-9.180***
	(0.000)	(0.000)
Soil water index	4.416***	4.446***
	(0.000)	(0.000)
Maximum temperature	86.8304**	89.89***
	(31.514)	(0.004)
Monsoon start date	−5.735	−4.224
	(6.064)	(5.876)
Growing length of rice	0.8719***	0.738***
	(0.008)	(0.001)
Growing length of rice: Mulching machines		0.013
		(0.4265)
Growing length of rice: Incorporation machines		0.0021
		(0.6591)
Num.Obs.	329	329
R^2	0.181	0.183
R^2 Adj.	−0.088	−0.094
AIC	4386.9	4390.0
BIC	4424.8	4435.6
RMSE	184.50	184.26

5.2 Regression Results

Following equation 1, Table 3 presents the OLS regression estimates of key variables' association with fire burning intensity. In the first OLS regression, we do not include interaction terms. In the second regression, we include interaction terms identified as important in the RF model.

In the OLS regression model, without interaction terms (Table 3 column A), the number of mulching machines is positively associated with residue-burning intensity. A unit increase in mulching machines was associated with an increase in almost 0.518 fire incidences. The mean growing length of rice was also positively associated with the intensity of residue burning, with one extra day of growing associated with an almost proportional increase in fires in the sub-tehsil. Temperature also had a large, positive, significant association with the number of fires, with each additional one degree Celsius associated with an increase of nearly 87 residue-burning incidences. We also find that seasonal rainfall is significantly associated with residue burning. We find that total rainfall increases fire burning with one unit increase in rainfall, proportionally increasing residue burning incidences and soil water index, which measures the amount of water in the soil, was positively and statistically significantly associated with residue burning. Further, we found that rainfall intensity was negatively associated with residue-burning incidences, with a one-unit increase in intensity associated with a reduction of nearly ten residue-burning incidences. This could be associated with reduced farmers' ability to burn. Alternatively, increased rainfall intensity in that period could cause increase cloud cover, which impedes satellites' detection of fire-burning incidents (Schroeder et al., 2008).

In column B of Table 3, we include interaction terms identified as important by the RF model. Specifically, we interact with the mean growing length of rice with incorporation and mulching machines. We find that mulching and incorporation machines have no significant association with residue burning when the growing length of rice is zero. However, the interaction between the growing length of rice and total mulching machines and the interaction between the growing length of rice and total incorporation machines is positive but not statistically significant.

Similar to the RF model our OLS model highlights the effect of the growing length of rice of on fire intensity. We do not find a strong effect of *in situ* residue management machines in the OLS regression. Further the OLS regression is unable to capture the non linear interaction effect of *in situ* machines and rice growing length. This emphasizes the importance of RF based approaches in understanding complex systems (B. Liu et al., 2020).

6. Discussion

Crop residue burning in the Indo-Gangetic Plains is a serious issue that threatens environmental sustainability and human health. This study uses a mixed-methods approach to unpack why, despite various interventions, this practice remains prevalent in Punjab, one of the hotspots of residue burning in India. We first use in-depth qualitative interviews to identify important factors influencing farmers' uptake of RRM strategies and their residue-burning practices. We then conduct a quantitative analysis using a Random Forest model and

OLS regression analysis to test and quantify drivers of seasonal residue burning. The mixed methods approach offered an opportunity to draw from the strengths of both quantitative and qualitative research approaches. Our qualitative analysis allowed us to explore why farmers continue to burn residue, integrating farmers' perceptions and beliefs to unpack complex decision-making processes (Östlund et al., 2011), while the quantitative analysis allowed us to triangulate our findings and provide more generalizable insights into seasonal residue burning practices across years (Ahmadi et al., 2022).

Our qualitative analysis highlights the diversity and complexity of farmers' residue management practices, emphasizing the role of landscape and household factors in shaping residue management strategies. While regional factors, including infrastructure, institutional extension services, and enforcement of laws against residue burning, shaped the residue management landscape, farmers' options for residue management were restricted by household socio-economic characteristics, including wealth and social agency. Wealthier farmers with larger landholdings had timely access to the most current technologies and had knowledge of the most appropriate use of technologies; poorer farmers faced barriers in their adoption and efficient usage of technologies. These findings support scholarship on the role of social and economic inequality in mediating access to technology and raise the question of whether interventions built upon existing social, political, and economic inequalities will only deepen unequal outcomes (Jarosz, 2014; Keil et al., 2016; Khoza et al., 2022).

