

UC Davis

UC Davis Electronic Theses and Dissertations

Title

Farmer Response and Resiliency to Rice Productivity Decline Following Sri Lanka's 2021 Agrochemical Ban

Permalink

<https://escholarship.org/uc/item/5dn4d8k0>

ISBN

9798193264118

Author

Heather, Alexis Rai

Publication Date

2026-09-08

Supplemental Material

<https://escholarship.org/uc/item/5dn4d8k0#supplemental>

Peer reviewed|Thesis/dissertation

Farmer Response and Resiliency to Rice Productivity Decline Following Sri Lanka's 2021
Agrochemical Ban
By

ALEXIS RAI HEATHER
THESIS

Submitted in partial satisfaction of the requirements for the degree of

MASTER OF SCIENCE

in

International Agricultural Development

in the

OFFICE OF GRADUATE STUDIES

of the

UNIVERSITY OF CALIFORNIA

DAVIS

Approved:

Cameron Pittelkow, Chair

Stephen Boucher

Robert Hijmans

Committee in Charge

2026

Abstract

Sri Lanka's 2021 ban on agrochemicals – and subsequent country-wide rice yield loss – offers a rare opportunity to study the components of yield resiliency during system-wide transitions away from synthetic agricultural inputs. We combine a six-year Sentinel-2 satellite based remote sensing analysis with semi-structured farmer interviews to assess heterogeneous yield impacts, recovery rates and post-ban adaptation strategies among rice farms in Sri Lanka's Anuradhapura District. Using Normalized Difference Red Edge (NDRE) and a panel of 100,000 pixels, we developed three tools for measuring rice farm productivity changes before, during and after the ban. In parallel, we analyzed farmer interview responses through partitioning-around-medoids cluster analysis to identify farm typologies linked to farm attributes, reported yield loss, and yield recovery times. Both methods found that farms with the lowest pre-ban productivity experienced the smallest relative yield losses and fastest recoveries. The two methods identified different categories of most impacted farmers: our remote sensing analysis pointed to the highest productivity farmers experiencing the largest yield loss and largest recovery, while our cluster analysis identified these impacts in the middle-resource farmer cluster. Interview data further indicated that crop rotation, access to large-scale irrigation resources, proximity to government extension, previous usage of organic farming practices, and participation in post-ban trainings were associated with greater yield resiliency. Our findings highlight the power of pairing landscape level satellite remote sensing monitoring with targeted, resource-sensitive farmer interventions for supporting any future large-scale transitions away from agrochemicals.

Introduction

Rice (*Oryza sativa*) is one of the most important food crops in the world, covering 165 million hectares of land and providing more than 20% of all calories consumed worldwide (Abdo et al., 2024; Fukagawa & Ziska, 2019). Modern rice yields are supported by the widespread adoption of chemical agricultural inputs, such as synthetic fertilizers and pesticides, with industrially produced fertilizer supplying an estimated 43% of all nitrogen inputs for global rice production over the last 50 years (Ladha et al., 2016). While industrially developed agrochemicals have created a steady supply of food, their intensive use in modern rice agriculture has been associated with strong negative externalities, such as environmental pollution and negative public health outcomes (J. Yang et al., 2025). Additionally, many countries import a large percentage of their agrochemicals, coupling domestic yield stability and food security to volatile international supply chains that can be impacted by economic and geopolitical turmoil (Sandström et al., 2024; Zhang et al., 2023). Organic agriculture and similar approaches – which aim to replace synthetic fertilizers and pesticides with biologically derived inputs and ecologically based practices – represent a potential pathway for reducing farmer reliance on external inputs and increasing ecosystem service outcomes (Wittwer et al., 2021). While there is a robust literature exploring challenges and benefits of organic adoption at the farm level – including a well-documented gap between conventional and organic farm yields (Badgley et al., 2026; De La Cruz et al., 2023) – few opportunities exist to study the implications of transitioning away from conventional agrochemical use at a regional or industry scale (Brunelle et al., 2024).

Only three contemporary cases of government efforts to eliminate agrochemical use at the regional level exist: Sikkim State, India's 2016 Organic Mission; Bhutan's 2018 Organic Agricultural Development Strategy; and Sri Lanka's 2021 Imports and Exports (Control)

Regulations No. 07 ban on imported agrochemicals (ICIMOD, 2018; Singh, 2020; USDA/FAS, 2021). Of these three experiments in large-scale conversions away from agrochemicals, Sri Lanka possesses the largest and most complex agricultural sector, attempted the most abrupt transition away from agrochemicals, and experienced the most intense post-transition yield shock (Babajani et al., 2023; Drechsel et al., 2025). The abrupt nature and severe impact of Sri Lanka's agrochemical ban creates a compelling case study for analyzing how farmers are impacted by – and adapt to – systemic transitions away from the use of agrochemicals.

Sri Lanka's official agrochemical ban was enacted from May to November 2021, amidst international economic instability and fertilizer price spikes emanating from COVID-19 supply chain disruptions and the Russia-Ukraine war (Vos et al., 2025). Though the ban only lasted six months, the impact was severe. Government of Sri Lanka data shows that the rice yield for the major growing season following the ban (September 2021 to March 2022, known locally as the “Maha” season) was 40% lower than the mean of the preceding three Maha seasons. Two years after the ban was rescinded, the national average Maha yield rate was still 17% lower than the pre-ban mean (Department of Census & Statistics, 2024). While international economic turmoil and local environmental conditions may have been contributed to the harvest 2022 yield shock, multiple studies have identified ban-related synthetic fertilizer shortages as the main contributor to yield losses (Drechsel et al., 2025; Ghose et al., 2023).

Much of the research exploring the impacts of Sri Lanka's attempted transition away from agrochemicals has focused on analyzing the macro-level effects of the agrochemical ban and the constraints that led the original policy to fail. Drechsel et al. (2025) explored the Governmental reasoning behind – and national impacts of – the agrochemical ban, finding that at the time of the ban, there were no logical pathways for preserving farm yields through successfully replacing

imported synthetic fertilizer with local organic alternatives. Fein-Cole et al. (2024) further confirmed this finding through a nutrient flow analysis, identifying that there was a fundamental gap between the local crop nutrient needs and the local production potential of organic fertilizer sources (manure and human fecal sludge composting). An economic analysis of the ban's effects on Sri Lanka's broader agricultural industry by Ghose et al. (2023) found the effects of the ban across crop sectors were negative but heterogeneous, with the rice sector facing the third highest yield loss (after maize and potatoes) and an overall average welfare loss equivalent to a 7% decrease in income across all agricultural workers. Köpke (2026) further explored the rationale and failure of the agrochemical ban through a political ecology framework, finding that though the need to decrease agrochemical pollution had been the subject of national debate for over ten years, the actual enactment of the 2021 ban had little chance of success due to the abrupt nature of ban enactment, opaque government reasoning provided for the ban, absence of transition supporting programs (organic fertilizer access, knowledge transfer programs, yield loss compensation schemes) and lack of local stakeholder consultation. However, few attempts have been made to understand the variability in yield loss for different farms, such as those with higher versus lower productivity, seeking to answer the question: "who was most affected and why"?

One of the most thorough analyses of farm-level ban impacts was conducted by Bandara et al. (2023), who administered surveys to 625 rice farmers immediately after the ban to collect data on farmer demographics, practice changes and coping strategies. Bandara et al. found that while 70% of farms reported using some chemical fertilizers in the Maha season following the ban, application rates were reduced across farms due to high fertilizer prices and limited availability. Additionally, Bandara et al. found that farms' irrigation schemes played an important role in post-ban chemical fertilizer use, with farms from major irrigation schemes 16% more likely

to apply chemical fertilizer than farms from minor schemes. This specific distinction between major and minor irrigation schemes is used by the Government of Sri Lanka to categorize rice paddies based on the size of their supporting reservoir – locally known as a tank. Major tank irrigation schemes are connected to large-scale reservoirs that service >80 ha of rice land and are usually municipally run with consistent irrigation during major (Maha) and minor (Yala) seasons. Minor tank irrigation schemes are connected to small, often locally run reservoirs, service <80 ha of rice land, and feature consistent irrigation in the major season with intermittent irrigation in the minor season. Finally, farms in rainfed land have no irrigation access, making rice cultivation only possible during the major season, and not in the minor season (Bebermeier & Schütt, 2020). Aside from Bandara et al. exploring post-ban farmer responses based on irrigation scheme, there has been little additional investigation of how farm-level characteristics influenced rice productivity outcomes following the ban.

Research exploring ban impacts at the farm-level is limited by data availability. Government of Sri Lanka agricultural data is aggregated at the District-scale and differentiated solely by irrigation scheme, making it difficult to understand the magnitude of yield loss across different fields and, in turn, how quickly those fields returned to their normal yield levels following the ban. If some farms were able to avoid a reduction in yield while others suffered greatly, important lessons can be learned about how different farming system attributes, practices, support structures, and adaptation strategies may have helped reduce the negative impacts of the ban – helping inform future programs and policies supporting a transition towards organic agriculture. This study addresses this knowledge gap by exploring whether different farmer attributes are associated with divergent abilities to preserve and recover yields post-ban.

Various studies have explored how different agricultural and environmental characteristics may promote yield resiliency, in this study defined as the ability to avoid prolonged yield loss following a perturbation such as extreme weather, pests/diseases, or input supply shocks (Urruty et al., 2016). Satellite remote sensing data has been used to measure components of yield resiliency through crop yield estimation and crop health assessment (Dela Torre et al., 2021; Yu et al., 2026), including for rice systems in Sri Lanka (Özdoğan et al., 2025). Ahvo et al. (2023) modeled the impact of different agricultural input shocks on expected yields and found that shocks to conventional fertilizer supplies were associated with the largest yield decreases (as compared to shocks in pesticides and machinery) and that high-yield farming regions were particularly vulnerable. Satellite remote sensing has also been used to analyze components of agricultural yield gaps (Jain et al., 2017), as well as predict risks and estimate the effects of crop yield shocks in large agricultural regions (Benami et al., 2021; Biggs et al., 2010; Murray et al., 2018; White et al., 2020).

