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Soil Nutrient Stress, Crop System Composition, and Agro-Climatic Confounding: A District-Level Analysis of Maharashtra's Agricultural Soils

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Abstract

Soil nutrient depletion in Indian agriculture, accelerated by urea-dominated fertiliser use and declining organic matter, varies substantially across Maharashtra's agro-ecological zones, from semi-arid Marathwada and Vidarbha to the intensively cropped Western Ghats belt, yet no district-level study has mapped this variation. This paper constructs a composite Soil Nutrient Stress Index (SNSI) from Soil Health Card microdata for 34 Maharashtra districts across two programme cycles, linked to fertiliser use behaviour and farmer characteristics from the 2016 Input Survey. The SNSI, an equal-weighted mean of five deficiency proportions across 551,955 village-level records, is validated through PCA (r = -0.872) and sensitivity analysis under alternative weighting schemes (Spearman r = 0.956, 0.876). Regressions controlling for rainfall test associations between crop composition, farmer characteristics, and soil stress; findings are reported as associations, not causal effects. In 2023-24, thirteen of 34 districts registered High or Severe stress, and 22 worsened by 2024-25. Pulse crop share was negatively associated with SNSI (coef = -0.847, p = 0.020) unadjusted, but attenuated substantially (partial r = -0.157, from r = -0.513) after controlling for rainfall, indicating agro-climatic confounding. No detectable association was found between soil testing adoption and SNSI (R-squared = 0.018, p = 0.456), while farmer age was positively associated with NPK imbalance (coef = 0.031, p < 0.001). The results indicate severe, worsening soil stress with no detectable corrective effect from SHC diagnostic infrastructure, pointing to pulse promotion, subsidy restructuring, and redesigned SHC delivery as priorities for soil health governance in India and comparable developing economies.

1. Introduction

Soil health is the foundational productive asset of Indian agriculture. India cultivates 168 million hectares, the largest area under cultivation globally, with agriculture contributing 14.5% to national GDP and supporting nearly half of all households (FAO, 2023; Gulati and Juneja, 2022). Indian agriculture operates under a negative nutrient balance of approximately 10 million tonnes of NPK annually, with crop removal substantially exceeding addition through fertiliser and organic inputs (Katyal and Chaudhari, 2021). The NPK application ratio deteriorated from 4.3:2:1 in 2009-10 to 10.9:4.4:1 by 2024-25, driven by flat-rate urea subsidies that constitute approximately 75% of total fertiliser subsidy expenditure (FAI, 2023; GoI, 2022). The Centre for Science and Environment (2025) documented that 64% of soil samples tested under the SHC scheme have low nitrogen and 48.5% have low organic carbon nationally.

Maharashtra exemplifies this national pattern at state scale. The state encompasses four agro-climatic zones: the semi-arid Vertisol-dominated Marathwada and Vidarbha belt under cotton-soybean systems, the irrigated sugarcane and horticultural zone of Western Maharashtra, and the high-rainfall Alfisol-dominated Konkan coastal region. Soil fertility studies in Latur, Beed, Nashik, and Yavatmal districts document widespread nitrogen and phosphorus deficiencies and zinc constraints under intensive cultivation. Long-term fertiliser experiments at Akola and Parbhani under the ICAR All-India Coordinated Research Programme confirmed progressive nutrient imbalance under sole chemical fertiliser application without organic matter supplementation (Jadho et al., 2019). Published soil health assessments for Maharashtra rely predominantly on plot-level agronomic trials or state-level aggregates; no study has constructed a district-level composite stress index from SHC microdata or linked it to input use behaviour and farmer characteristics across the state's 34 districts.

The Government of India's Soil Health Card scheme, launched in 2015, constitutes the primary institutional response to soil degradation. The programme tested approximately 1.3 crore soil samples nationally in 2023-25 across 8,000 soil testing laboratories (PIB, 2023). Maharashtra's data cover 551,955 village-level records across 34 districts and two cycles. Assessment studies report awareness levels of 82% among farmers nationally (Reddy, 2019) but

compliance with recommended fertiliser rates of only 48%. No published study has tested whether district-level soil testing adoption has produced measurable improvements in actual soil nutrient status as measured by the SHC's own diagnostic data.

The pattern documented in Maharashtra is not a state-specific anomaly. Kishore et al. (2021), reviewing fertiliser policy and soil-testing interventions across Bangladesh, India, Nepal, and Sri Lanka, report that soil health card programmes have had limited measurable impact on fertiliser use at the national scale in India, and that subsidy rationalisation attempts have been repeatedly reversed across South Asian governments once implemented, including in Bangladesh and Nepal. Price increases on phosphatic and potassic fertilisers in India in 2011-12 did not durably correct the nitrogen-dominant application ratio, indicating that price signals alone are insufficient without complementary information and delivery mechanisms. Sri Lanka's experiment with direct cash transfers as an alternative to universal fertiliser subsidies illustrates that credible policy alternatives exist but carry substantial implementation requirements, including land record integration and a competitive retail sector, that are not trivially available across the region. Maharashtra's district-level diagnostic approach, situated within this broader South Asian pattern of diagnosis without correction, offers a replicable analytical method for other states and countries confronting the same structural gap between soil health information systems and farmer behaviour change.

Three analytical questions organise the empirical analysis. First, what is the spatial distribution of soil nutrient stress across Maharashtra's districts, and how has it changed between the 2023-24 and 2024-25 SHC cycles? Second, are 2016 input use patterns and farmer characteristics associated with 2023-24 soil stress outcomes after controlling for agro-climatic conditions? Third, does the association between pulse diversification and soil stress vary across the stress distribution?

The paper makes four contributions. A validated district-level SNSI is constructed from SHC microdata, providing the first quantitative map of Maharashtra's soil nutrient stress landscape. Cross-dataset regressions link historical input behaviour to soil health outcomes with explicit agro-climatic controls. Quantile regression assesses distributional heterogeneity in the crop system association. The sensitivity of the SNSI to alternative weighting schemes is systematically examined.

Section 2 reviews the literature. Section 3 describes data sources and methods. Section 4 presents empirical results. Section 5 discusses findings and limitations. Section 6 derives policy implications. Section 7 concludes.

2. Review of Literature

2.1. Soil Nutrient Depletion and the Soil Health Card Programme

Chemical fertiliser consumption in India rose from 69.8 thousand tonnes in 1950-51 to 29.8 million tonnes in 2021-22, yet soil nutrient status has deteriorated over the same period (FAI, 2022; Katyal and Chaudhari, 2021). Soil organic carbon has declined below 0.5% across large areas of cultivated land (CSE, 2025). The NPK ratio deteriorated from 4.3:2:1 in 2009-10 to 10.9:4.4:1 by 2024-25, driven by the differential subsidy structure under which urea is sold at a statutorily fixed price while phosphatic and potassic fertilisers are partially decontrolled (Mankunnummal, 2023; Chand and Pavithra, 2015). Approximately 75% of total fertiliser subsidies are allocated to urea (GoI, 2022), and only 35–40% of applied nitrogen is absorbed by crops (Sahu et al., 2025). Zinc deficiency affects 36–49% of cultivated land nationally (Agriculture.Institute, 2025).