The government's efforts have resulted in a diverse landscape of residue management options available to farmers; our study finds that farmers select residue management practices congruent with their farm, including cropping patterns and local field conditions such as soil. However, they are also influenced by beliefs and perceptions that are not always factful. For example, commonly held biases against the surface retention of straw impacted the adoption of surface mulching machines despite evidence that mulching can improve soil quality and productivity (Erenstein, 2002; Keil et al., 2015).

Emerging research has shown that trust, attitudinal, and normative barriers are prominent psychological hindrances to innovation adoption among farmers (Chindasombatcharoen et al., 2024) and are often unaddressed by the unidirectional knowledge model prevalent in the global south (P. K. Joshi & Chandra Babu, 2019; Krishnapriya et al., 2024). Clear and sustained access to expert knowledge, including participatory research with localized and demonstrated evidence and education on the efficacy of machinery for their local conditions, can help farmers navigate the diverse options available to them (David et al., 2022; Takahashi et al., 2020).

Farmers demonstrate relative nimbleness in their residue management practices, regularly switching between practices, including burning, in response to seasonal factors. This "portfolio effect," where farmers diversify their practices in an environment of unpredictability and complexity, has been observed in other farm management practices (Burbano-Figueroa et al., 2022). Farmers' management choices, such as rice varietal and seasonal bio-physical characteristics, such as weather, played a significant role in residue burning patterns. Importantly, we found that these variables mediate the usefulness of RRM machinery for reducing residue burning.

This study's evidence shows that the incongruity between new technology and prevailing farmer practices can seriously impede attempts to reduce residue burning. For example, longer-duration rice generates more residue, impacting the efficacy of *in situ* residue management machinery. While the government has widely promoted shorter-duration varieties of rice, farmers still prefer long-duration varieties primarily because of their perceived higher yield and opt to partially burn residue before using *in situ* RRM machinery. Our findings highlight the negative consequences of promoting technology apart from local contexts and reiterates the need for appropriate incentives and technology bundling considering dependencies, complementarities, tradeoffs, and local conditions (Abay et al., 2018; Wainaina et al., 2016). Agricultural improvements adapted to the context of smallholder farming systems, considering the region's agroecological, socio-cultural, economic, and institutional dimensions, have shown to be more widely adopted and efficacious (Descheemaeker et al., 2019; Guto et al., 2012).

Notably, weather factors, including rainfall and temperature, emerged as important drivers of seasonal residue-burning practices. While other studies have identified the importance of weather for air quality as affected by residue burning, no studies have acknowledged the effect of weather on residue-burning practices (Agarwala & Chandel, 2020; Ravindra et al., 2019; Sembhi et al., 2020). This is a significant omission, given the large effect of weather documented in our study.

Temperature had a relatively large positive impact on seasonal residue burning; farmers proactively adapted to higher temperatures by planting wheat earlier to protect the Rabi crop from terminal heat stress, possibly burning rice to shorten the field preparation time. This finding has potentially serious implications. As climate change increasingly leads to shorter winters and earlier commencement of summer in India, increasing terminal heat stress and affecting wheat production (Dubey et al., 2020), farmers will potentially adopt maladaptive solutions such as residue burning with adverse environmental, social, health, and well-being impacts. Further, the indirect effects of higher temperatures, including increased pest loads, could be motivating farmers to burn residue.

Rainfall during the harvest period and water retention in the soil during that season also impacted burning practices significantly. Studies show that wet rice residues restrict the operation of sowing machines (Happy Seeder and Super Seeder) into rice residues, as wet residues do not slide on furrow openers/tines (Manpreet-Singh et al., 2024).

6.1 Policy Implications

We use insights identified from our research to suggest long and medium-term policy avenues to facilitate permanent transitions to no-burn residue management strategies as well as short-term tactical solutions that may limit the frequency of burning.

6.1.1. Short-Term: Burning Hotspots and Tactical Solutions

Our study identified important seasonal factors that significantly increase the probability of burning. Satellite mapping of crop management practices, including sowing dates, rice varieties, seasonal weather factors, and real-time monitoring, can help identify regions with the highest risk of burning in a particular season. In the short term, to prevent burning in that season, rapid deployment of crop residue collection, payments to deter burning, and fines against farmers who burn crop residue can help alleviate immediate risks from burning. While tactical responses have typically focused on punitive action against farmers (Pati, 2024), payments for farmers and alternate arrangements to manage residue have shown to be effective in reducing burning (Jack et al., 2025).

6.1.2. Medium-Term: Improving Residue Management Options

In our study, almost all farmers wanted the option of *ex situ* residue management; however, local infrastructure was lacking, including bioenergy and biochar plants, balers and storage infrastructure (Kurinji & Kumar, 2021). While a concerted effort from the government to develop a supply chain and build infrastructure can provide this option for more farmers, adequate attention should be paid to the costs and benefits associated with developing *ex situ* residue management to ensure fiscal viability (Kurinji & Kumar, 2021).