At the farm level, numerous case studies have worked to explore how different farmer attributes are related to post-shock yield resiliency. Research studying farm-level adaptation patterns to regional-level climate change impacts by Shukla et al. (2019) found that diverse farmer adaptation strategies clustered into distinct categories based on a farmers' personal attributes, resource/capital endowments, and production practices. Modeling by Michalscheck et al. (2023) also found categorical differences in predicted farmer outcomes to various shocks based on low, medium, or high resource endowment classifications. The authors found that farmers in the middle class would experience the worst post-shock profit and food security outcomes – speculating that these farmers are particularly vulnerable due to overextending their accessible resources. As of drafting, we have yet to find any research combining landscape-scale assessment tools – such as

satellite remote sensing – with farm-level outreach to analyze factors related to farmer yield resiliency during periods of agricultural transition.

The abrupt and ubiquitous nature of Sri Lanka’s agrochemical ban, and subsequent yield shock, creates an opportunity for studying mechanisms associated with farm-level yield resiliency and adaptation strategies during transitions away from conventional agrochemical inputs. In this paper we conduct a multimethod analysis of post-ban farmer yield resiliency in Sri Lanka’s Anuradhapura District, combining a six-year, district-wide remote sensing time-series analysis with in-country farmer interviews. Our research builds upon previous methods for exploring farmer resiliency to yield shocks to contribute to research exploring the impacts of Sri Lanka’s agrochemical ban. The objectives are to a) map and assess landscape-level heterogeneity of rice yield impacts related to the 2021 agrochemical ban on farms in Anuradhapura, and b) identify factors related to heterogeneous post-ban yield preservation and recovery at the landscape and farm level.

Materials and Methods

Study Area and Remote Sensing Data

This study consists of a six-year remote sensing timeseries analysis (2019-2024) and a 2025 in-country farmer survey in Sri Lanka’s Anuradhapura District, the district with the highest amount of domestic rice production. Located in the north-central dry zone, the district contributed between 13% and 17% of annual national Maha-season rice production during our study interval (Department of Census and Statistics, 2025). The main Maha growing season runs roughly from October through March the following year, with average seasonal monsoon precipitation of 1,000

mm providing the basis for rice production water inputs (*Department of Census and Statistics, n.d.-a; HDX, 2026*). Maha seasons and year labels are designated by harvest year in this study.

In the 2025 Maha season, rice was grown on approximately 127,200 ha in the Anuradhapura district, with approximately 44% in major tank irrigation, 42% in minor tank irrigation, and 14% in rainfed systems. Average district Maha seasonal yield rates across all irrigation systems in the three years prior to the ban ranged from 5,098 to 5,414 kg ha⁻¹ (*Department of Census and Statistics, 2025; Slycan Trust, 2022*). Additional seasonal Anuradhapura District Maha environmental and agricultural data can be found in Supplementary Materials Figure A4 through A6, and Tables A1 through A4.

To assess the impact of the agrochemical ban across different farms in the Anuradhapura District, we used high-resolution satellite imagery from the European Space Agency Sentinel-2 satellites (*European Space Agency, n.d.*) to create a panel dataset of the pixel-level Normalized Difference Red Edge (NDRE, Equation 1) values for 100,000 rice farm pixels. NDRE is a remote sensing vegetation index which measures the spectral reflectance of wavelengths correlated with chlorophyll content – a strong predictor of plant health – and has proven to be one of the highest-quality remote sensing proxies for rice yield (*Rehman et al., 2022*). Pixels are scaled at 10m x 10m resolution, approximately .5% of the 2.2 ha average rice farm size reported by this study’s interviewed farmers. We treat each sampled pixel as an in-field representative crop area for its respective farm, allowing us to compare post-ban yield impacts in farms across the region.

$$\text{NDRE: } \frac{\text{Near Infrared} - \text{Red-Edge}}{\text{Near Infrared} + \text{Red-Edge}} = \frac{\text{Band 8} - \text{Band 5}}{\text{Band 8} + \text{Band 5}} \quad (1)$$

To create our remote sensing panel data, we processed Sentinel-2 satellite images in Google Earth Engine over a six-year timeseries (*Google Earth Engine, n.d.; Sentinel-2 Datasets in Earth*

Engine, n.d.; Gorelick et al., 2017). Imagery acquisition followed the approach of Yewle et al. (2025) for Sentinel-2 based yield prediction in monsoon climates; images with less than 60% cloud coverage after cloud masking were acquired in a 60-day crop maturation interval to ensure an adequate catalog of imagery data for yield modeling during cloudy conditions. We collected the maximum NDRE (hereafter referred to as max NDRE) value for each sample pixel between January 1 and March 1 of each year in our time series, approximately 70 to 90 days after the beginning of Maha season. This timeframe corresponded to approximately 11 Sentinel-2 satellite regional passes and coincides with the booting stage of rice, a plant development period when rice NDRE reaches its maximum potential level and field max NDRE is a strong predictor of yield (De Lima et al., 2021; Rao et al., 2024).

The spatial extent of the analysis was defined as rice pixels within a 50 kilometer radius of the Anuradhapura district capital, as delineated by the FAO-EOSTAT 2024 land-use rice pixel map (FAO - EOSTAT, 2025), encompassing 119,400 ha of rice land, approximately 94% of the 2025 Maha reported harvest acreage (Department of Census and Statistics, 2025). We created a random sample of 100,000 rice pixels (corresponding to 1,000 hectares) in our study area to generate our max NDRE timeseries panel data, the annual mean max NDRE of all sample pixels strongly correlated with Government of Sri Lanka reported Anuradhapura District average Maha seasonal rice yield rates ($R^2 = 0.84$, Appendix A3) (Department of Census & Statistics, 2024). Of all the various remote sensing vegetation index configurations we tested, max NDRE was the most highly correlated with GOSL reported yield, a methodological flowchart of our remote sensing survey and analyses of different vegetation indices can be found in Supplementary Figure A1 and A2.

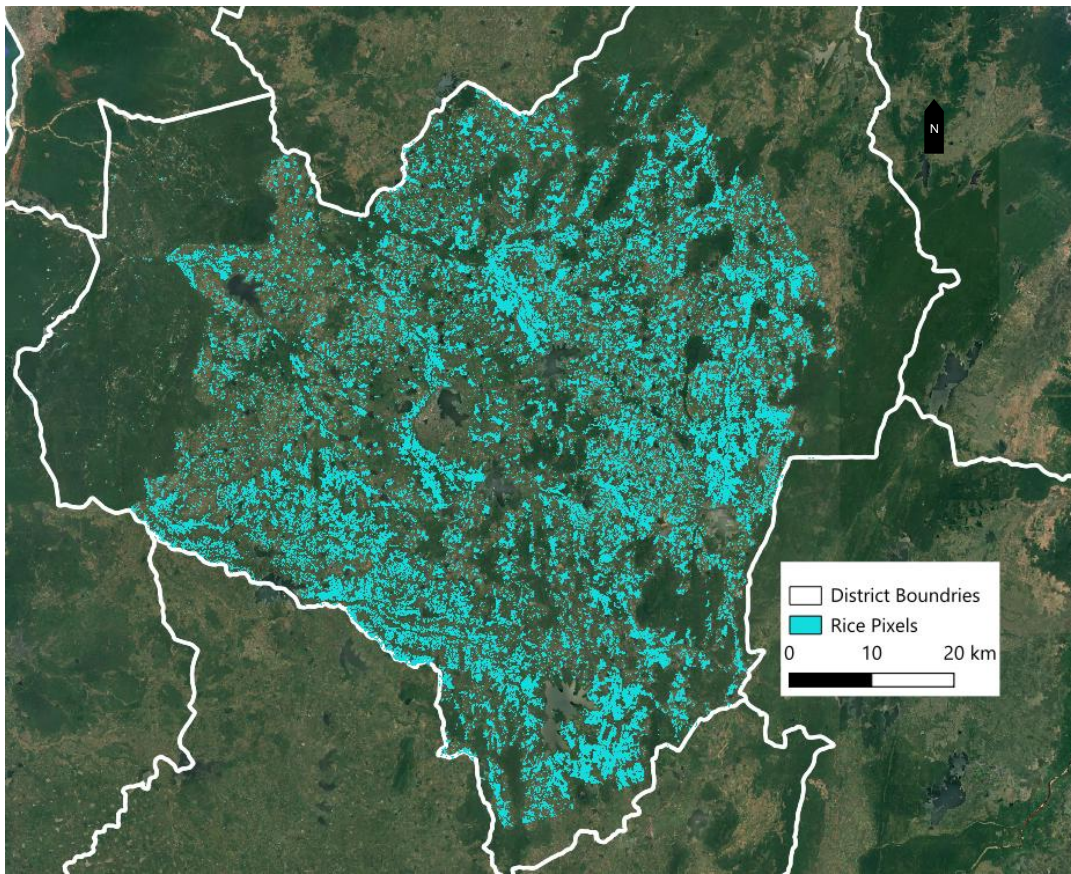


Figure 1. Our study region in the Anuradhapura District in north-central Sri Lanka; identified rice pixels encompass approximately 119,446 hectares.

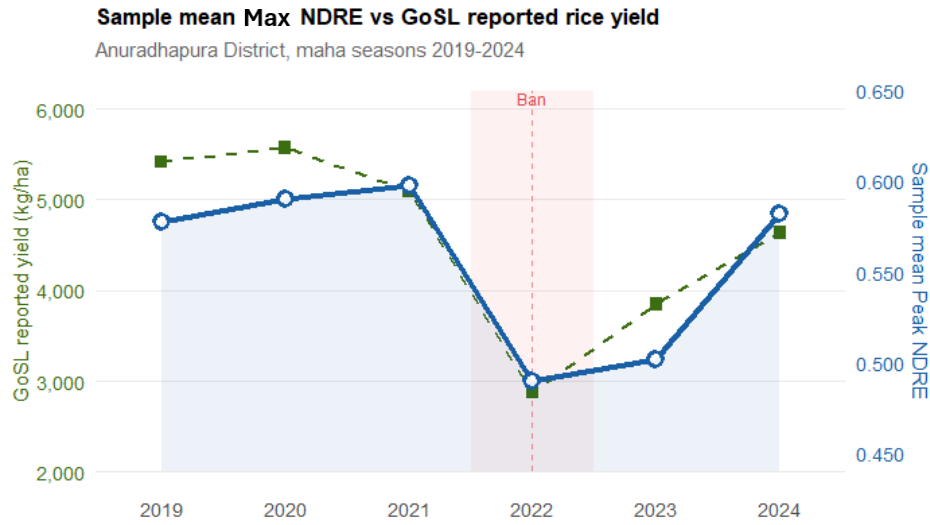


Figure 2. Comparison of 100,000 pixel sample median max NDRE with Government of Sri Lanka reported annual Anuradhapura district average maha season rice yield rates ($r^2 = .8443$, P-value = .00961), shaded band identifies approximate ban period. (Department of Census and Statistics, 2024)

Remote Sensing Indicators

Three remote sensing indicators were derived from the Maha seasonal max NDRE composites to gauge the immediate and medium-term impact of the 2021 agrochemical ban. In order to characterize the geospatial diversity of farm yield recovery at the district-scale, we adapted remote sensing indicators from landscape-level disturbance ecology methodology for their ability to measure comparative vegetative recovery after large-scale disturbances (Miller & Thode, 2007; Van Ruijven & Berendse, 2010; White et al., 2020).