The Soil Health Card scheme, launched in 2015, provides farmers with individualised soil assessments testing twelve chemical parameters alongside crop-specific fertiliser recommendations. By 2023, over 23.5 crore SHCs had been

distributed through a network of over 8,000 soil testing laboratories (PIB, 2023). Singh et al. (2022) documented crop yield increases among farmers adopting soil-test-based recommendations in Uttar Pradesh, and Makadia et al. (2017) reported reduced fertiliser consumption in Gujarat. Reddy (2019) found that while SHC awareness reached 82% of farmers, only 66% understood the recommendations and only 48% followed recommended rates. Singh et al. (2023) documented soil testing laboratory capacity constraints across states, with testing throughput insufficient to cover target sampling density in several regions. A critical empirical gap remains: the SHC evaluation literature addresses programme awareness and self-reported compliance at the farmer level, and district-level composite indexing of soil nutrient stress from SHC microdata, linked to input use behaviour and farmer characteristics, remains unaddressed for Maharashtra.

2.2. Crop System Composition and Soil Health

Leguminous crops fix atmospheric dinitrogen through root-nodule symbiosis, with quantified fixation rates of 80 to 200 kg N per hectare annually (Herridge et al., 2008). The AICRP long-term fertiliser experiment at Akola documented that combined organic and inorganic inputs maintained soil nutrient availability over three decades (Jadho et al., 2019), and Meena et al. (2022) demonstrated that pulse inclusion in rain-fed rotations restores degraded lands through nitrogen fixation and organic matter contributions. Nitrogen fixation efficiency declines on organically depleted soils, since Rhizobium populations require a minimum organic matter substrate to sustain nodulation (Herridge et al., 2008). This conditionality matters for observational analysis: district-level studies face the confounding challenge that high-pulse cultivation districts also tend to share other agro-ecological characteristics, particularly higher rainfall, that independently support soil health. The present paper addresses this confounding challenge directly through rainfall controls. Oilseed crops in Maharashtra, particularly soybean, contribute little nitrogen fixation due to poor inoculant availability and starter nitrogen applications that suppress nodulation (Virk et al., 2024), and are cultivated with minimal fertiliser guidance.

2.3. Farmer Behaviour and Analytical Methods

Age is consistently identified as a predictor of input use habit persistence, with older farmers operating under entrenched mental models formed during the Green Revolution era (Baumgart-Getz et al., 2012). Education effects on input behaviour are context-dependent: in commercially intensive systems, education is associated with higher input expenditure through improved access to credit and advisory networks (Pingali, 2012), while Fishman et al. (2016) showed that input market accessibility, not information alone, constrains balanced nutrition in rain-fed districts. Composite soil health indices commonly use principal component analysis to derive weighted scores (Singh et al., 2019), though Karlen et al. (1997) demonstrated that unweighted composite indices perform comparably to PCA-weighted indices for ranking soil health status. Hou et al. (2022) applied panel quantile regression to provincial fertiliser use data in China, demonstrating heterogeneous effects of fertiliser intensity across the efficiency distribution, a method extended in the present analysis to the pulse-soil stress relationship.

2.4. Research Gap and Contribution

Four gaps motivate the present analysis. No published study has constructed a district-level composite SNSI from SHC microdata for Maharashtra or any Indian state. The SHC evaluation literature does not assess whether district-level testing coverage has altered soil nutrient trajectories. The relationship between crop system composition and district-level soil stress has not been tested econometrically with explicit agro-climatic controls. The sensitivity of district-level SNSI rankings to alternative weighting schemes has not been examined for Indian conditions. This paper addresses each gap: a validated district-level SNSI is constructed from 551,955 SHC records across two programme cycles; cross-dataset regressions with rainfall controls report confounding attenuation explicitly; quantile

regression with bootstrap confidence intervals assesses distributional heterogeneity; and systematic sensitivity analysis under three weighting schemes validates the index construction.

3. Data and Methodology

3.1. Data Sources

Three primary data sources underpin the analysis. Soil Health Card microdata, sourced from the national SHC portal, provide village-level soil nutrient testing records for Maharashtra across two programme cycles, 2023-24 and 2024-25, comprising 551,955 records across 34 districts. Each record reports sample counts classified Low, Medium, or High for twelve nutrient parameters, including nitrogen, phosphorus, potassium, organic carbon, and seven micronutrients. The Input Survey, compiled by the National Sample Survey Organisation, provides district-level chemical fertiliser consumption data by crop, fertiliser type, and farm size for 2016. The non-crop schedule supplies farm structural data including soil testing adoption rates, farmer age distribution, educational attainment, and irrigation intensity. District-level mean annual rainfall was computed from India Meteorological Department daily station data for 2009 to 2022. Three district names were harmonised to reflect administrative renamings between 2016 and 2023: Ahmednagar to Ahilyanagar, Aurangabad to Chhatrapati Sambhajinagar, and Osmanabad to Dharashiv.

Palghar district was carved from Thane in 2014. The 2016 Input Survey crop schedule predates this bifurcation and records fertiliser consumption at the combined pre-bifurcation Thane boundary; crop system composition variables for Palghar should be interpreted accordingly. Village-level coverage rates, assessed against Census 2011 village counts, ranged from 2.9% (Thane) to 35.3% (Kolhapur) in 2023-24. Thirteen of 34 districts recorded coverage below 10%, as presented in Supplementary Table A1, carrying additional measurement uncertainty since the direction of selection bias in the underlying testing coverage cannot be determined from available data. Yavatmal recorded declining coverage between cycles, the only district where absolute coverage contracted.

3.2. Soil Nutrient Stress Index Construction

A composite Soil Nutrient Stress Index (SNSI) was constructed at the district level. For each of five components, nitrogen, phosphorus, potassium, organic carbon, and zinc, the deficiency proportion was computed as the share of samples classified Low (Deficient for zinc) in total samples tested per district-year cell. The SNSI is defined as the unweighted mean of these five proportions:

$$SNSI(d,t) \;=\; (1/5)\,x\,[def_N(d,t) \;+\; def_P(d,t) \;+\; def_K(d,t) \;+\; def_OC(d,t) \;+\; def_Zn(d,t)]$$

Equal weighting is applied for transparency and interpretive accessibility. This choice is justified empirically: sensitivity analysis under PCA-derived weights produces a Spearman rank correlation of 0.956 with the equal-weighted index. An agronomic hierarchy exists among the five components; nitrogen deficiency at a state mean of 83.7% is far more prevalent than potassium deficiency at 5.1%, and the PCA-weighted index better reflects this distributional reality. Both specifications are reported throughout, and primary findings are confirmed under PCA weighting.

3.3. Variables and Analytical Methods

N_dominance captures the nitrogen share of total nutrient content applied across fertiliser types: N_dominance(d) = wtd_N(d) / [wtd_N(d) + wtd_P(d) + wtd_K(d)]. Soil_test_rate is the proportion of operational holdings performing soil

testing in 2016. Additional variables include irrigated area share, graduate educational attainment share, mean holder age, and crop composition shares for pulses, oilseeds, and cereals.