In addition to investments associated with residue management costs, *ex situ* residue management has been discouraged as residue removed from soils can decrease soil quality (Klopp & Blanco-Canqui, 2022). However, in our interviews, farmers expressed a preference for alternating years when practicing *ex situ* and *in situ* management techniques to control pests and disease loads while minimizing the negative effects of *ex situ* practices on soil. Further, as rainfall can impact the moisture content and quality of straw, affecting their usability, *ex situ* alone cannot be reliably used as the only residue management strategy.

Punjab has prioritized *in situ* management of residue by aggressively promoting machinery through campaigns and subsidies; this has been largely successful in increasing the number of machines, and studies show that Punjab currently has sufficient *in situ* residue management machinery to manage all its rice residue (Kurinji & Kumar, 2021). However, increased availability has not significantly reduced residue burning, suggesting a re-evaluation of this model.

Technologies require infrastructure and investment, and switching from incumbent technologies to new ones is challenging. Hence, it is important to reduce technology turnover by designing and promoting suitable and appropriate technologies for the local ecosystem's ecological and agronomic context (Jackson-Smith & Veisi, 2023). The development of new *in situ* residue management machinery should focus on increasing fuel efficiency and suitability with lower HP tractors, further machinery should be first tested on local farmers' fields with farmers in a participatory manner to understand their impacts on multiple short and long-term outcomes, including yield, pests and diseases, soil, economic costs, their suitability to farmers' existing practices, and nuances of their usage before wide-scale promotion (Le Gal et al., 2011).

Further, farmers' opinions and preferences should be considered when designing new technologies, and emerging misconceptions and apprehensions should be addressed through targeted campaigns and two-way communication channels between experts and farmers. Farmers should also be provided information on standard operating procedures and best practices about machinery suited to their farm management practices and field conditions. One avenue to do this can be by strengthening the service economy for *in situ* residue management machinery; increasing the availability and maintenance of machinery can improve access to machinery, particularly for small farmers. Further, the service economy should be equipped to provide information on best practices and machinery suitability for farmers.

Our study strongly highlights the need to shift to shorter-duration rice varieties along with the promotion of *in situ* machinery. The policy should focus on phasing out longer-duration varieties of rice, such as PUSA 44, likely using a combination of regulations and incentives. Farmers in our study reported reluctance to shift away from longer-duration varieties due to perceptions of associated yield penalties while cost of cultivation is only slightly higher due to free electricity for irrigation and no charges for groundwater extraction (K. Joshi et al., 2018; Dhillon et al., 2018). Charging farmers for electricity to externalize these costs may be politically untenable (Singh, 2009), but providing farmers with payments to compensate for profitability losses could help farmers shift to shorter-duration varieties (Kaur & Pollitt, 2024). Communicating the agronomic specifications required to maximize yield and addressing farmers perceptions may also contribute to increased uptake of shorter duration varieties among farmers (Dhillon & Gill, 2024).

While subsidies have increased the spread of RRM technologies, timely access to appropriate RRM technologies remains an issue, particularly for farmers with limited resources. Models for formalizing the rental market for RRM machinery has been piloted in the state using an app called i-Khet; however, farmers still need to be made aware of the app, with only 10,000+ downloads as of September 2023 (Kurinji & Kumar, 2021). Increasing the app's visibility, adding features for farmer-to-farmer rental, and incorporating a more user-friendly interface could improve the app's uptake and inclusive machinery access. Further, in addition to *in situ* machinery, higher HP tractors should be made available to rent at a subsidized rate to facilitate the usage of machines. Additional subsidies and support should be given to small farmers who may otherwise lack the resources to access machines (Erbaugh et al., 2024). Demand side subsidies in the form of vouchers for machinery rentals and conditional cash transfers to not burn maybe more effective than capital subsidies on machinery (Caunedo & Kala, 2021; Jack et al., 2025)

6.1.3. Long-Term: Shifting to Sustainability and Resilience

Climate change is already causing increases in temperature in the rice and wheat growing seasons and a decrease in total monsoonal rainfall in Punjab (Kurinji & Kumar, 2021). Farmers adapt to these changes by increasing irrigation, depleting already scarce groundwater, and sowing wheat earlier, thereby shortening the period for field preparations and providing incentives for residue burning to narrow the gap between rice harvest and wheat sowing. Foundational changes in farm management practices may be required to address these issues. One of those could lie in adopting rice cultivation methods such as direct seeding of rice (DSR), which dramatically reduces water requirements for crop establishment thereby reducing pressure on groundwater systems and permitting earlier crop establishment without threatening conservation goals. However, while DSR is an attractive option, further research is required to address some of the common risks associated with DSR, including increased weeds and soil nutrient disorders (V. Kumar & Ladha, 2011; Mahajan et al., 2013).