$Baseline_p$ (Equation 2) is the mean value of each rice pixel's max NDRE for Maha harvest seasons 2019 through 2021, and serves as an indicator of pre-ban rice productivity.

$\text{MaxNDRE}_{p,2022}$ is each rice pixel's max NDRE value for Maha harvest season 2022. $\text{MaxNDRE}_{p,2024}$ is each rice pixel's max NDRE for Maha harvest season 2024. Shock_p (Equation 3) computes the ratio of each pixel's 2022 MaxNDRE to its Baseline, serving as a pixel-level indicator of immediate ban yield impact on rice productivity. Recovery_p (Equation 4) computes the ratio of each pixel's 2024 MaxNDRE to its baseline, serving as an indicator of medium-term rice productivity recovery.

$$\textbf{Baseline: } \text{Baseline}_p = 1/3 \sum_{t=2019}^{2021} \text{MaxNDRE}_{p,t} \quad (2)$$

$$\textbf{Shock Ratio: } \text{Shock}_p = \frac{\text{MaxNDRE}_{p,2022}}{\text{Baseline}_p} \quad (3)$$

$$\textbf{Recovery Ratio: } \text{Recovery}_p = \frac{\text{MaxNDRE}_{p,2024}}{\text{Baseline}_p} \quad (4)$$

Each indicator was applied to our 100,000-pixel sample and categorized into three classes (high, medium, and low) based on sample tertiles. Class thresholds were then applied to our Google Earth Engine study area to create a geospatial distribution of each indicator class. To analyze correlations between farm Baseline class and ability to preserve or recover yields post-ban, a Sankey diagram was constructed to trace the flow of Baseline Class pixels through Shock Ratio and Recovery Ratio in our sample.

	High	Medium	Low	Mean
Baseline	>0.6208	0.6208 – 0.5519	<0.5519	0.579
Shock Ratio	<0.7813	0.9139 – 0.7813	>0.9139	0.847
Recovery Ratio	>1.0435	1.0435 – 0.9413	<0.9413	0.997

Table 1. Sample means and high, medium, and low-class thresholds for Baseline, Shock Ratio and Recovery Ratio, class established through pixel sample tertiles for each respective indicator. (Note: for the Shock Ratio indicator, a lower value indicates a greater yield reduction, and thus a higher shock).

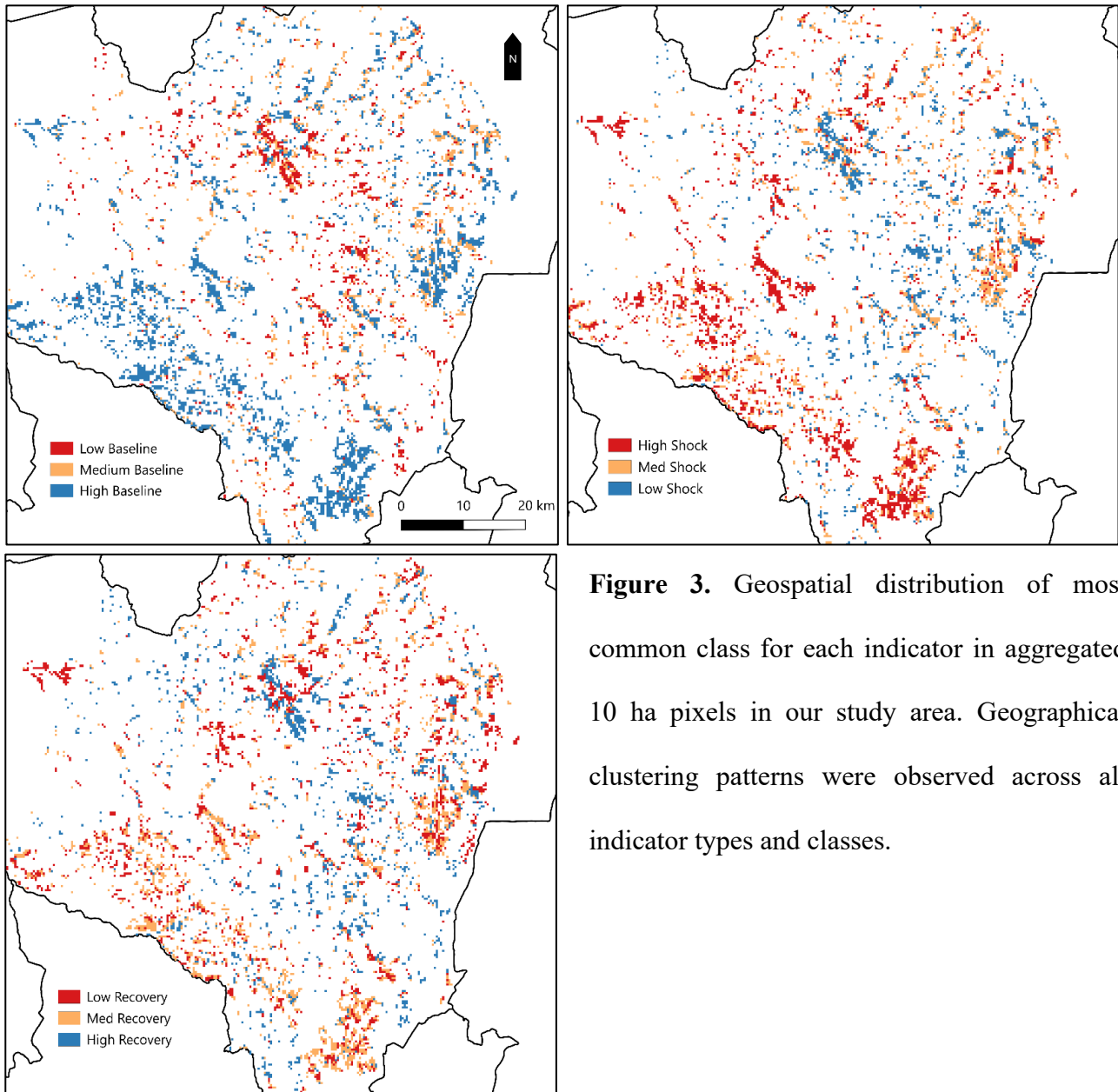


Figure 3. Geospatial distribution of most common class for each indicator in aggregated 10 ha pixels in our study area. Geographical clustering patterns were observed across all indicator types and classes.

Semi-structured Farmer Interviews

We conducted 30 semi-structured interviews with rice farmers in the Anuradhapura District in August 2025, collecting data on farmer attributes, agricultural practices, and ban impacts. Interview methodology drew on previous work analyzing how different smallholder farmer characteristics were associated with perceptions and adoption of low agrochemical practices (Batas et al., 2025; Digal & Placencia, 2019; Sujianto et al., 2024), blending semi-structured interviews with a structured questionnaire to generate quantitative and qualitative data on farmer demographics, farm characteristics, ban impacts, input characteristics, supporting structures, and sentiments towards local organic farming. The interviews were conducted in Sinhala through a local research assistant, and responses were recorded using the *KoboToolbox* survey software (*KoboToolbox*, n.d.). A full list of interview questions and participant responses can be found in Supplementary Table A6.

Survey participants were recruited through criterion-based opportunistic sampling in our study area (Kondo et al., 2014; Patton, 2014). To identify potential participants, we generated random points in our rice map using Google Earth Engine and conducted household visits in areas logistically accessible and proximate to random sample points. Participants were selected based on house proximity to a random sample point, evidence of rice farming, and willingness to interview.

Variable	Included in CA/CP	Data Type	Mean / Most Reported (Frequency)
Farmer Demographics			
Gender	CA	Categorical	Male (80%)
Mean age	CA	Continuous	50.34 years
Mean years rice farming	CA	Continuous	22.07 years
Education level (primary/secondary/university)	CA	Categorical (ordinal)	Secondary (73%)
Farm Characteristics			
Irrigation scheme type (major/minor/rainfed)	CA	Categorical	Minor (53%)
Farm area	CA	Continuous	2.227 ha
2025 yield rate	CA	Continuous	3,662 kg ha ⁻¹
Distance to nearest extension office	CA	Continuous	7.35 km
Multicrops in offseason	CA / CP	Categorical	27%
Ban Impacts			
Estimated Maha 2022 yield loss (n=27)	CA	Continuous	48.5%
Estimated years to recovery (n=27)	CA	Continuous	2.1(2023 maha)
Most reported non-yield ban effects (n=27)	CP	Categorical	66% Higher labor need (n=27); 55% lower cost of management (n=27); 47% increased pest pressure (n=17)
Most reported practices that helped recover post-ban yields (n=27)	CP	Categorical	76% black market urea (n=17); 55% inclusion of organic inputs (n=27)
Inputs Characteristics			
Using organic inputs/methods before ban (n=27)	CP	Categorical	No (80%)
Use organic or reduced chemical practices in the last two years (Maha 2024 or 2025) (n=27)	CP	Categorical	No (80%)
Seed/input supply	CP	Categorical	90% Small agribusiness; 53% government station; 46% saved seeds
2024 Pesticide usage (n=27)	CP	Categorical	76% pesticide and 70% herbicides as needed
Supporting Structures			
Primary market access	CP	Categorical	Middlemen (97%); home consumption (100%); no access to organic premium market (97%)
Primary source of farming information	CP	Categorical	Fellow farmers (73%); government extension

			(66%); personal experience (57%)
External support received for organic adoption	CP	Categorical	None (56%)
Sentiments towards local organic farming			
Sentiments on Organic Agriculture in Sri Lanka – 1 (low) to 5 (high)	CP	Continuous (Likert scale)	2.93

Table 2 Summary statistics and descriptions of survey variables used for cluster analysis (CA) and cluster profiling (CP). Due to survey adaptation on day 2 and 4 some categories have fewer total responses than others, unless otherwise noted n=30. Percentages may not sum to 100% due to multiple responses.