Five analytical approaches were used. An OLS regression identified correlates of N_dominance using 2016 data. A cross-dataset OLS regression associated 2023-24 SNSI with 2016 predictors; the seven-year temporal separation reduces contemporaneous reverse causality but introduces an unresolved challenge from unobserved time-varying confounders, and the cross-sectional design with n = 31 does not support causal identification. Three districts, Ahilyanagar, Chhatrapati Sambhajinagar, and Dharashiv, are excluded from crop-system specifications because the 2016 crop schedule recorded zero pulse fertiliser application, a structural rather than random gap. These three districts include the sole Severe stress district and two High stress districts, constituting the primary external validity constraint on the regression findings. Quantile regression was estimated at the 25th, 50th, 75th, and 90th percentiles with bootstrap standard errors from 1,000 replications and Koenker-Machado pseudo-R-squared goodness of fit. Sensitivity analysis was conducted under equal, PCA-derived, and entropy weighting schemes with Spearman rank correlation assessment. Moran's I with a k = 4 nearest-neighbour matrix tested spatial autocorrelation, with spatial lag and error models as robustness checks. With n = 31 and five to eight regressors, coefficients with p-values between 0.05 and 0.10 are presented as directional evidence rather than confirmatory findings.

4. Empirical Analysis

4.1. Soil Nutrient Stress Patterns Across Maharashtra Districts

Table 1 presents the distribution of Maharashtra's 34 districts across SNSI stress categories. In 2023-24, one district registered Severe stress, twelve High, sixteen Moderate, and five Low, yielding thirteen districts in the High or Severe categories. By 2024-25, High-stress districts rose to fifteen and Low-stress districts fell to three. Figure 1 maps the classification, documenting a clear agro-climatic gradient: Marathwada and Vidarbha districts in the semi-arid interior occupy the High and Severe categories, while Konkan coastal districts register Low stress, a pattern examined against rainfall confounding in Section 4.5.

Table 1
Distribution of Maharashtra districts by SNSI stress category, 2023-24 and 2024-25.

Stress Category	SNSI Range	2023-24 (n)	2024-25 (n)	Mean SNSI 2023-24
Severe	>=0.60	1	1	0.739
High	0.45–0.59	12	15	0.521
Moderate	0.30–0.44	16	15	0.373
Low	< 0.30	5	3	0.231
Total	--	34	34	0.428

Note: SNSI = Soil Nutrient Stress Index; equal-weighted mean of deficiency proportions for N, P, K, OC, and Zn.

Nitrogen deficiency dominated the stress profile, with a mean district-level proportion of 0.837 and a median of 0.932 (93.2%). Dharashiv recorded complete deficiency (1.000); Jalna, Nanded, Ahilyanagar, and Chhatrapati Sambhajinagar each exceeded 99.8%. Organic carbon deficiency averaged 0.526, with 28 of 34 districts above 0.40. Potassium deficiency was structurally low at 0.051. Twenty-two of 34 districts recorded a higher SNSI in 2024-25 than in 2023-24. Figure 2 maps this trajectory. Raigad recorded the largest deterioration (+ 0.227), while Akola and

Ahilyanagar recorded the largest improvements (-0.092 and − 0.082). The worsening pattern spans multiple agro-climatic zones rather than a single region.

4.2. PCA Validation and Sensitivity Analysis

Table 2 presents PCA loadings. PC1 explained 39.1% of variance, loading heavily on organic carbon (-0.615), nitrogen (-0.483), and zinc deficiency (-0.468), representing a general degradation axis. PC1 correlated with SNSI at r = -0.872, and a validation regression on PC1 and PC2 produced R-squared = 0.768 (p < 0.001).

Table 2
PCA component loadings for nutrient deficiency proportions, Maharashtra districts, 2023-24 (n = 34).

Component (variance %)	def_N	def_P	def_K	def_OC	def_Zn
PC1 (39.1%)	-0.483	-0.027	+ 0.411	-0.615	-0.468
PC2 (21.3%)	+ 0.041	-0.823	+ 0.363	-0.079	+ 0.429
PC3 (20.0%)	-0.523	-0.457	-0.653	+ 0.179	-0.243
Note: Cumulative variance explained by PC1-PC3 = 80.4%.					

Sensitivity analysis produced Spearman rank correlations of 0.956 (equal versus PCA), 0.876 (equal versus entropy), and 0.784 (PCA versus entropy). Dharashiv was ranked most stressed under all three schemes. The correlation matrix of the five components reveals moderate positive correlations among def_N, def_OC, and def_Zn (r = 0.41 to 0.49), confirming co-variation along the PC1 degradation axis; equal weighting assigns this axis approximately three times the weight it would receive under orthogonal decomposition. The high Spearman consistency between equal and PCA weighting indicates that this does not materially alter district rankings. Entropy weighting assigns disproportionate weight to potassium deficiency (0.423) due to its high cross-district variance despite being the least deficient nutrient, explaining its lower correlation with the equal-weighted index.

4.3. Spatial Structure and District Typology

Moran's I for SNSI was 0.284 (p = 0.002), confirming positive spatial autocorrelation; N_dominance showed stronger clustering (Moran's I = 0.420, p < 0.001). Lagrange Multiplier tests did not reject the null of no spatial lag (p = 0.342) or spatial error dependence (p = 0.396), indicating that spatial clustering is absorbed by the crop system regressors rather than reflecting unmodelled spillovers; OLS is retained as the primary specification. K-means clustering (k = 2, silhouette = 0.336) identified an interior cluster (n = 27, mean SNSI = 0.427) and a Konkan coastal cluster (n = 4, mean SNSI = 0.224). Coastal districts apply more nitrogen-dominant fertiliser (mean N_dominance = 0.753) yet record lower stress, consistent with buffering from high rainfall, forest-derived organic matter, and lower cultivation intensity. This qualifies N_dominance as a universal correlate of degradation: its association with outcomes depends on agro-ecological context.

4.4. Correlates of NPK Application Imbalance

Table 3 presents OLS results for N_dominance (n = 34). The model was jointly significant (F = 5.352, p = 0.001, adjusted R-squared = 0.397). Mean farmer age was the strongest correlate (coef = 0.031, p < 0.001), and graduate educational attainment was associated with lower N_dominance (coef = -0.994, p = 0.050). Soil testing adoption showed no association (p = 0.807).

Table 3
OLS regression: correlates of district-level N_dominance, Maharashtra 2016 (n = 34).