Another possible solution could be crop diversification away from the dominant rice-wheat cropping system. While this solution has been proposed in the past, the centrality of staple crop production in Punjab for national food security has prevented progress. However, recent studies show that several other regions in India, including the Eastern Gangetic Plains and Central India, have the potential to increase rice production and yields (Downing et al., 2022; Hoda et al., 2017; Nayak et al., 2024). Significant support mechanisms, including state-assured procurement, real time minimum support prices, and input subsidies to ensure the risks of diversification are not entirely borne by farmers, are needed to convince farmers to shift cropping patterns (Downing et al., 2022). Finally, political and institutional influences promote the persistence of the existing rice-wheat system. This includes minimum support prices for both rice and wheat and the provision of free electricity for irrigation. These factors have resulted in a disconnect between production and demand, as well as between the drivers of both production and demand from environmental and market influences (Downing et al., 2022). These complexities will need to be taken into account in the promotion of diversified cropping in the region.

7. Conclusions

Despite government efforts and multiple technical interventions, rice residue burning continues in India. After almost a decade of investment, it is clear that 'one size fits all' technical solutions are insufficient, and strategies that embrace bio-physical and socio-economic diversity are required. We use a multi-scalar mixed methods approach to present insights into critical leverage points to reduce residue burning in Punjab, India.

First, farmers will choose residue management practices based on structural and institutional factors, their socio-economic resources, and the bio-physical conditions of the field. However, they remain biased toward certain residue management strategies based on perceptions and beliefs. Secondly, we find that incompatibility between *in situ* residue management machines and farming practices, particularly the variety of rice cultivated and harvesting methods, have contributed to their ineffectiveness in stopping burning practices and may instead have led to a shift to partial burning. Thirdly, poorer farmers remain disadvantaged in their access to *in situ* machinery and the knowledge and resources required to use the machinery, including tractors and fuel and complementary technologies. Finally, we find that farmers' residue management practices and burning practices are responsive to seasonal factors, including temperature and rainfall during harvest, and farm management practices, including the variety of rice cultivated and subsequent delays in harvest.

Our research uses qualitative methods based on in-depth interviews with 90 farmers, who were selected to represent different spatial and temporal clusters of fire-burning patterns across Punjab. In addition, we conducted interviews with approximately equal numbers of small, medium and large farmers. These methods capture important variations in farmer perspectives across key analytical variables but do not necessarily represent the broader population distribution. Future research should include a larger sample of farmers and capture the changing perspectives of farmers through time. Further, we did not unpack market and political factors that influence residue-burning practices; future studies should focus on the region's political ecology.

While we attempted to quantify all variables identified in the qualitative analysis, data on some variables were not available and were omitted from the analysis**.** These include direct information on pests and diseases. Further, we do not have direct information on *in situ* residue machinery usage and instead use subsidies availed for *in situ* machinery as a proxy. This may fail to capture actual utilization of machinery and possibly dis-adoption of technology. We were also unable to quantitatively test the qualitative hypothesis on the themes related to farmers' adoption of rice residue management methods due to data limitations.

For our quantitative analysis, we relied on secondary data, including spatial data, to measure fires, crop growing patterns, and weather. Satellite data have their sources of biases and errors, which could lead to biased inference (Jain, 2020). Importantly, we cannot discern the levels of fire burning, whether partial or complete, from satellite data, leading to uncertainty in inferences on the effects of interventions on residue burning behavior (T. Liu et al., 2020). Ground truthing with large-scale surveys that capture residue management practices could help alleviate this issue. Finally, our study focuses on factors associated with burning and does not provide causal estimates. Future studies must focus on causal estimates of the drivers of residue burning.

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CRediT author statement

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Supplementary Materials

Table S1. Punjab cropping profile, wheat and rice remain the primary crops cultivated in the region

Kharif	**Area* *(in lakh hectares)***	**% share**	**Rabi**	**Area*(in lakh hectares)**	**% share**
Rice	30.20	86.78	Wheat	35.24	97.86
Cotton	2.43	6.98	Mustard	0.43	1.19
Maize	1.03	2.97	Total**	36.01	100.00
Sugarcane	0.89	2.57	**Five-year-average from 2019-20 to 2023-24 **Includes other crops. Source: Department of Agriculture & Farmers' Welfare.*		
Total**	34.81	100.00			