Statistical Analysis of Farmer Responses

We identified key variables from our semi-structured interviews to conduct a statistical cluster analysis and construct cluster profiles (Table 2). All statistical analyses were conducted in RStudio (version 2026.04) and proceeded in three stages. First, descriptive statistics (means, standard deviations, ranges) were computed for all continuous variables, and frequency distributions were tabulated for categorical variables.

Second, a multivariate cluster analysis of key farmer demographics, farm characteristics, and ban impacts (percent yield loss in Maha season following ban and number of years until full yield recovery) was conducted to identify latent farm typologies and examine whether naturally occurring farm groupings occurred. Partitioning around medoids (PAM) was used as the clustering algorithm. Gower distance was used to construct a dissimilarity matrix (Szepannek et al., 2025), accommodating the mixed data types (numeric and categorical) present in the dataset. Clusters

were characterized using group means and frequency tables, and differences in recovery time across clusters were tested with the Kruskal-Wallis H-test. Two-dimensional visualization of cluster structure was achieved via Multidimensional Scaling (MDS) of the Gower distance matrix.

Once initial clusters were identified, we computed means and frequencies for each cluster's continuous and categorical variables (ban impacts, farm practices, input characteristics, and supporting structures) to analyze meaningful variations among farm typologies. Cluster comparisons were adapted from Shukla et al.'s (2019) methods for exploring how smallholder farmer typologies were related to climate change adaptation strategies.

Results

Both our remote sensing indicator and our semi-structured interview analyses found distinct and heterogeneous post-ban impact and recovery patterns across different types of farms.

Remote Sensing Indicator Outcomes by Baseline Class

Projecting our Baseline, Shock Ratio, and Recovery Ratio indicator classes onto our study area shows distinct geospatial clustering patterns (Figure 2). High Baseline pixels are most represented in the eastern and south-western areas of the Anuradhapura District, while Low Baseline pixels are most highly concentrated in central and northern areas. The clustering pattern remains consistent as each Baseline class moves through a distinctive Shock Ratio and Recovery Ratio path. Publicly available geographic data for this region lacks the resolution for comparative analysis, but maps published by the Government of Sri Lanka and previous researchers show that higher Baseline areas tend to feature slightly high relative soil type diversity (Marambe et al., 2020), higher population densities (Perera, 2015) and higher historic investment in major irrigation schemes (Weligamage, 2005).

In our 100,000-pixel sample, the magnitude of negative rice productivity impacts (Shock Ratio) and degree to which productivity returned to pre-ban levels (Recovery Ratio) were strongly influenced by whether pixels had low, medium, or high productivity prior to the ban (Figure 3). Low Baseline pixels experienced the lowest yield declines and strongest recovery trajectories by 2024. Out of the 33,334 Low Baseline pixels, 56% (n=18,613) experienced a Low Shock Ratio and 60% (n=19,832) experienced a High Recovery Ratio. Among the Low Baseline with High Recovery Ratio pixels, 63% came from Low (n=12,472), 22% from Medium (n=4,433) and 15% from High (n=2,927) Shock Ratio pixels, indicating that strong recovery among low-productivity pixels was broadly distributed across all shock severity levels.

This pattern was reversed for the High Baseline pixels, of which 51% (n=17,083) experienced a High Shock Ratio and 50% experienced a Low Recovery Ratio (n=16,539). Among High Baseline with Low Recovery Ratio pixels, 9% came from Low (n=1,423), 34% came from Medium (n=5,667) and 57% came from High (n=9,449) Shock Ratio pixels.

Medium Baseline pixels (n=33,333) were much more evenly distributed than the other two Baseline Classes. 32% of Medium Baseline pixels experienced a Low (n=10,542), 38% experienced a Medium (n=12,502) and 31% experienced a High Shock Ratio (n=10,289). These distributions were consistent for Medium Baseline Recovery Ratio: 32% experienced a Low (n=10,513), 36% experienced a Medium (n=11,959) and 32% experienced a High (n=10,861) Recovery Ratio (regardless of Medium Baseline Shock Ratio).

We constructed a Sankey diagram to better illustrate each pixel's path through Shock and Recovery Indicators based on their original Baseline class. Band color represents the different Baseline class (Low Baseline = red, Medium Baseline = light blue, High Baseline = dark blue); the nodes represent the different classes Shock and Recovery indicators; and the width of each

band is directly proportional to the number of pixels that took a given path between nodes. The Sankey diagram assists in observing both trends – like the most common paths mentioned above – as well as outliers – like the rarest High Baseline-Low Shock-High Recovery path (2% of all High Baseline pixels).

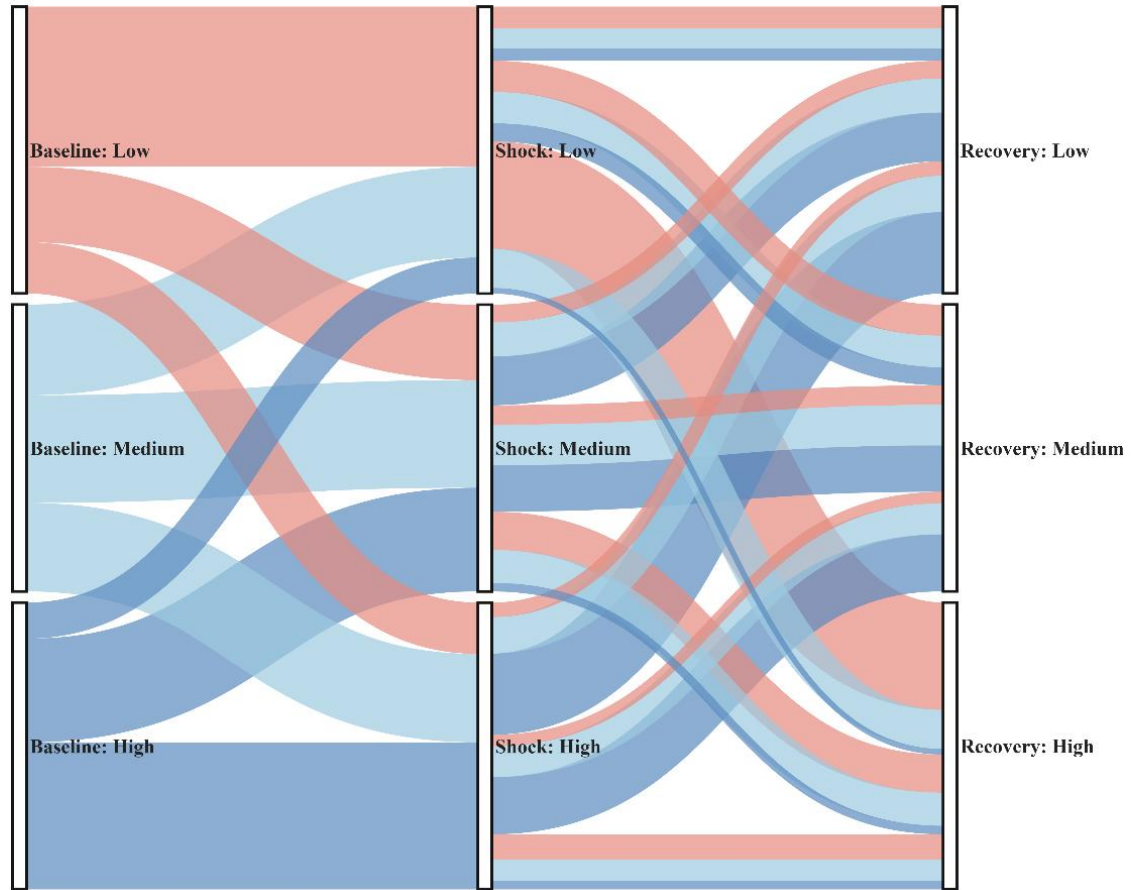


Figure 4. Sankey Diagram of Shock Ratio and Recovery Ratio by Baseline Class for our 100,000-pixel sample. Colored paths indicate original Baseline Class of the pixel; Low, Medium and High categories are assigned via tertiles for each indicator.

The mirrored patterns of the Low Baseline and High Baseline pixels' paths through Shock and Recovery indicators in Figure 4 are likely partially attributed to a disproportionate amount of sample data noise in the High and Low Baseline classes leading to a regression to the mean for pixels which experienced an unusually high or low max NDRE in one of the years comprising our Baseline timeseries. The coefficients of variation across all pixels per year (Table 3) show that the percentage of the coefficient of variation in 2022 (18%) is within the pre-ban range of the preceding three years (16.0% to 19.6%), suggesting that all pixels experienced a broadly similar post-ban shock. The coefficient of variation fluctuates out of the pre-ban range for the next two years, with 2023 having the highest coefficient of variation (20.5%) and 2024 having the lowest coefficient of variation (14.4%) percentage of the entire timeseries. This narrowing may reflect a convergence in max NDRE across Baseline classes; Low Baseline pixels are rising above their pre-ban max NDRE while High Baseline pixels remained below their pre-ban levels, closing the gap between the two groups – a phenomenon that corresponds with trends seen in Table 1, Figure 4 and in Figure 6 of our farm cluster analysis (discussed later).

Year	Mean	CV (%)
2019	0.569	16.5%
2020	0.581	16.0%
2021	0.587	19.6%
2022	0.485	18.0%
2023	0.496	20.5%
2024	0.572	14.4%

Table 3. Sample means and coefficients of variation percentages across all 100,000 rice pixels for each year.

Cluster analysis

While our remote sensing analyses explored post-ban yield resiliency at the landscape level, our semi-structured interview cluster analysis allowed us to test whether similar patterns between productivity levels and ban impacts hold at the farm-level, and identify any characteristics that distinguish more resilient farms.