Variable	Coef.	SE	t	p
Intercept	-0.808	0.325	-2.483	0.019*
soil_test_rate	0.033	0.136	0.246	0.807
irrig_share	-0.340	0.178	-1.913	0.066+
share_graduate	-0.994	0.485	-2.050	0.050*
avg_age	0.031	0.007	4.409	< 0.001***
fert_intensity_per_ha	-0.131	0.514	-0.256	0.800
Adj. R-sq / F / p	0.397	--	5.352	0.001
*Note: Dependent variable = N_dominance. *** p < 0.001; * p < 0.05; + p < 0.10.*				

4.5. Crop System Composition and Soil Nutrient Stress

Table 4 presents OLS results for 2023-24 SNSI using 2016 predictors (n = 31). The parsimonious specification was jointly significant (F = 3.736, p = 0.012, adjusted R-squared = 0.313). Pulse share was negatively associated with SNSI (coef = -0.847, p = 0.020); the full specification confirmed this (coef = -0.898, p = 0.034). Oilseed share was positively associated at the 10% level (coef = 0.393, p = 0.081). Figure 3 maps pulse share, with high shares concentrated in eastern districts where the bivariate correlation between pulse share and rainfall was r = 0.51. The partial correlation between pulse share and SNSI, controlling for rainfall, was r = -0.157, attenuated from the bivariate r = -0.513. When rainfall entered the regression, the pulse coefficient lost significance. Districts with higher pulse cultivation also receive higher rainfall, independently associated with lower stress through forest-derived organic matter and reduced evapotranspiration demand; the cross-sectional design cannot disentangle pulse cultivation from this broader agro-ecological context.

Table 4
OLS regression: correlates of district-level SNSI (2023-24), Maharashtra. Predictors from 2016 Input Survey.

Variable	M3 Coef.	SE	t	M4 Coef.	p (M4)
Intercept	0.162	0.463	0.351	0.353	0.139
share_pulses	-0.847*	0.340	-2.491	-0.898*	0.034
share_oilseeds	0.393+	0.216	1.818	0.376	0.306
N_dominance	0.005	0.257	0.020	-0.045	0.877
soil_test_rate	0.297+	0.156	1.908	0.167	0.362
avg_age	0.004	0.010	0.369	--	--
irrig_share	--	--	--	-0.083	0.815
share_graduate	--	--	--	0.916	0.152
Adj. R-sq / F / p / n	0.313	--	3.736	0.320/3.014/0.021	n = 31

*Note: Three districts excluded from crop-system specifications: Ahilyanagar (SNSI = 0.473), Chhatrapati Sambhajinagar (SNSI = 0.482), Dharashiv (SNSI = 0.739), due to zero recorded pulse fertiliser application in 2016. Results cannot be extrapolated to these districts. When rainfall is added, the pulse coefficient loses significance. * p < 0.05; + p < 0.10.*

4.6. Distributional Analysis: Quantile Regression

Table 5 presents quantile regression results. Pulse share was negatively associated with SNSI at Q25 (coef = -1.332, 95% CI: -2.426 to -0.238, p = 0.033) but not at Q50, Q75, or Q90. The Wald test of slope equality was marginal (p = 0.067). Pseudo-R-squared declined from 0.304 at Q25 to 0.184 at Q90. With rainfall controlled, pulse share lost significance at every quantile, indicating the association was detectable only at the lower tail before rainfall control and was not robust to it.

Table 5
Quantile regression: SNSI as dependent variable, Maharashtra. Bootstrap SE, 1,000 replications.

Variable	OLS	Q25	Q50	Q75	Q90
share_pulses	-0.847*	-1.332*	-0.791	-1.153+	-0.302
share_oilseeds	0.393+	0.434	0.115	0.494	0.383
N_dominance	0.005	0.513	-0.311	-0.162	0.174
soil_test_rate	0.297+	0.435	0.328	0.114	0.130
avg_age	0.004	-0.010	0.011	-0.002	0.005
OLS: Adj. R-sq / F / p	0.313/3.736/0.012	--	--	--	--
QR Pseudo-R-sq (KM)	--	0.304	0.233	0.236	0.184

*Note: n = 30 (complete cases); Ratnagiri excluded due to missing rainfall data. Wald test of slope equality: p = 0.067. * p < 0.05; + p < 0.10.*

4.7. Farmer Age, Education, and NPK Application Imbalance

Farmer age was positively associated with N_dominance (coef = 0.031, p < 0.001) but not independently associated with SNSI after controlling for crop composition (p = 0.715), indicating the age-stress relationship does not operate primarily through the fertiliser imbalance channel; long-term management practices correlated with age cohort represent a plausible alternative pathway that the cross-sectional design cannot confirm. Graduate educational attainment was associated with higher SNSI in the direct-effects model (coef = 1.211, p = 0.032). Districts with higher graduate shares (Pune, Nashik, Kolhapur, Sangli) record higher irrigated area share (0.24 versus state mean 0.14) and horticultural and sugarcane fertiliser share (0.41 versus 0.19), consistent with commercial intensification. An alternative interpretation through rural out-migration, leaving farming to older and less-educated household members, cannot be distinguished from commercial intensification in this design. The finding is treated as hypothesis-generating, consistent with Pingali (2012).

5. Discussion

5.1. The Structural Soil Degradation Trajectory

The SNSI analysis documents advanced and worsening multi-nutrient depletion across Maharashtra. Nitrogen deficiency affects 83.7% of tested soils on average, organic carbon deficiency exceeds 40% in 28 of 34 districts, and 22 of 34 districts worsened between cycles. Maharashtra's Green Revolution transition created a production system calibrated to chemical nitrogen inputs on soils that were, at adoption, nitrogen-responsive. Sustained urea application on organically depleted soils produces diminishing returns, contributes to secondary micronutrient limitations through competitive ion displacement, and accelerates loss of the organic matrix sustaining water retention and biological nitrogen fixation (Sahrawat et al., 2000).

5.2. Crop System Composition, Rainfall, and Soil Stress

Pulse crop share was negatively associated with SNSI in unadjusted specifications, consistent with the well-established biological basis for legume nitrogen fixation (Herridge et al., 2008; Peoples et al., 2009). The rainfall control substantially attenuated this association, with the partial correlation declining from r = -0.513 to r = -0.157 and the pulse coefficient losing significance across specifications. High-pulse districts in eastern Maharashtra also receive substantially higher rainfall than low-pulse Marathwada and Vidarbha districts, and rainfall is independently associated with lower soil stress through forest-derived organic matter and reduced evapotranspiration. The pulse-SNSI association is best interpreted as reflecting the co-occurrence of legume cropping with high-rainfall agro-ecological zones rather than an independent crop-system effect. This attenuation does not preclude a genuine biological contribution: controlled experiments consistently document legume benefits (Jadho et al., 2019; Meena et al., 2022), but this study's cross-sectional evidence cannot confirm the direction or magnitude of a causal effect at district scale. The Konkan coastal cluster illustrates the same confounding: coastal districts apply the most nitrogen-dominant fertiliser yet record the lowest stress, reflecting high rainfall, organic matter inputs, and lower cultivation intensity rather than fertiliser composition.

5.3. Soil Testing and the Information System

Soil testing adoption at the 2016 state mean of 32.6% showed no statistically detectable association with NPK imbalance (R-squared = 0.027, p = 0.354) or with soil stress seven years later (R-squared = 0.018, p = 0.456). This pattern is consistent with the broader South Asian evidence noted in the Introduction, where soil health card programmes have shown limited measurable impact on fertiliser use at national scale (Kishore et al., 2021). Alternative explanations remain plausible and cannot be distinguished in this design: testing may concentrate in districts already deteriorating; recommendation specificity may vary; and fertiliser market availability of balanced

products may constrain corrective application even among informed farmers. The finding is best characterised as an absence of any detectable district-level corrective effect, not as proof of programme failure.