Figure S1. Residue burning incidences by year per unit area by sub-district obtained from Visible Infrared Imaging Radiometer Suite (VIIRS) remotely sensed fire observations during rice harvest season in Punjab

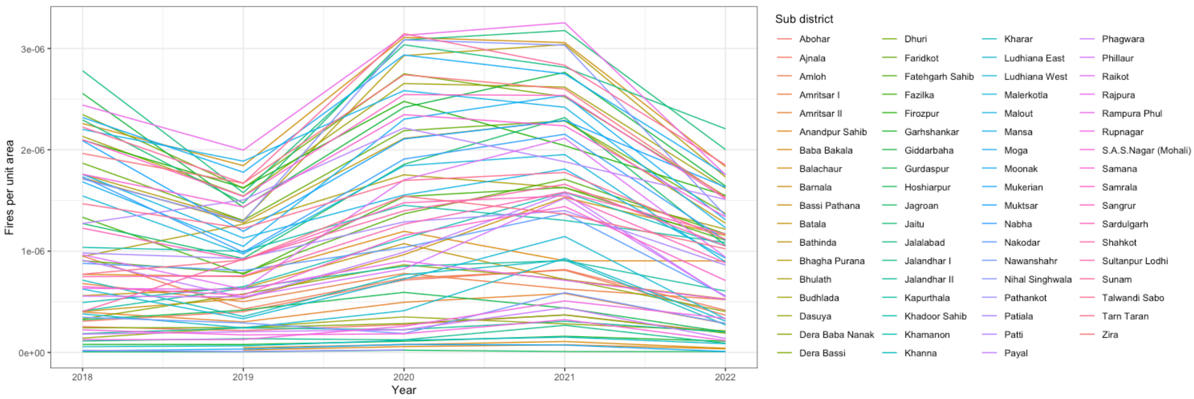


Figure S2. Machinery subsidies by sub tehsil

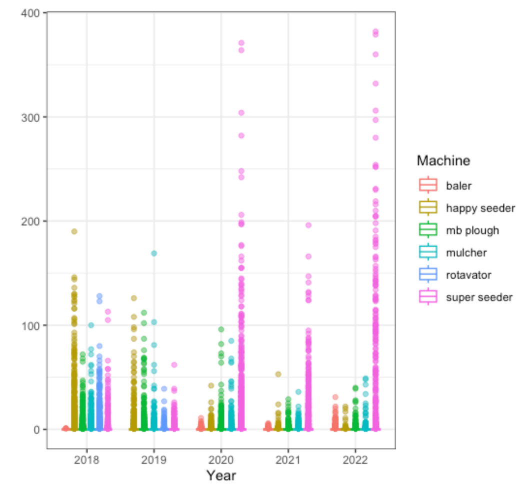


Table S2. Topic guide for semi- structured interviews

Topic	**Specifics**
Farmer demographic and socio-economic data	Farmer age, gender, education, alternate sources of income
Farm and crop information	Farm size, soil type, crop type, crop calendar, yield
Residue management practices currently employed and employed in the past	Practices followed, machinery used, perceptions of practices
Factors influencing residue management decisions	Socio-economic, institutional, environmental, bio-physical farm characteristics
Residue-management perceptions, priorities, and beliefs	Effects on crop yields, pests and disease, field soil, and water characteristics
Residue-burning behavior, knowledge of externalities, and perceptions of government measures	