Semi-structured interview participants tended to be male (frequency 80%) and highly experienced (mean age of 50 years with 22 years rice farming). Participants reported 14% lower average 2025 yield than the Anuradhapura District average reported by the Government of Sri Lanka (3,662 compared to 4,263 kg ha⁻¹), and were slightly more likely to be connected to minor irrigation schemes than major schemes (53% versus 47%) (Department of Census and Statistics, 2025). Interviewed farmers tended to rely on local and market systems over government services for resources, favoring fellow farmers over government extension when seeking farming information (73% versus 66%), selling produce to local middlemen over government buyers (97% versus 10%), and buying inputs from small agribusinesses over government stations (90% versus 53%). Though 57% of farmers reported the inclusion of organic inputs/methods immediately after the ban, there was no fundamental shift towards organic agriculture as a result of the ban – the frequency of participants utilizing organic inputs/methods in Maha 2024 or 2025 was equal to the pre-ban frequency (20%), though 27% of participants reported rotating different crops into their rice paddy during the off season. Potentially one of the most impactful farmer practices, the inclusion of black-market urea (76%), was identified later in our interview process. Since only 17 farmers had an opportunity to discuss their black-market urea usage, this variable was not included in the farmer cluster analysis.

Three distinct clusters of farm typologies were identified based on relationships between ban impacts, farmer demographics, and farm characteristics categories (Figure 4). The most influential variables in determining clusters – which featured the strongest Spearman correlation between each variable and the two PCoA axes – included differences in irrigation tank scheme, crop rotation, yield shock, average yield, years to recovery, and distance to agricultural extension office.

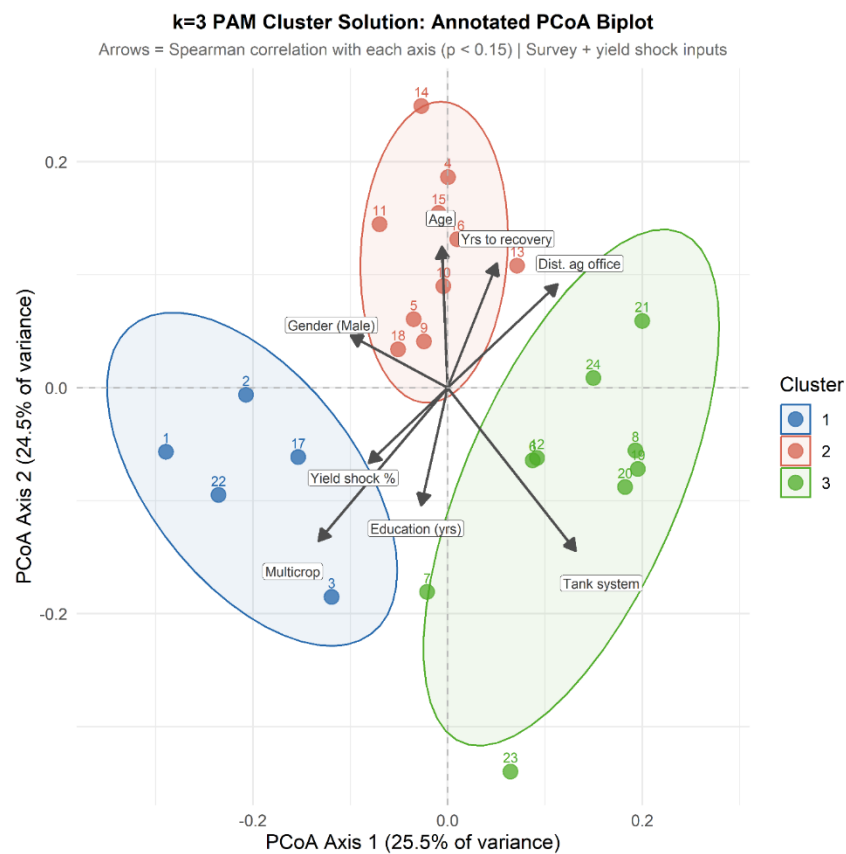


Figure 5. Annotated Principal Coordinates Analysis (PCoA) of the three-cluster PAM solution on our fully completed farmer interviews (n=24). Points represent individual farms colored by cluster membership; shaded ellipses indicate the approximate boundary of each cluster. Arrows indicate

the direction and relative strength of Spearman correlation between each variable and the two PCoA axes (only variables with $p < 0.15$ on at least one axis are shown; arrow length is proportional to correlation magnitude).

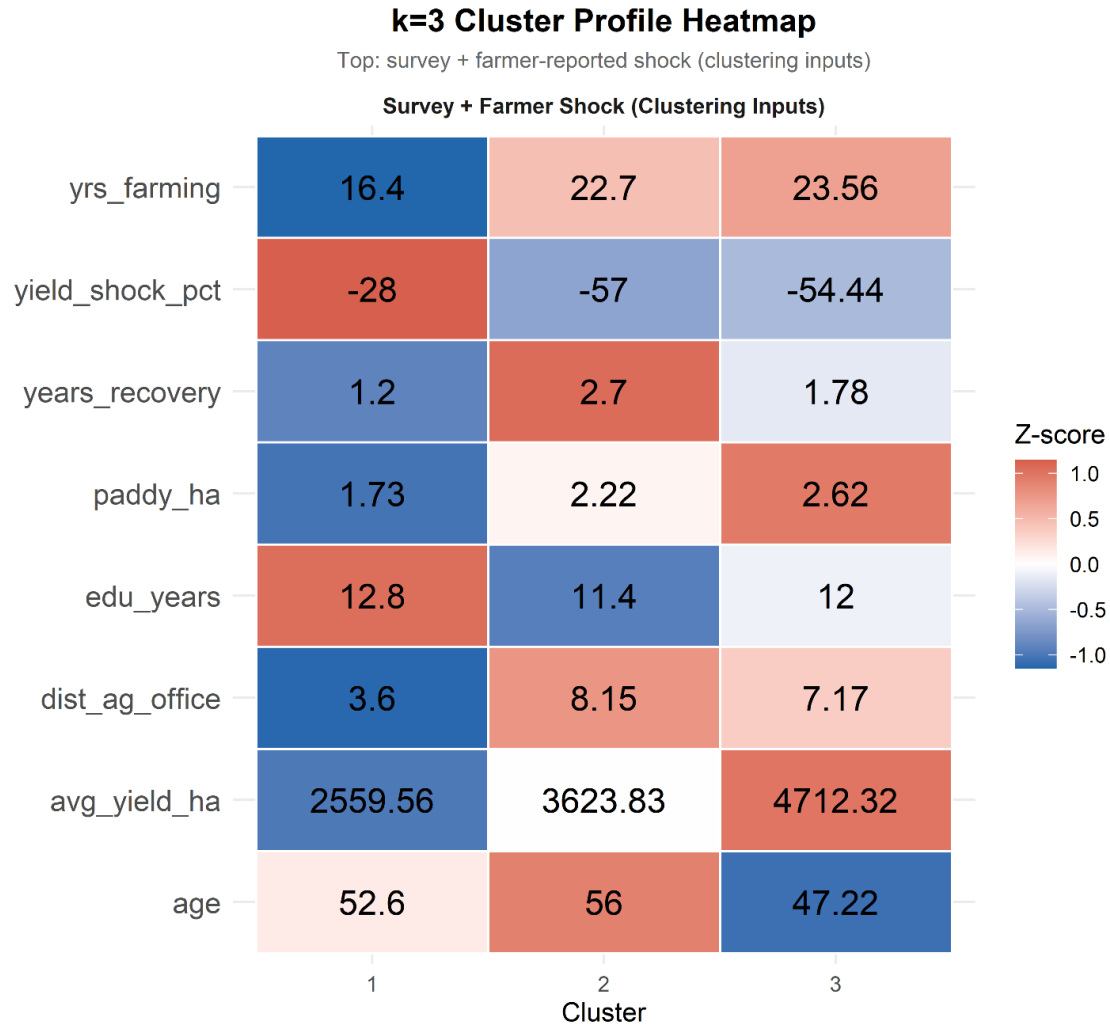


Figure 6. Cluster profile heatmap showing the mean values for each variable by cluster. Cell shading indicates z-score relative to the cross-cluster mean (red = above average, blue = below average).

Of continuous variables, Cluster 1 exhibited the lowest yield shock (-28%) and fastest recovery (1.2 years) but also the lowest average yield (2,560 kg ha⁻¹), a similar trend observed in our remote sensing sample. This cluster had the smallest rice area (22% and 34% smaller than Clusters 2 and 3, respectively), the fewest number of years farming, and the shortest distance to the nearest extension office. Clusters 2 and 3 both experienced a larger yield shock and longer time to recovery than Cluster 1. While the yield shock for Clusters 2 and 3 was similar (-57% and -54%, respectively), the recovery time for Cluster 3 was 33% faster than Cluster 2 (1.8 versus 2.7 years, respectively). Cluster 3 had the highest average yield (4,712 kg ha⁻¹) and largest farm area (2.6 ha). Cluster 2 had intermediate yield and the greatest distance to extension, more than double that of Cluster 1.

Further profiling of categorical variable frequencies across clusters revealed notable variation among farm typologies (Table 3). The largest practice-based divergence across clusters was observed in the variable measuring crop rotation (100% of Cluster 1 farmers, compared to 0% and 22% in Clusters 2 and 3), with 67% of crop-rotating farmers reporting growing mung bean – a nitrogen-fixing legume (Diatta et al., 2020) – in rice paddies during the offseason. Connections to minor irrigation scheme showed the second largest cross-cluster divergence (90% of Cluster 2 farmers, compared to 60% and 11% in Clusters 1 and 3). Cluster 1 farmers were much more likely to utilize government resources for buying seeds (80% versus 40% and 67% in Clusters 2 and Cluster 3) and seeking farming information (100% versus 50% and 67%), and had the highest frequency of consistent organic input/practice usage (40% versus 10% and 11%). Farmers in Cluster 3 were the most likely to report steps for post-ban adaptation, with 89% incorporating organic inputs/methods immediately post-ban (compared to 40% and 30% in Clusters 1 and 2) and

56% receiving beneficial training on organic practices immediately post-ban (compared to 40% and 20% in Clusters 1 and 2).

Variable	Cluster 1 (n=5)	Cluster 2 (n=10)	Cluster 3 (n=9)
Minor irrigation scheme	60%	90%	11%
Multicrops in paddy	100%	0%	22%
Higher post-ban labor Requirements	60%	70%	56%
Higher post-ban cost of management	40%	70%	11%
Pre- ban organic inputs/methods use	40%	10%	11%
Immediate post-ban organic inputs/methods use	40%	30%	89%
2024 or 2025 maha organic inputs/methods use	40%	10%	11%
Buys seed from government stations	80%	40%	67%
Pesticide use	100%	60%	67%
Herbicide use	80%	50%	67%
Seeks out farming information from government extension	100%	50%	67%
Seeks out farming information from fellow farmers	80%	90%	67%
Received beneficial training on organic practices post-ban	40%	20%	56%
Sentiment toward organic farming 1-5	2.4	3.6	2.9

Table 3. Variables that show meaningful variation across clusters. Only variables that had data for all 24 farmers included.