5.4. Farmer Age and Education

The positive association between farmer age and NPK imbalance is consistent with habit persistence in urea-centric practices established during the Green Revolution (Baumgart-Getz et al., 2012; Pingali, 2012). The absence of an independent age-SNSI association suggests this relationship does not operate primarily through the chemical fertiliser channel. The education-stress association is consistent with commercial intensification (Pingali, 2012), supported by higher irrigated area and horticultural share in the relevant districts, though the out-migration alternative cannot be excluded and the finding requires replication in larger samples.

5.5. Limitations

Five limitations bound the generalisability of the results. Agro-climatic confounding is the primary constraint: the pulse-SNSI partial correlation declined from r = -0.513 to r = -0.157 after rainfall control, and stronger identification would require plot-level data, longitudinal tracking, or a natural experiment generating exogenous variation in pulse cultivation. Statistical power constrains inference throughout, with approximately five observations per parameter at the lower boundary of conventional guidance; coefficients with p-values between 0.05 and 0.10 are treated as directional. SNSI weighting sensitivity introduces moderate index uncertainty, with rank correlations across schemes ranging from 0.876 to 0.956. The temporal gap between 2016 predictors and 2023-24 outcomes provides quasi-prospective structure but does not resolve confounding from unobserved changes in cropping patterns or extension coverage over the intervening period, a challenge sharpened by three specific events: the Maharashtra drought of 2018-19, COVID-19 disruption to extension services in 2020-21, and the post-Ukraine fertiliser price shock of 2022-23, each capable of shifting cropping patterns or NPK ratios in ways this design cannot isolate.

6. Policy Implications

6.1. Closing the Recommendation Translation Gap

The SHC programme has generated diagnostic information at scale, 551,955 village-level records across Maharashtra in two cycles alone; the empirical finding is an absence of detectable corrective effect, not an absence of coverage. Three changes would close this gap. Soil health cards should be accompanied by crop-specific and product-specific input schedules rather than generic nutrient classifications, specifying quantity, application timing, and expected yield response. Subsidised fertiliser allocations should be linked to soil test recommendations rather than remaining unconstrained by soil health status. Post-testing advisory visits by trained extension officers should be mandated within 30 days of card issuance in High and Severe stress districts. Integration of soil test results into the PM-KISAN beneficiary database would extend soil-test-conditioned advisory to approximately 1.2 crore enrolled farmers in Maharashtra at the point of subsidy payment, a delivery channel that bypasses extension capacity constraints.

6.2. Pulse Promotion and Subsidy Restructuring

The agronomic literature on legume nitrogen fixation (Herridge et al., 2008; Peoples et al., 2009; Jadho et al., 2019) provides the primary evidentiary basis for pulse crop promotion as a soil restoration strategy; the policy case rests on this literature rather than on the present study's cross-sectional associations, since the independent contribution of crop composition cannot be confirmed after controlling for rainfall. Minimum Support Price parity for pulses relative to cereals and cotton, communicated predictably, addresses price risk, the primary reason for low pulse cultivation in

Marathwada and Vidarbha. Districts satisfying an observable criterion, SNSI above 0.45, pulse share below the state mean of 9.8%, and rainfall below 900mm, constitute a defensible priority target for input subsidy bundling with Rhizobium inoculant and zinc sulphate supplement, avoiding false precision in district-specific naming.

The current fertiliser subsidy architecture provides urea at a flat rate irrespective of soil status or agro-climatic zone. A restructured system would differentiate subsidy access by soil health status, increasing effective access to balanced products in High and Severe stress districts while reducing urea's price advantage there. Zinc sulphate subsidy prioritisation in districts with zinc deficiency above 50% would address a yield gap that persists even where macronutrient application is adequate. Table 6 translates the SNSI classification into a district-specific intervention matrix spanning four categories defined by stress level and trajectory.

Table 6. District-level soil health intervention matrix based on SNSI classification and trend, Maharashtra.

Category	Districts	SNSI Profile	Priority Interventions
Severe / Worsening	Dharashiv, Parbhani, Buldhana, Akola, Amravati	SNSI > 0.55; worsening	Organic matter remediation; Rhizobium subsidy; block-level extension officer; fertiliser entitlement linked to soil test
High / Worsening	Bhandara, Chandrapur, Jalgaon, Jalna, Solapur, Gadchiroli, Nagpur	SNSI 0.45-0.55; worsening	MSP parity enforcement; crop-specific NPK dose cards; 30-day advisory visit mandate
Moderate / Reversible	Pune, Nashik, Satara, Kolhapur, Sangli, Dhule, Nandurbar	SNSI 0.30-0.45; mixed	Crop rotation incentives; graduated subsidy linked to test compliance; farmer field schools
Improving / Low Stress	Ratnagiri, Sindhudurg, Raigad, Palghar, Thane	SNSI < 0.35; improving	Monitoring continuity; organic certification incentives; preservation of cropping diversity

Note: District assignments based on 2023-24 SNSI values and trajectory.

6.3. Institutional Redesign and the Farmer Age Transition

Scaling the SHC programme without redesigning delivery will not alter detectable soil nutrient trajectories. The Agriculture Technology Management Agency framework should mandate dedicated soil health advisors at block level in High and Severe stress districts, covering approximately 180 blocks across 13 priority districts, and third-party accredited soil testing would increase throughput and introduce competitive pressure on recommendation quality. The positive association between farmer age and imbalanced fertiliser application identifies a demographic dimension that agrochemical policy alone cannot address; mean farmer age in the Agrarian Stress Belt cluster was 47.1 years in 2016, and a substantial fraction of Maharashtra's operational holdings will transition to younger farmers within the decade. State agricultural university curricula should embed soil health management as a foundational module for young farm entrants, and digital extension platforms under the Digital Agriculture Mission should calibrate soil health advisory content to district-specific SNSI profiles.

7. Conclusion

This paper diagnoses the structural condition of soil nutrient health across Maharashtra's 34 districts through a composite Soil Nutrient Stress Index constructed from Soil Health Card microdata, linked to fertiliser use behaviour and farmer characteristics from the 2016 Input Survey. Four findings carry direct implications for soil health policy in India and comparable agricultural economies.

Soil nutrient depletion in Maharashtra is severe, widespread, and worsening, with the SNSI validated through PCA and confirmed stable across three alternative weighting schemes (Spearman r = 0.876 to 0.956). Pulse crop share was negatively associated with soil stress in unadjusted specifications, but this association was substantially confounded by rainfall, and the policy case for pulse promotion accordingly rests on the agronomic literature rather than on this study's observational associations. Soil testing adoption showed no detectable association with either NPK imbalance or subsequent soil stress, a pattern consistent with independent multi-country evidence on soil health card effectiveness in South Asia (Kishore et al., 2021). Farmer age was positively associated with NPK imbalance but not independently with soil stress, while graduate educational attainment was associated with higher stress, consistent with commercial intensification though an out-migration alternative cannot be excluded.