Table S3. Description of *in situ* straw management machinery

RRM machine	Specific functioning	Requirements	Description	Potential advantages	Potential drawbacks
Happy seeder (Mulching machine)	Sows of wheat in untilled field with anchored and loose residue after uniformly placing and pressing chopped rice residue in inter row area as mulch	Tractor required: 45 HP tractor Capacity: 0.2-0.3 ha/hr Cost: >1500 USD	It is an active type seeding machine having flails at the front and seeding attachment at rear.	Fewer field operations Reduced need for pre sowing irrigation	Inefficient under moist residue condition Low field capacity compared with conventional seed drills Increased pests and rodents Poor germination of seeds under heavy straw load Lesser efficacy of herbicide Buildup of weeds seed bank in upper soil layer
Baler	After usage of cutter and raker tractor mounted baler collects rice residue and compresses in to rectangular or spherical bales which are transported	Tractor required: 45 HP Capacity: 0.3-0.45 ha/ hr. Cost: >a1200 USD	Gathers windrows of cut residue, feeds them through a chamber where they are progressively compressed by belts and rollers, and then	Higher capacity Can manage large amounts of residue Reduced pests and vermin	Expensive and not easily available for rent Requires additional field operations Requires additional equipment including trolleys and loaders Requires labor to remove the baled straw from the fields
Super seeder (Incorporation machine)	A rotavator with the provision of drilling seed and fertilizer	Tractor required: 50 HP Capacity: .03-.04 ha/hr Cost: >3500 USD	Consists of rotavator and zero till drill for managing the rice residue and sowing of wheat respectively	Fewer field operations seeder Less tillage intensive compared to conventional tillage machines	High cost and higher fuel consumption Deprives surface of mulch cover Potential for uneven seed depth Higher maintenance costs Hardpan formation below the tilled zone affecting root growth and water infiltration.
MB plough (Incorporation machine)	Slicing, lifting, fracturing, and inverting the soil, burying crop residue, weeds and insects left on the field surface Usually followed by secondary tillage practices such as disking or harrowing.	Tractor required: 35 HP Capacity: 0.16-0.4 ha/hr Cost: >300 UDS	Has sharp steel bottoms with the point that inverts into the soil with pressure	Cheaper and easier to access Lesser maintenance cost Improve drainage and soil aeration in the short term	Hardpan formation below the tilled zone Erosion due to exposure of the topsoil Soil can lose its aggregate structure and eventually be prone to reduced air and water movement, Soil crusting occurs after multiple rainfall events that hinder water infiltration. The need for subsequent secondary tillage operations.
Rotavator (Incorporation machine)	Designed to break up and turn over the soil, are used to till the soil and incorporate crop residues into the soil	Tractor required: 30 HP Capacity: 0.4-0.6 ha/hr Cost: >200 USD	Consists of a blade that rotates and ploughs the land	Cheaper and easier to access Takes less time and less fuel consumption Beneficial for breaking up compacted soil	Disturb the soil extensively and can disrupt the soils ecosystem
Smart seeder (Mulching machine)	Strip tillage seeding system tills the land in narrow strips (7.5 cm wide) in front of the furrow opener only and places seed and fertilizer in rows at a right depth in a single operation leaving the inter-row with complete residue cover	Tractor required: 50 HP Capacity: 0.2-0.3 ha/hr		Can work in wet fields and with moist straw Manages rice straw and simultaneously sow wheat into heavy straw load Provides the lookj of a clean field	New technology that is unavailable to farmers

Table S4. Codes developed from thematic analysis of the transcripts of 90 semi-structured interviews conducted with farmers

Initial code	N of participants contributing	No of transcript excerpts assigned	Sample quote
Familiarity with technology	72	81	"Prefer this technology as it is regularly practiced in village"
No resources or knowledge of technology	64	68	"Have not heard of the technology" "Don't know how the technology works" "No availability of these machines in the village"
Training/demonstration received from KVK /Agricultural university	32	38	" Have been part of training given at the village KVK" "KVK officers have visited my field and given demonstrations" "I have seen the machine work in other farmers fields"
Availability of ex situ residue management	28	34	"Prefer balers because nearby factory picks up residue" "Easier for balers to pick up"
Lack of enforcement of rules against residue burning	45	52	"Officials do not monitor residue burning in this village" "Officials cannot fine us as we are supported by farmers group"
Lack of infrastructure for ex situ residue management	18	20	"There are no proper roads for bailing machines to access the village" "Bailing machines are not available in the village"
Financial resources to buy in situ residue management machinery	56	72	"We cannot afford the high cost of super seeders"
Lack of complementary infrastructure/machinery	43	46	"Super seeders are heavy and need high hp tractors which we cannot afford" "SMS needs to be fitted to the combine for SS to work properly"
Social networks and peer learning	24	28	"Learned about RRM method from trials on neighbour farmer fields"

			"Waiting to adopt machinery based on others experiences"
Technology lock-in effects impede adoption of new machines	26	32	"I have already invested in HS and cannot shift" "The local CHCs do not keep the latest machines, they try to make use of older machines
Technology appropriateness for cropping patterns	28	32	"Crop grown in the Rabi requires particular type of residue management" "Residue must be cleared for potato"
Technology appropriateness and efficacy in local bio physical conditions	48	52	"My soil is heavy so I prefer to use incorporation to break up the soil" "Since my soil is very light I need to keep moisture in the soil.. mulching helps with that"
Avoid terminal heat stress for rabi crop	72	95	"We need to plant early to prevent exposing the plants to higher temperatures especially in hotter years" "High temperatures in April and May reduces yields by 20-20%, we prefer to plant by Nov1 if it is a very hot year" "To plant earlier we need to harvest and prepare fields quickly"
Rainfall effects residue burning options	24	20	"Rainfall during the harvest season delays removal of straw and increases burning" "Rainfall increases time for in situ management of residue" "We cannot burn residue when there are very heavy rains"
Time for field preparation	82	84	"Delayed planting of rice reduces time to prepare the field"
Rice varieties planted impacts amount of residue	80	92	"The amount of residue determines whether partial burning has to be done