Discussion

In this paper, we combined a landscape-level satellite remote sensing survey and a cluster analysis of semi-structured farmer interview responses to analyze how different types of farmers were associated with diverse post agrochemical ban outcomes in Sri Lanka's Anuradhapura

District. At both scales, our analysis found indicators of variation in post-ban yield preservation and recovery outcomes across farmer categories. Both of our methods found evidence that farmers with the lowest levels of yield were more likely to experience lower ratios of immediate yield loss and quicker paths to yield recovery as compared to farmers with more productive operations. Additional exploration of attributes at the farmer level found that resource access and diversified farm management strategies were also associated with post-ban yield resiliency.

Mapping Changes in Rice Productivity

The geospatial clustering of indicator classes in our remote sensing analysis highlights the power of passive satellite tools for helping support farmers through transitions away from agrochemicals. The ability to identify landscape-scale patterns associated with pre-transition farm yield resiliency can help governments better tailor supportive programming and resources to target farmer needs throughout transitions – identifying farms in predicted high yield resiliency areas to serve as potential early organic adopters while developing more targeted support programs for farms in predicted low yield resiliency areas.

At the landscape level, our remote sensing analysis found significant variability in a pixel's Shock Ratio and Recovery Ratio outcome based on its original Baseline class, with Low and High Baseline pixels diverging in opposite directions and Medium Baseline pixels falling consistently between them. This finding is in line with Ahvo et al.'s (2023) remote sensing model's prediction that higher-productivity agricultural regions are more susceptible to input-related yield shocks than lower-yielding regions. This finding is expected given the well-documented link between rice yields and fertilizer usage (Linguist et al., 2013). Rice fields with Low Baseline pixels are more likely to be from fields with lower relative rates of agrochemical usage compared to more productive counterparts and thus have less harvest to lose when agrochemicals become suddenly

less available. This category of rice farmers represents an important target for any future transition away from agrochemicals, as their yields – while low – are the least dependent on cheap, accessible chemical inputs, and may have the lowest opportunity cost for phasing them out.

Factors Influencing Yield Loss and Time to Recovery

Our cluster analysis found a similar trend between low farm productivity and low post-ban yield impact, with farmers in Cluster 1 reporting a mean yield rate 29% and 46% lower than those in Clusters 2 and 3 but experiencing a mean immediate post-ban yield loss 51% and 48% smaller and a mean recovery time 1.5 years and 0.6 years faster than the other two Clusters, respectively. Cluster 1 farmers reported the highest likelihood of engaging with organic-adjacent practices, with every farmer in Cluster 1 reporting multicropping in their fields outside of the main growing season (as opposed to 0% and 22% in Clusters 2 and 3), and 40% utilizing organic inputs/methods pre-ban (10% and 11%, respectively). Mung bean – a leguminous, nitrogen-fixer – was the most commonly rotated crop amongst all multicropping farmers (67%), aligning with established associations between rice-legume crop rotations and increased rice yield stability (He et al., 2021; R. Yang et al., 2024; Zhao et al., 2022). A familiarization with organic practices pre-ban and the inclusion of legume-based nitrogen sources likely decreased Cluster 1 farmers' dependency on agrochemicals, insulating them from large and sustained yield shocks.

Additionally, farmers in Cluster 1 also reported a relatively stronger connection to Government of Sri Lanka agricultural resources than those in Clusters 2 and 3, with a shorter mean distance to government extension (3.6 km compared with 8.15 km and 7.17 km, respectively), 100% seeking government extension for farming information (50% and 67%, respectively), 80% buying seeds from government stations (40% and 67%, respectively), and 40% receiving beneficial training on organic practices post-ban (20% and 56%, respectively). Our finding that

access to governmental extension services is correlated with greater post-ban yield resiliency is in line with research conducted by Cole et al. (2025), which identified that increasing access to government extension information – specifically through digital extension – can help farmers mitigate shock-related yield losses. As not all farmers can benefit from proximity to government resources, improving digital capacities to provide farmers with clear, easily accessible extension information and guidance is an important step in any transition away from agrochemicals.

High farm productivity was less associated with high and sustained yield loss in our cluster analysis than in our remote sensing survey. Cluster 3 had the highest mean yield rate in our analysis ($4,712.32 \text{ kg ha}^{-1}$), but featured a lower mean reported shock percentage (-54% versus -57%) and shorter recovery time (1.8 years versus 2.7 years) than Cluster 2 (mean yield rate $3,623.83 \text{ kg ha}^{-1}$). The similar shock percentage but divergent recovery times between Clusters 2 and 3 are notable, as they indicate that greater access to resources may have helped Cluster 3 farmers recover faster than their similarly shocked counterparts.. Cluster 3 diverged from Cluster 2 in frequency of major irrigation schemes (89% versus 10%). Because major irrigation schemes tend to lie closer to towns and are supported by more advanced infrastructure (Ginigaddara & Kodithuwakku, 2024) they likely to have better access to resources. Additionally, Cluster 3 farmers had the highest acreages (2.62 ha versus 1.73 ha and 2.22 ha for Clusters 1 and 2), were the most likely to immediately use organic inputs/methods post-ban (89% versus 40% and 30%, respectively), and most likely to receive beneficial training on organic practices (56% versus 40% and 20%, respectively), suggesting that greater resource access may have assisted Cluster 3 farmers in adapting post-ban, shortening their yield recovery period.

We found that Cluster 2 – which best represents middle-resource-endowed farmers in terms of yield rates ($3,624 \text{ kg ha}^{-1}$ versus $2,560$ and $4,712$ for Clusters 1 and 3), being primarily

associated with minor irrigation schemes (90%, versus 60% and 11%), and acreage (2.22 ha versus 1.73 and 2.62) – was the most susceptible to a sharp and prolonged yield shock. This finding is in line with Michalscheck et al.'s (2023) model exploring connections between smallholder farmer resource access and shock vulnerability. Cluster 2 farmers are moderately producing, but faced significant resource constraints, relying almost entirely on minor irrigation schemes, were the furthest away from government resources (8.15 km versus 3.6 and 7.17), and were the least likely to receive post-ban organic training (20% versus 40% and 56%) – likely decreasing flexibility for adaptation. Any successful organic conversion program must work to promote yield-supporting mechanisms in this population of farmers, through either targeted programming or the reduction of information-access barriers.

Overall, interviewed rice farmers reported no long-term shift towards organic farming. Indeed, after a brief uptake of organic inputs and practices in the season following the ban in Clusters 2 and 3, farmers across all clusters reverted to pre-ban frequencies of organic input/practice usage by harvest season 2025. It is well established that organic agricultural practices often feature higher labor demands and decreased yields, and thus require a price premium to be economically competitive (Crowder & Reganold, 2015). Interviewed farmers reported very little market incentive to transition to organic agriculture, with only one out of the original 30 interviewees reporting access to subsidized organic inputs and only one reporting potential access to a premium price for their organic produce. Additional market-based supports, either subsidizing inputs/labor or offering a premium for organic produce, are essential for encouraging the transition to organic practices.

Despite the lack of adoption of organic practice, sentiment towards organic agriculture was close to neutral (2.93 on a 5-point Likert scale) across all interviewed farmers with 93% reporting

an interest in additional training on organic agriculture. Interestingly, farmers from Cluster 2 – which experienced the largest yield shock and longest recovery – had the highest sentiment towards organic farming. With a mean Likert score of 3.6 (compared to 2.4 and 2.9 in Clusters 1 and 3), Cluster 2 farmers may represent a key category of farmers to support in any future agrochemical reduction programs, as they have both the most to gain from increased support and express the most interest in adapting to organic practices.

Divergences Between Remote Sensing Survey and Farmer Interviews

While both of our methods identified low-productivity farms as the least impacted by post-ban yield losses (Low Baseline and Cluster 1) they diverged in their assessment of the most impacted classes – with the remote sensing survey identifying High Baseline farmers and interview cluster analysis identifying middle-yielding Cluster 2. This disagreement may arise from key differences between NDRE-based productivity estimates, which predicts crop health through spectral reflectance of plant chlorophyll (Al-Shammari et al., 2025), and in-field rice yields, which are influenced by a huge multitude of factors that may not necessarily be represented by chlorophyll content alone – such as cultivar yield potential, planting techniques and harvesting techniques. This may indicate that Cluster 2’s low yield resiliency may be related to factors other than crop health outcomes and perhaps be the product of a more foundational constraint like resource access or poor seed quality.

Prospects and Limitations

Our study shows the potential for blending remote sensing tools with in-person programming to support transitions away from agrochemicals, but further applied research is needed to build on our exploratory findings. Though similar trends of most impacted farms were

seen between our remote sensing and interview cluster analyses, challenges correcting regression to the mean effects in the remote sensing sample may add bias to our Baseline, Shock and Recovery indicators. Our interview methods were limited by field conditions, relying on low sample size, farmer recall, farm location accessibility, and translation services to explore ex post facto impacts of Sri Lanka's agrochemical ban. Additionally, attempts to link interview participants with accurate GPS coordinates for their rice fields were unsuccessful as field research took place in August, outside of the rice growing seasons – most rice farmers were not actively farming at this time and interview participants were found almost exclusively at their residence. Further work pairing remote sensing data with farmer reporting and accurate rice farm GPS coordinates is a crucial next step for ground truthing the effectiveness of remote sensing yield resiliency indicators. While we have highlighted some potential avenues for increasing farm yield resiliency during agrochemical transitions, these insights need to be tested through applied field experimentation, advanced remote sensing modeling, and randomized control trials with larger sample populations.