Three policy priorities follow. Pulse cultivation should be promoted through MSP parity and an observable criterion-based targeting framework, grounded in agronomic mechanism evidence. Fertiliser subsidy architecture should be restructured to link urea access to soil health status. The SHC programme should be redesigned to close the recommendation translation gap through crop-specific dose cards, PM-KISAN database integration, and dedicated soil health advisors in priority districts.

Three directions for future research follow from this study's limitations. Extension of the SHC dataset to additional cycles would enable panel analysis and stronger identification of programme effects. Plot-level survey data linking soil test results to subsequent fertiliser decisions, with explicit agro-climatic controls, would directly measure the recommendation translation gap and better isolate the crop system effect from rainfall. Multi-state replication across Punjab, Haryana, and Andhra Pradesh would assess whether the patterns documented here generalise nationally, and cross-country replication in Bangladesh, Nepal, or Sri Lanka would test whether the diagnosis-without-correction pattern identified in this study and in Kishore et al. (2021) reflects a structural feature of soil health card design across South Asia.

Declarations

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Competing Interests. On behalf of all authors, the corresponding author states that there is no conflict of interest.

Data Availability. The datasets generated and analysed during the current study are available in the Harvard Dataverse repository, https://doi.org/10.7910/DVN/QPAW2H. Raw Soil Health Card microdata are publicly available at soilhealth.dac.gov.in. The 2016 Input Survey data are available from the Ministry of Statistics and Programme Implementation, Government of India.

Author Contribution. Prakash Vhankade is the sole author and is responsible for all aspects of conceptualisation, data curation, formal analysis, methodology, visualisation, and writing.

Data Sources

Government of India, Ministry of Agriculture and Farmers' Welfare, 2023-25. Soil Health Card Scheme Microdata. National SHC Portal, soilhealth.dac.gov.in. [Accessed: January 2025].

Government of India, Ministry of Statistics and Programme Implementation (MoSPI), 2016. Input Survey 2016: Crop Schedule, Non-Crop Schedule, and Composite Schedule. National Sample Survey Organisation, New Delhi.

India Meteorological Department (IMD), 2022. District-Level Daily Rainfall Data, 2009-2022. IMD, Pune.

References

1. Anand, S.P., 2002. Long-term effects of fertilizers on soil potassium under different cropping systems. In: Swarup, A., Reddy, D.D., Prasad, R.N. (Eds.), Long-term Soil Fertility Management through Integrated Plant Nutrient Supply. Indian Institute of Soil Science, Bhopal, pp. 170-179.
2. Ankhila, P.H., Kumar, N., Singh, A., 2023. Soil Health Card scheme and nutrient use efficiency: evidence from adopting farmers in India. Journal of Soil Science and Plant Nutrition 23(4), 4521-4535. https://doi.org/10.1007/s42729-023-01456-x
3. Baumgart-Getz, A., Prokopy, L.S., Floress, K., 2012. Why farmers adopt best management practices in the United States: a meta-analysis of the adoption literature. Journal of Environmental Management 96(1), 17-25. https://doi.org/10.1016/j.jenvman.2011.10.006
4. Chand, R., Pavithra, S., 2015. Fertiliser use and imbalance in India: analysis of states. Economic and Political Weekly 50(44), 98-106.
5. Centre for Science and Environment (CSE), 2025. Sustainable Food Systems: An Agenda for Climate-Risked Times. Centre for Science and Environment, New Delhi.
6. Fertiliser Association of India (FAI), 2022. Fertiliser Statistics 2021-22. FAI, New Delhi.
7. Fertiliser Association of India (FAI), 2023. Fertiliser Statistics 2022-23. FAI, New Delhi.
8. Fishman, R., Kishore, A., Rothler, Y., Ward, P., Jha, S., Singh, R., 2016. Unintended consequences of development interventions: the case of imbalanced fertilizer use in India. Food Policy 60, 1-9. https://doi.org/10.1016/j.foodpol.2015.11.004
9. Food and Agriculture Organization of the United Nations (FAO), 2023. FAOSTAT Statistical Database. FAO, Rome. https://www.fao.org/faostat
10. Food and Agriculture Organization of the United Nations (FAO), 2024. The State of the World's Land and Water Resources for Food and Agriculture. FAO, Rome.
11. Government of India (GoI), 2022. Economic Survey 2021-22. Department of Economic Affairs, Ministry of Finance, New Delhi.
12. Gulati, A., Juneja, R., 2022. Transforming Indian Agriculture: Challenges and Opportunities. ICRIER Policy Paper. Indian Council for Research on International Economic Relations, New Delhi.
13. Herridge, D.F., Peoples, M.B., Boddey, R.M., 2008. Global inputs of biological nitrogen fixation in agricultural systems. Plant and Soil 311(1-2), 1-18. https://doi.org/10.1007/s11104-008-9668-3
14. Hou, M., Xi, Z., Zhao, S., 2022. Evaluating the heterogeneity effect of fertilizer use intensity on agricultural eco-efficiency in China: evidence from a panel quantile regression model. International Journal of Environmental Research and Public Health 19(11), 6612. https://doi.org/10.3390/ijerph19116612
15. Jadho, J.N., Deshmukh, V.N., Mahajan, S.S., 2019. Effect of INM on available soil nutrient under long-term fertilizer experiment in sorghum-wheat system in Vertisol at Akola. Journal of Soils and Crops 29(1), 1-8.
16. Karlen, D.L., Mausbach, M.J., Doran, J.W., Cline, R.G., Harris, R.F., Schuman, G.E., 1997. Soil quality: a concept, definition, and framework for evaluation. Soil Science Society of America Journal 61(1), 4-10. https://doi.org/10.2136/sssaj1997.03615995006100010001x
17. Katyal, J.C., Chaudhari, S.K., 2021. Soil health in India: status, challenges, and way forward. Current Science 120(11), 1729-1737. https://doi.org/10.18520/cs/v120/i11/1729-1737