			Longer duration varieties produce more residue and we need to at least do partial burning" "Long duration rice reduces the time for field preparation so we try to sow earlier"

Table S5. Themes identified from codes developed in Table 2 that answer our research questions

Theme	*n* of participants contributing (N=90)
Research question: What are the factors contributing to RRM portfolio	
Theme 1: Village socio economic characteristics and location Familiarity with technology No resources or knowledge of technology Training/demonstration received from KVK /Agricultural university Availability of ex situ residue management Lack of enforcement of rules against residue burning Lack of infrastructure for ex situ residue management	82
Theme 2: Farmer socio economic resources Financial resources to buy in situ residue management machinery Lack of complementary infrastructure/machinery Social networks and peer learning Technology lock-in effects impede adoption of new machines	74
Theme 3: Farm bio physical characteristics Technology appropriateness for cropping patterns Technology appropriateness and efficacy in local bio physical conditions	82
Research question: What are the seasonal factors determining residue burning decisions of farmers	
Theme 1: Rainfall and Temperature Avoid terminal heat stress for rabi crop Rainfall effects residue burning options	62
Theme 2: Rice planting date Delayed planting of rice reduces time to prepare the field	79
Theme 3: Rice variety Time for field preparation Rice varieties planted impacts amount of residue	82

Table S6. Details on data satellite data sources used in quantitative analysis

MODIS Vegetation Index Products (NDVI and EVI)	Produced on 16-day intervals and at multiple spatial resolutions, provide consistent spatial and temporal comparisons of vegetation canopy greenness, a composite property of leaf area, chlorophyll and canopy structure. Two vegetation indices are derived from atmospherically corrected reflectance in the red, near-infrared, and blue wavebands; the normalized difference vegetation index (NDVI), which provides continuity with NOAA's AVHRR NDVI time series record for historical and climate applications, and the enhanced vegetation index (EVI), which minimizes

	canopy-soil variations and improves sensitivity over dense vegetation conditions.
FIRMS	The NASA Suomi-NPP VIIRS Active Fire product suite systematically mapping global fire activity at ≤12 hour interval
CHIRPS	Climate Hazards Center InfraRed Precipitation with Station data (CHIRPS) is a 30+ year quasi-global rainfall dataset. CHIRPS incorporates 0.05° resolution satellite imagery with *in situ* station data to create gridded rainfall time series
CPC	A station observation-based global land monthly mean surface air temperature dataset at 0.5 x 0.5 latitude-longitude resolution for the period from 1948 to the present
CLMS	Averages the daily Soil Water Index product over 10 days. The data are produced every 10 days over the globe at the spatial resolution of 0.1° and with the temporal extent from January 2007 to present.

Table S7. Descriptive statistics of variables included in the Regression analysis and Random Forest model

Dependent Variable	Unit	Mean	SD
Burn intensity	Number	860.8	825.43
Rainfall in harvest period	mm	56.2	56.63
Rainfall intensity in harvest period	mm/day	13.16	10.61
Monsoon start date	DOY	185.46	7.42
Growing length of rice	Days	117.10	10.788
Maximum temperature	°C	37.15	1.038
Soil water index		129.73	20.97
Total incorporation machinery	Number	405.95	414.802
Total mulching machinery	Number	229.19	205.88
Total Bailers	Number	3.32	6.273