Conclusion

Though Sri Lanka's 2021 agrochemical ban proved disastrous for short-term agricultural stability and unsuccessful at ushering in a large-scale organic farming adoption, this outcome was perhaps not inevitable. Important lessons from Sri Lanka's short-lived organic experiment can help other countries interested in decreasing their dependence on synthetic inputs. While some lessons seem obvious – a phased, long-term approach to any large-scale agricultural transition and the need for easily accessible resources to help support systemic transformations. Others highlight the need for nuanced policy and programming: transitioning low-productivity farms first, an emphasis on supporting middle-resource farmers, and the integration of diversified farming practices such as multicropping. The consistently increasing resolution and temporal coverage of satellite remote

sensing data continues to create new tools for assessing crop health and yield resiliency, allowing governments to find new ways to direct farmer-supporting policies. Further research should work collaboratively with farmers and governments to empirically test this study's exploratory findings, helping generate an iterative process for increasing international agricultural sustainability and domestic food sovereignty at a systemic level.

REFERENCES

- Abdo, A. I., Tian, M., Shi, Z., Sun, D., Abdel-Fattah, M. K., Zhang, J., Wei, H., & Abdeen, M. A. (2024). Carbon footprint of global rice production and consumption. *Journal of Cleaner Production*, 474, 143560. <https://doi.org/10.1016/j.jclepro.2024.143560>
- Ahvo, A., Heino, M., Sandström, V., Chrisendo, D., Jalava, M., & Kummu, M. (2023). Agricultural input shocks affect crop yields more in the high-yielding areas of the world. *Nature Food*, 4(12), 1037–1046. <https://doi.org/10.1038/s43016-023-00873-z>
- Al-Shammari, D., Whelan, B. M., Wang, C., Bramley, R. G. V., & Bishop, T. F. A. (2025). Assessment of red-edge based vegetation indices for crop yield prediction at the field scale across large regions in Australia. *European Journal of Agronomy*, 164, 127479. <https://doi.org/10.1016/j.eja.2024.127479>
- Babajani, A., Muehlberger, S., Feuerbacher, A., & Wieck, C. (2023). Drivers and challenges of large-scale conversion policies to organic and agro-chemical free agriculture in South Asia. *International Journal of Agricultural Sustainability*, 21(1), 2262372. <https://doi.org/10.1080/14735903.2023.2262372>
- Badgley, C., Perfecto, I., & Moghtader, J. (2026). Revisiting organic agriculture and the global food supply, twenty years on. *Renewable Agriculture and Food Systems*, 41, e21. <https://doi.org/10.1017/S1742170526100416>
- Bandara, M. A. C. S., Buhary, R., & Ramnpgagedara, M. H. K. (2023). *IMPORT BAN OF FERTILIZER AND OTHER AGROCHEMICALS (2021): ASSESSING SHORT-TERM EFFECTS ON THE PADDY SECTOR* [Report].

- Batas, M. A. A., Flor, R. J., Khumairoh, U., Rala, A., Asmara, D. H., Laborte, A., & Yadav, S. (2025). Understanding smallholder farmers' perceptions of agroecology. *Npj Sustainable Agriculture*, 3(1), 13. <https://doi.org/10.1038/s44264-025-00056-2>
- Bebermeier, W., & Schütt, B. (2020). *Tanks as Ancient Measure of Integrated Watershed Managements in the Dryzone of Sri Lanka*. <https://www.geo.fu-berlin.de/en/v/tanks-in-the-dryzone-of-sri-lanka/anuradhapura-hinterland/archaeology/index.html>
- Benami, E., Jin, Z., Carter, M. R., Ghosh, A., Hijmans, R. J., Hobbs, A., Kenduiywo, B., & Lobell, D. B. (2021). Uniting remote sensing, crop modelling and economics for agricultural risk management. *Nature Reviews Earth & Environment*, 2(2), 140–159. <https://doi.org/10.1038/s43017-020-00122-y>
- Biggs, T. W., Gangadhara Rao, P., & Bharati, L. (2010). Mapping agricultural responses to water supply shocks in large irrigation systems, southern India. *Agricultural Water Management*, 97(6), 924–932. <https://doi.org/10.1016/j.agwat.2010.01.027>
- Brunelle, T., Chakir, R., Carpentier, A., Dorin, B., Goll, D., Guilpart, N., Maggi, F., Makowski, D., Nesme, T., Roosen, J., & Tang, F. H. M. (2024). Reducing chemical inputs in agriculture requires a system change. *Communications Earth & Environment*, 5(1), 369. <https://doi.org/10.1038/s43247-024-01533-1>
- Cole, S., Goldberg, J., Harigaya, T., & Zhu, J. (2025). *The impact of digital agricultural extension service: Experimental evidence from rice farmers in India*.
- Crowder, D. W., & Reganold, J. P. (2015). Financial competitiveness of organic agriculture on a global scale. *Proceedings of the National Academy of Sciences*, 112(24), 7611–7616. <https://doi.org/10.1073/pnas.1423674112>

De La Cruz, V. Y. V., Tantriani, Cheng, W., & Tawaraya, K. (2023). Yield gap between organic and conventional farming systems across climate types and sub-types: A meta-analysis. *Agricultural Systems*, 211, 103732.

<https://doi.org/10.1016/j.agsy.2023.103732>

De Lima, I. P., Jorge, R. G., & De Lima, J. L. M. P. (2021). Remote Sensing Monitoring of Rice Fields: Towards Assessing Water Saving Irrigation Management Practices. *Frontiers in Remote Sensing*, 2, 762093. <https://doi.org/10.3389/frsen.2021.762093>

Dela Torre, D. M. G., Gao, J., & Macinnis-Ng, C. (2021). Remote sensing-based estimation of rice yields using various models: A critical review. *Geo-Spatial Information Science*, 24(4), 580–603. <https://doi.org/10.1080/10095020.2021.1936656>

Department of Census and Statistics. (2024). *Paddy Statistics—Paddy average yield and production by district—Average Yield—Maha Season 1979-2024*.

<https://www.statistics.gov.lk/Agriculture/StaticallInformation/PaddyStatistics>

Department of Census and Statistics. (n.d.-a). Retrieved June 8, 2026, from

<https://www.statistics.gov.lk/Agriculture/StaticallInformation/PaddyStatistics>

Department of Census and Statistics. (n.d.-b). *PADDY STATISTICS - EXTENT, SOWN,*

HARVESTED (GROSS & NET), AVERAGE YIELD AND PRODUCTION BY DISTRICT

2024/2025 MAHA SEASON (IMPERIAL UNITS). Retrieved December 18, 2025, from

<https://www.statistics.gov.lk/Agriculture/StaticallInformation/PaddyStatistics/ImperialUnits/IncludingMahaweli/2024-2025Maha>

Department of Census and Statistics. (2025). *PaddyStatistics 2024/2025 MahaSeason*.

https://www.statistics.gov.lk/Resource/en/Agriculture/paddystatistics/PaddyStatsPages/2024_25_Maha.pdf

Diatta, A. A., Thomason, W. E., Abaye, O., Thompson, T. L., Battaglia, M. L., Vaughan, L. J.,

Lo, M., & Filho, J. F. D. C. L. (2020). Assessment of Nitrogen Fixation by Mungbean

Genotypes in Different Soil Textures Using ^{15}N Natural Abundance Method. *Journal of Soil Science and Plant Nutrition*, 20(4), 2230–2240.

<https://doi.org/10.1007/s42729-020-00290-2>

Digal, L. N., & Placencia, S. G. P. (2019). Factors affecting the adoption of organic rice

farming: The case of farmers in M'lang, North Cotabato, Philippines. *Organic*

Agriculture, 9(2), 199–210. <https://doi.org/10.1007/s13165-018-0222-1>

Drechsel, P., Madhuwanthi, P., Nisansala, D., Ramamoorthi, D., & Bandara, T. (2025). On

the feasibility of an agricultural revolution: Sri Lanka's ban of chemical fertilizers in

2021. *Food Security*. <https://doi.org/10.1007/s12571-025-01528-6>

European Space Agency. (n.d.). *Sentinel-2*. Retrieved September 4, 2026, from

https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-2

FAO - EOSTAT. (2025, April 7). *Rice mask (Anuradhapura, Srilanka—2024—10 m)—EOSTAT -*

“FAO catalog.” FAO. <https://data.apps.fao.org/catalog/iso/d843d71c-b419-4d0b-a3f9-dd69dee1e114>

Fein-Cole, M. J., Esham, M., Jayathilake, N., Otoo, M., Koliba, C., Galford, G. L., Porterfield,

K. K., Wijethunga, I. B., & Roy, E. D. (2024). Lessons from the Short-Lived 2021

Fertilizer Import Ban in Sri Lanka Based on Analysis of Nutrient Flows. *ACS*

- Sustainable Resource Management*, 1(11), 2361–2371.
- <https://doi.org/10.1021/acssusresmgt.4c00149>
- Fukagawa, N. K., & Ziska, L. H. (2019). Rice: Importance for Global Nutrition. *Journal of Nutritional Science and Vitaminology*, 65(Supplement), S2–S3.
- <https://doi.org/10.3177/jnsv.65.S2>
- Ghose, D., Fraga, E., & Fernandes, A. (2023). *Trade policy and access to intermediate inputs: Quantifying the welfare costs of a fertilizer shortage* (Policy Research Working Paper No. 10642). World Bank.
- <https://documents.worldbank.org/en/publication/documents-reports/documentdetail/099557412122318720>
- Ginigaddara, G. A. S., & Kodithuwakku, A. N. (2024). Building climate-resilient food systems in sri lanka through site-specific agricultural management. *European Journal of Agronomy*, 156, 127148. <https://doi.org/10.1016/j.eja.2024.127148>
- Google Earth Engine. (n.d.). Retrieved January 14, 2026, from <https://earthengine.google.com>
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>
- HDX. (2026). *Sri Lanka: Rainfall Indicators at Subnational Level | Humanitarian Dataset | HDX*. <https://data.humdata.org/dataset/lka-rainfall-subnational>
- He, D.-C., Ma, Y.-L., Li, Z.-Z., Zhong, C.-S., Cheng, Z.-B., & Zhan, J. (2021). Crop Rotation Enhances Agricultural Sustainability: From an Empirical Evaluation of Eco-