18. Kishore, A., Alvi, M., Krupnik, T.J., 2021. Development of balanced nutrient management innovations in South Asia: perspectives from Bangladesh, India, Nepal, and Sri Lanka. Global Food Security 28, 100464. https://doi.org/10.1016/j.gfs.2020.100464
19. Makadia, J.J., Mistry, H.H., Kuthe, S.B., 2017. Impact of soil health card on fertilizer consumption and yield of sugarcane and kharif paddy in Gujarat State. Economic Affairs 62(1), 61-66. https://doi.org/10.5958/0976-4666.2017.00009.X
20. Mankunnummal, A., 2023. Nutrient imbalance in India. Economic and Political Weekly 58(52), 4-5.
21. Meena, R.S., Das, A., Yadav, G.S., Lal, R. (Eds.), 2022. Legumes for Soil Health and Sustainable Management. Springer, Singapore. https://doi.org/10.1007/978-981-15-1211-5
22. Peoples, M.B., Herridge, D.F., Ladha, J.K., 2009. Biological nitrogen fixation: an efficient source of nitrogen for sustainable agricultural production? In: Ladha, J.K., George, T., Bohlool, B.B. (Eds.), Biological Nitrogen Fixation for Sustainable Agriculture. Springer, Dordrecht, pp. 3-28.
23. Pingali, P.L., 2012. Green Revolution: impacts, limits, and the path ahead. Proceedings of the National Academy of Sciences of the United States of America 109(31), 12302-12308. https://doi.org/10.1073/pnas.0912953109
24. Press Information Bureau (PIB), 2023. New Soil Health Card Scheme. PIB Delhi, 11 August 2023. Press Information Bureau, Government of India, New Delhi. https://www.pib.gov.in
25. Reddy, A.A., 2019. The Soil Health Card scheme in India: lessons learned and challenges for replication in other developing countries. Journal of Natural Resources Policy Research 9(2), 124-156. https://doi.org/10.5325/naturesopolirese.9.2.0124
26. Sahu, B., Juneja, R., Nand, S., Gulati, A., 2025. India's Soil Health Crisis: Fertiliser Policy, Nutrient Imbalance, and the Path to Reform. ICRIER Policy Paper. Indian Council for Research on International Economic Relations, New Delhi.
27. Sahrawat, K.L., Wani, S.P., Rego, T.J., Pardhasaradhi, G., Murthy, K.V.S., 2000. Widespread deficiencies of iron, zinc, manganese and copper in dryland soils of the Indian semi-arid tropics. Current Science 78(9), 1139-1142.
28. Singh, B.P., Kumar, V., Chander, M., Reddy, M.B., 2022. Impact of Soil Health Card scheme on soil fertility and crop production among the adopted farmers. Indian Journal of Extension Education 59(1), 122-126.
29. Singh, V.K., Shukla, A.K., Dwivedi, B.S., 2023. Challenges in soil testing and fertiliser recommendation system in India: gaps and way forward. Indian Journal of Fertilisers 19(3), 224-234.
30. Singh, R.K., Hussain, S.M., Bhatt, S., Bisht, J.K., Parihar, C.M., 2019. Soil quality index: a tool to assess soil health status under long-term cropping systems in India. Current Science 116(9), 1520-1529. https://doi.org/10.18520/cs/v116/i9/1520-1529
31. Virk, H.K., Singh, G., Kaur, R., 2024. Recent advances in application of biofertilizers in pulses. Legume Research 47(4), 511-518. https://doi.org/10.18805/LR-4808

Figures

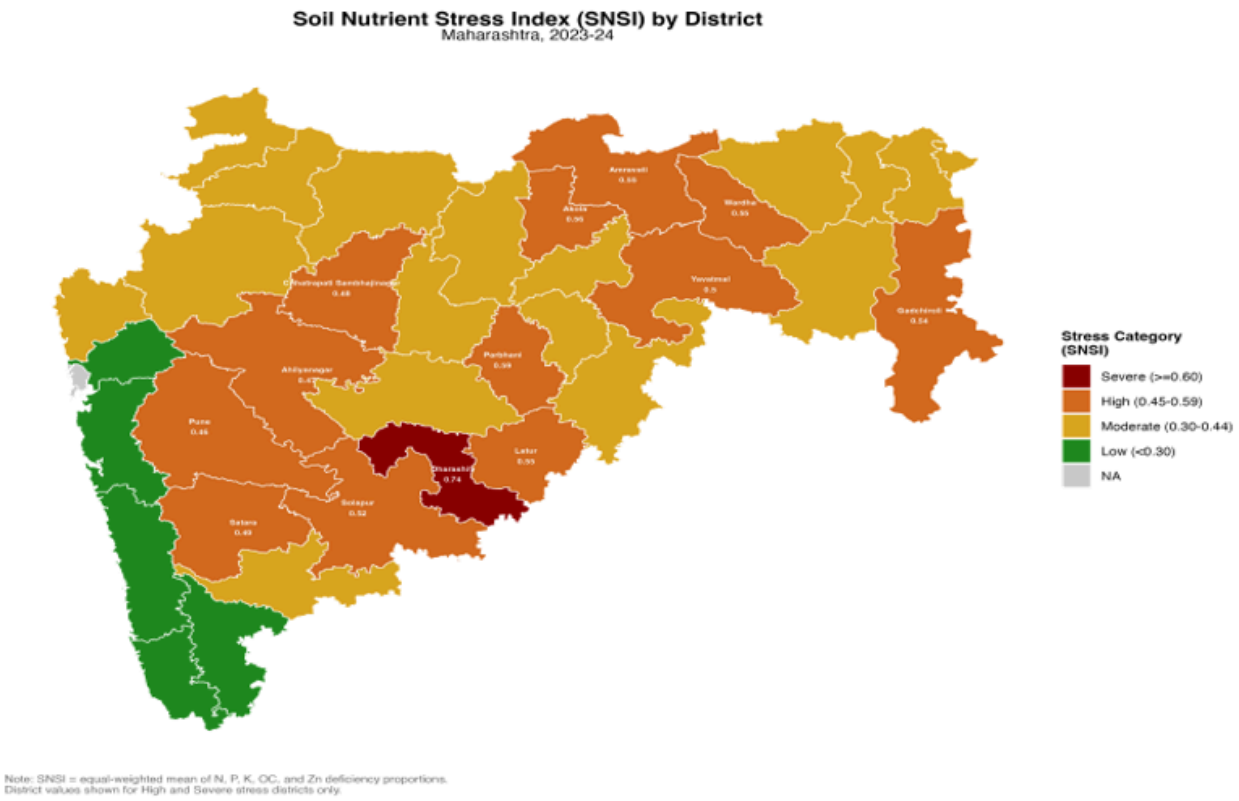


Figure 1

Pulse crop share of total fertiliser application by district, Maharashtra, 2016. Darker green indicates higher pulse share. Grey indicates missing or zero data.