Figure S3. Distribution of variables in regression analysis and Random Forest

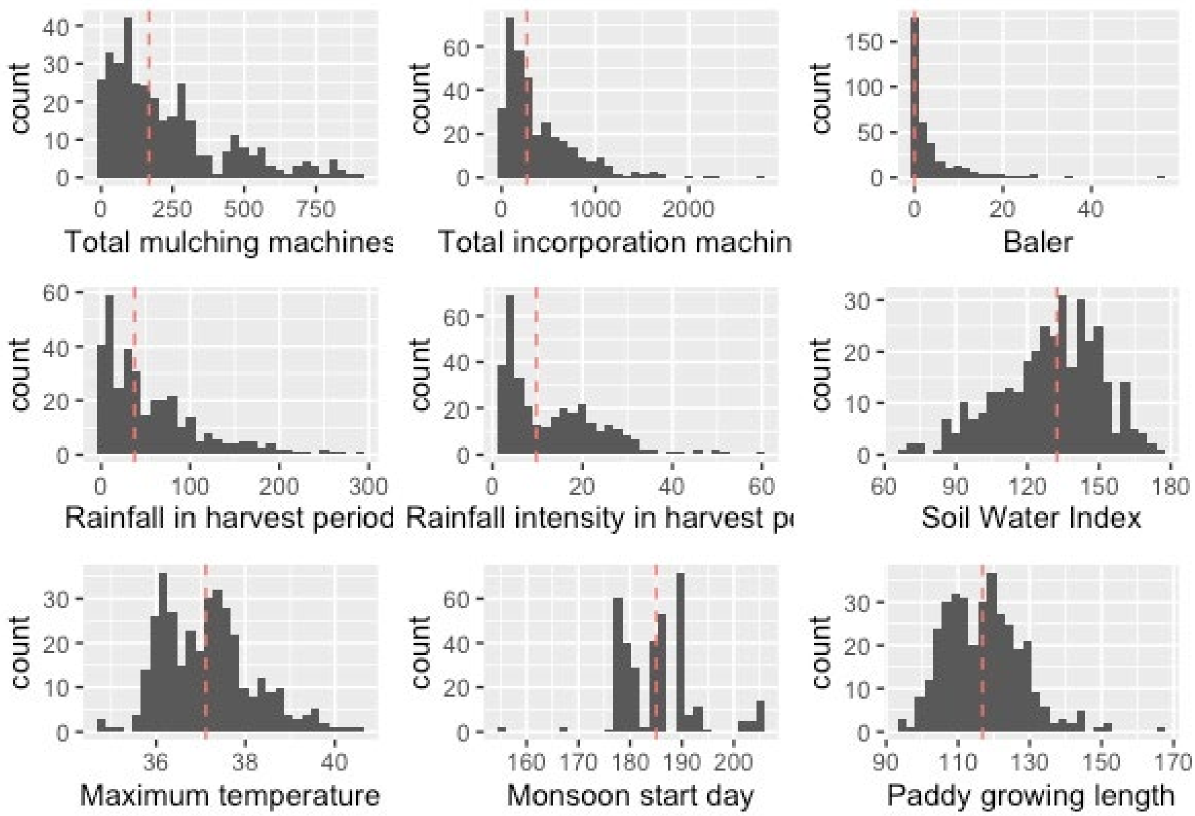
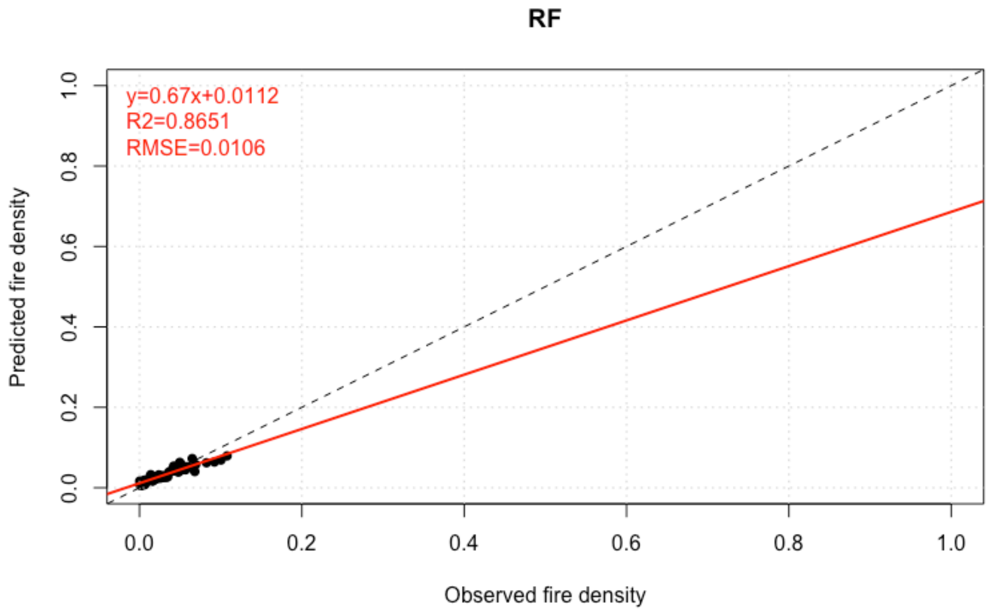


Table S8. Random forest model used to asses to predict the intensity of fire burning.

Type:	Regression
Number of trees:	500
Sample size:	280
Number of independent variables:	8
Mtry:	2
Target node size:	5
Variable importance mode:	impurity
Splitrule:	variance
OOB prediction error (MSE):	6029749
R squared (OOB):	0.641967

Figure S4. Calibration plot for selected models predicting residue burning intensity in the test set.



Ethics disclaimer: The studies involving humans were approved by Research Ethics Committee of Cornell University, protocol number IRB0148290