- Economic Benefits in Rice Production. *Agriculture*, 11(2), 91.
<https://doi.org/10.3390/agriculture11020091>
- ICIMOD. (2018). *Organic Agriculture Development Strategies: Roadmap for 12th Five Year Plan and Beyond* (0 ed.). International Centre for Integrated Mountain Development (ICIMOD). <https://doi.org/10.53055/ICIMOD.733>
- Jain, M., Singh, B., Srivastava, A. A. K., Malik, R. K., McDonald, A. J., & Lobell, D. B. (2017). Using satellite data to identify the causes of and potential solutions for yield gaps in India's Wheat Belt. *Environmental Research Letters*, 12(9), 094011.
<https://doi.org/10.1088/1748-9326/aa8228>
- KoboToolbox. (n.d.). KoboToolbox. Retrieved January 15, 2026, from
<https://www.kobotoolbox.org/>
- Kondo, M. C., Bream, K. D., Barg, F. K., & Branas, C. C. (2014). A random spatial sampling method in a rural developing nation. *BMC Public Health*, 14(1), 338.
<https://doi.org/10.1186/1471-2458-14-338>
- Köpke, S. (2026). The transition that wasn't: Why Sri Lanka's organic farming approach failed. *Sustainability: Science, Practice and Policy*, 22(1), 2629055.
<https://doi.org/10.1080/15487733.2026.2629055>
- Ladha, J. K., Tirol-Padre, A., Reddy, C. K., Cassman, K. G., Verma, S., Powlson, D. S., Van Kessel, C., De B. Richter, D., Chakraborty, D., & Pathak, H. (2016). Global nitrogen budgets in cereals: A 50-year assessment for maize, rice and wheat production systems. *Scientific Reports*, 6(1), 19355. <https://doi.org/10.1038/srep19355>

- Linguist, B. A., Liu, L., Van Kessel, C., & Van Groenigen, K. J. (2013). Enhanced efficiency nitrogen fertilizers for rice systems: Meta-analysis of yield and nitrogen uptake. *Field Crops Research*, 154, 246–254. <https://doi.org/10.1016/j.fcr.2013.08.014>
- Marambe, B., Weerahewa, J., & Dandeniya, W. S. (Eds.). (2020). *Agricultural Research for Sustainable Food Systems in Sri Lanka: Volume 1: A Historical Perspective* (1st ed. 2020). Springer Singapore. <https://doi.org/10.1007/978-981-15-2152-2>
- Michalscheck, M., Kizito, F., Kotu, B. H., Avornyo, F. K., Timler, C., & Groot, J. C. J. (2023). Preparing for, coping with and bouncing back after shocks. A nuanced resilience assessment for smallholder farms and farmers in Northern Ghana. *International Journal of Agricultural Sustainability*, 21(1), 2241283. <https://doi.org/10.1080/14735903.2023.2241283>
- Miller, J. D., & Thode, A. E. (2007). Quantifying burn severity in a heterogeneous landscape with a relative version of the delta Normalized Burn Ratio (dNBR). *Remote Sensing of Environment*, 109(1), 66–80. <https://doi.org/10.1016/j.rse.2006.12.006>
- Murray, N. J., Keith, D. A., Bland, L. M., Ferrari, R., Lyons, M. B., Lucas, R., Pettorelli, N., & Nicholson, E. (2018). The role of satellite remote sensing in structured ecosystem risk assessments. *Science of The Total Environment*, 619–620, 249–257. <https://doi.org/10.1016/j.scitotenv.2017.11.034>
- Özdoğan, M., Wang, S., Ghose, D., Fraga, E., Fernandes, A., & Varela, G. (2025). Field-Scale Rice Area and Yield Mapping in Sri Lanka with Optical Remote Sensing and Limited Training Data. *Remote Sensing*, 17(17), 3065. <https://doi.org/10.3390/rs17173065>

- Patton, M. Q. (2014). *Qualitative Research & Evaluation Methods: Integrating Theory and Practice*. SAGE Publications.
- Perera, N. G. R. (2015). CLIMATE-SENSITIVE URBAN PUBLIC SPACE: A SUSTAINABLE APPROACH TO URBAN HEAT ISLAND MITIGATION IN COLOMBO, SRI LANKA. *SRI LANKA*.
- Rao, D. V. K. N., Badri, J., & Sundaram, R. M. (2024). Sentinel-2 Derived Indices to Understand Rice Vegetation Dynamics at Pixel Level. In H. N. Saha, H. Ray, & P. G. Bradford (Eds.), *International Conference on Systems and Technologies for Smart Agriculture* (pp. 153–165). Springer Nature. https://doi.org/10.1007/978-981-97-5157-0_13
- Rehman, T. H., Lundy, M. E., & Linquist, B. A. (2022). Comparative Sensitivity of Vegetation Indices Measured via Proximal and Aerial Sensors for Assessing N Status and Predicting Grain Yield in Rice Cropping Systems. *Remote Sensing*, 14(12), 2770. <https://doi.org/10.3390/rs14122770>
- Sandström, V., Huan-Niemi, E., Niemi, J., & Kummu, M. (2024). Dependency on imported agricultural inputs—Global trade patterns and recent trends. *Environmental Research: Food Systems*, 1(1), 015002. <https://doi.org/10.1088/2976-601X/ad325e>
- Sentinel-2 Datasets in Earth Engine | Earth Engine Data Catalog*. (n.d.). Google for Developers. Retrieved April 24, 2026, from <https://developers.google.com/earth-engine/datasets/catalog/sentinel-2>

- Shukla, R., Agarwal, A., Gornott, C., Sachdeva, K., & Joshi, P. K. (2019). Farmer typology to understand differentiated climate change adaptation in Himalaya. *Scientific Reports*, 9(1), 20375. <https://doi.org/10.1038/s41598-019-56931-9>
- Singh, M. (2020). *Sikkim: The Organic Farming Journey*. (1).
- Slycan Trust. (2022). *The Farmers' Perspective: Climate Risk & Risk Management in Sri Lanka's Agriculture Sector*. https://weadapt.org/wp-content/uploads/2023/05/farmers_perspective_brief.pdf
- Sujianto, S., Hasibuan, A. M., Mahendri, I. G. A. P., Pribadi, E. R., Pujiharti, Y., Ardana, I. K., Ermianti, Sudjarmoko, B., Sukamto, & Gunawan, E. (2024). Drivers of Organic Rice Adoption Among Smallholder Farmers: Implications for Sustainable Development. *International Journal of Sustainable Development and Planning*, 19(1), 289–299. <https://doi.org/10.18280/ijstdp.190127>
- Szepannek, G., Aschenbruck, R., & Wilhelm, A. (2025). Clustering large mixed-type data with ordinal variables. *Advances in Data Analysis and Classification*, 19(3), 749–767. <https://doi.org/10.1007/s11634-024-00595-5>
- Urruty, N., Tailliez-Lefebvre, D., & Huyghe, C. (2016). Stability, robustness, vulnerability and resilience of agricultural systems. A review. *Agronomy for Sustainable Development*, 36(1), 15. <https://doi.org/10.1007/s13593-015-0347-5>
- USDA/FAS. (2021). *Sri Lanka Restricts and Bans the Import of Fertilizers and Agrochemicals*_ (Global Agricultural Information Network New Delhi_Sri Lanka_05-14-2021).

- Van Ruijven, J., & Berendse, F. (2010). Diversity enhances community recovery, but not resistance, after drought. *Journal of Ecology*, 98(1), 81–86.
<https://doi.org/10.1111/j.1365-2745.2009.01603.x>
- Vos, R., Glauber, J., Hebebrand, C., & Rice, B. (2025). Global shocks to fertilizer markets: Impacts on prices, demand and farm profitability. *Food Policy*, 133, 102790.
<https://doi.org/10.1016/j.foodpol.2024.102790>
- Weligamage, P. (2005). *Irrigation and Inland Fisheries in Sri Lanka: Mutually Coexisting Systems for Food and Livelihood Options for Local People*.
- White, H. J., Gaul, W., Sadykova, D., León-Sánchez, L., Caplat, P., Emmerson, M. C., & Yearsley, J. M. (2020). Quantifying large-scale ecosystem stability with remote sensing data. *Remote Sensing in Ecology and Conservation*, 6(3), 354–365.
<https://doi.org/10.1002/rse2.148>
- Wittwer, R. A., Bender, S. F., Hartman, K., Hydbom, S., Lima, R. A. A., Loaiza, V., Nemecek, T., Oehl, F., Olsson, P. A., Petchey, O., Prechsl, U. E., Schlaeppli, K., Scholten, T., Seitz, S., Six, J., & Van Der Heijden, M. G. A. (2021). Organic and conservation agriculture promote ecosystem multifunctionality. *Science Advances*, 7(34), eabg6995. <https://doi.org/10.1126/sciadv.abg6995>
- Yang, J., Gao, B., Xia, F., Wei, H., & Fan, S. (2025). Internalizing the external costs to achieve environmental and economic Goals: A Case study of rice production in China. *Food Policy*, 132, 102857. <https://doi.org/10.1016/j.foodpol.2025.102857>

- Yang, R., Shen, Y., Kong, X., Ge, B., Sun, X., & Cao, M. (2024). Effects of Diverse Crop Rotation Sequences on Rice Growth, Yield, and Soil Properties: A Field Study in Gewu Station. *Plants*, 13(23), 3273. <https://doi.org/10.3390/plants13233273>
- Yewle, A. D., Mirzayeva, L., & Karakuş, O. (2025). *Multi-modal Data Fusion and Deep Ensemble Learning for Accurate Crop Yield Prediction* (arXiv:2502.06062). arXiv. <https://doi.org/10.48550/arXiv.2502.06062>
- Yu, W., Xiong, Y., Li, X., Zheng, H., Jiang, C., Yao, X., Zhu, Y., Cao, W., Qiu, L., Song, L., & Cheng, T. (2026). Rice yield prediction in unseen years at field level with high-resolution gross primary productivity derived from Sentinel-2 imagery. *Remote Sensing of Environment*, 332, 115061. <https://doi.org/10.1016/j.rse.2025.115061>
- Zhang, Z., Abdullah, M. J., Xu, G., Matsubae, K., & Zeng, X. (2023). Countries' vulnerability to food supply disruptions caused by the Russia–Ukraine war from a trade dependency perspective. *Scientific Reports*, 13(1), 16591. <https://doi.org/10.1038/s41598-023-43883-4>
- Zhao, J., Chen, J., Beillouin, D., Lambers, H., Yang, Y., Smith, P., Zeng, Z., Olesen, J. E., & Zang, H. (2022). Global systematic review with meta-analysis reveals yield advantage of legume-based rotations and its drivers. *Nature Communications*, 13(1), 4926. <https://doi.org/10.1038/s41467-022-32464-0>