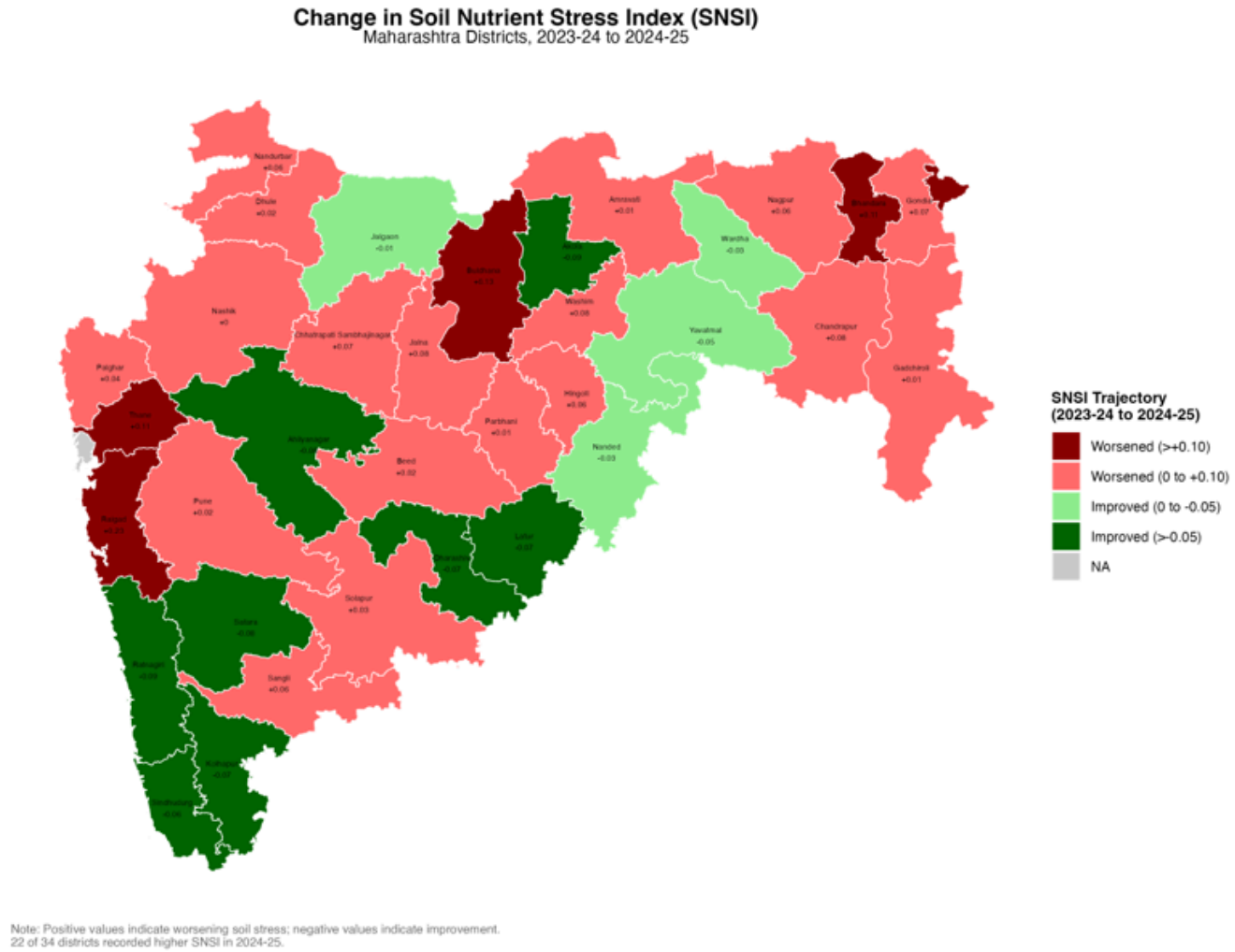


Figure 2

Change in SNSI between 2023-24 and 2024-25 by district, Maharashtra. Red indicates worsening; green indicates improvement. 22 of 34 districts recorded higher SNSI in 2024-25.

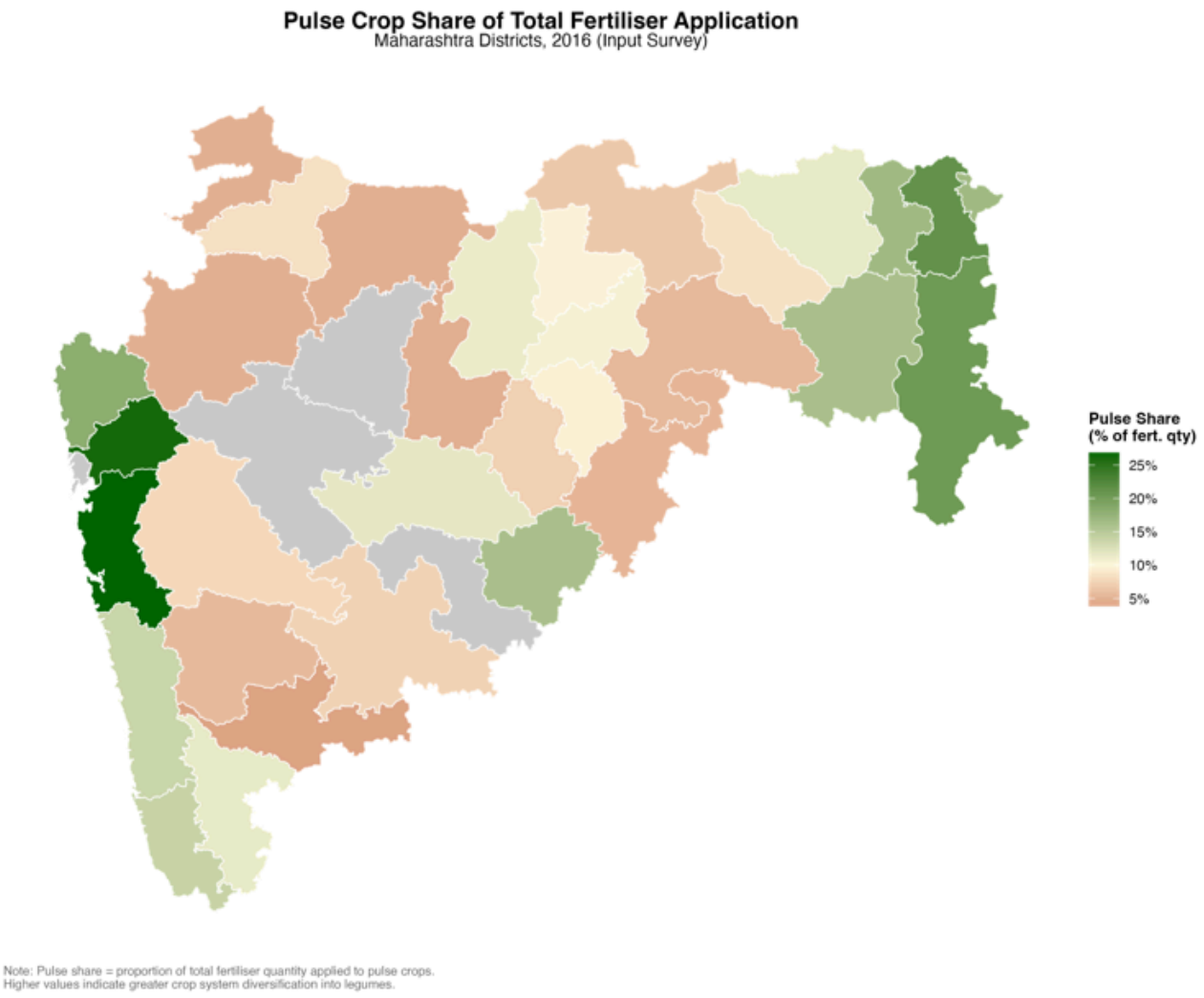


Figure 3

Pulse crop share of total fertiliser application by district, Maharashtra, 2016. Darker green indicates higher pulse share. Grey indicates missing or zero data.

Supplementary Files

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- masterfinalmaharashtra.csv
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- masterv3rainfall.csv
- masterv3rainfall.csv
- snsichange.csv
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