Soil quality perceptions: Characterizing bias and linkage with farming decisions for rice-growers in India

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Selected Paper prepared for presentation at the 2023 Agricultural & Applied Economics Association Annual Meeting, Washington, D.C.; July 23 - July 25

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Abstract:

Maintaining soil quality in the face of increasing human pressure on lands is a major challenge. Policy efforts to improve soil fertility tend to inform farm-level decisions – but adoption of policy mandates will depend upon *farmer perceptions about soil quality* which drives their *subjective* cost benefit calculations. Perceptions are likely to be inconsistent with the corresponding data-based evidence because expectations about unobserved soil quality are typically formed on the basis of observable indicators (e.g., crop yields) which are (at best) an imperfect proxy for soil fertility. We characterize soil quality perceptions of rice-growers in India with a focus on the *distance* between *subjective* soil quality perceptions (from primary surveys) and corresponding data-based evidence (recorded in soil maps). Specifically, we address *how*, if at all, soil quality perceptions deviate from corresponding data-based measurements? *What* spatial patterns might emerge in farmer *misperceptions* about soil quality given that soils typically exhibit geographic variations? We also evaluate potential drivers of soil quality misperceptions, including growers' economic status, demographic information and farming history. Finally, we evaluate linkages between soil quality misperceptions and farm-level decision making to understand whether farmers exhibit psychological motives (such as 'motivated' reasoning) to rationalize their farming decisions. We found that a majority of farmers in our sample consistently perceived soil texture but inconsistently perceived soil fertility on their farms relative to the respective data-based measurements. Higher crop yields and greater ease of farming (measured by wealth and irrigation availability) were associated with better soil quality perceptions. Educated, landowning farmers and those belonging to forward castes were more likely to perceive higher soil quality when compared with the respective counterparts. Finally, a Chi-squared test of independence revealed that under-perceptions in soil quality were less likely to affect (and be affected by) farm-level decisions while over-perceptions of soil quality were associated with lower nutrient supplementation and lower incidence of end of season crop residue burning. Our findings suggest that land management policy can be improved by incorporating farmers' *subjective* perceptions about their soil quality.

JEL Codes: C210; D220; D910; Q120; Q150

Keywords: Soil Quality Perceptions; Farming Decisions; Motivated Beliefs; Ordered Logit

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1. INTRODUCTION:

Human dependence on soil resources has a rich history spanning centuries (Polanyi 1944; Vittoria & Goldberg 1975; Blum 1988; Blum 1990; McNeill & Winiwarter, 2004; Blum 2005; Baveye, at al. 2016; Bünemann et al. 2018). But maintaining soil quality in the face of climate change, population expansion, and increasing food demand is a pressing challenge facing humanity (Anderson & Thampapillai 1990; Ajayi et al. 2007; Barrett & Mutambatsere 2008; Barrett & Mutambatsere 2015). According to the 2015 United Nations Convention to Combat Desertification, about forty percent of total global land and more than half of global agricultural lands are facing soil degradation with long-term adverse impacts on rural and agricultural incomes (Ajayi et al. 2007; Barrett & Bevis 2015). Such impacts are likely salient in low-income areas since natural capital accounts for nearly half of the wealth in low-income countries and soil capital accounts for ~70 percent of this wealth (World Bank 2006; World Bank 2018). The degradation of soil resources coupled with weak institutions that inhibit farm-level risk management underscore the importance of understanding soil quality dynamics and its implications for agricultural outcomes (Cleaver & Schreiber 1994; Gray and Morant 2003; Barrett 2008; Barrett & Mutambatsere 2008; Barrett & Bevis 2015). Policy efforts to improve soil fertility tend to inform farm-level decisions such as crop choices, input application and land management (Anderson & Thampapillai 1990; Jager 2005; Ajayi et al. 2007; Barrett 2008; Marenya et. al. 2012; Gomiero 2016; Bationo et al. 2018). Adoption of policy mandates however, will depend upon *farmer perceptions about soil quality* which drives their subjective cost benefit calculations (Ervin and Ervin 1982; Green and Heffernan 1987; Barrett et al. 2002; Barbier 1988; Barrios & Trejo 2003; Gray and Morant 2003; Barrios at al. 2006; Moser and Barrett 2006; Barrett 2008; Pham et al. 2021).

Importantly, farmers' perceptions about soil quality may not be accurate or even consistent with the corresponding data-based evidence because expectations about unobserved soil quality are typically formed on the basis of observable bio-physical indicators like agricultural yields (i.e., output per acre) which are themselves stochastic due to uncertainty in temperature, rainfall, and other environmental conditions like weed incidence or pest infestations. Moreover, soil quality dynamics, i.e., the pattern of changes in soil fertility and soil nutrient balance over time (due to agricultural or human activities in general,) is *highly non-linear* in nature. For example, soil organic matter and related nutrients like nitrogen and phosphorus often follow exponential decay patterns in soils which are continuously cultivated without fertilizer supplements, but the rate and limit of decay as well as soil resilience varies significantly with soil texture and mineralogy (Perrings 1989; Lal 1993; Barrett et al. 2002; Pell et al. 2004; Marenya and Barrett 2007; Barrett 2008; Sietz et al. 2017; Nord & Snapp 2020). Hence, farmers' perceptions of soil quality – a complex, dynamic entity - are often based on lagged, and imperfect information regarding the underlying soil quality dynamics and are thus likely to be inconsistent with or *biased* away from the scientific data-based measures for the same (Ervin and Ervin 1982; Barrett et al. 2002; Barrios & Trejo 2003; Andrews et al. 2003; Gary and Morant 2003; Oudwater & Martin 2003; Barrios et al. 2006; Gruver & Weil 2007; Barrett 2008; Marenya et al. 2008; Berazneva et al. 2018; Nord and Snapp 2020).

The distance between farmers' subjective soil quality perceptions and the corresponding scientific, data-based evidence is crucial in determining farmer behaviour and hence soil quality dynamics. Imperfect information about the level of and particularly changes in a natural resource base (like soil) leads to actions which may be optimal for that information set but could actually lead to mis-management of the resource and corresponding resource degradation (Barrett 2008; Marenya and Barrett 2007; Woodford 2020). For example, if farmers under-perceive the soil degradation level, it can lead to over-application of fertilizer to adjust for poor soil quality, or, it could lead to under-application of fertilizer and diversion of resources such as weeding hours to alternate crops which farmers expect to be relatively more profitable (Gray & Morant 2003; Barrett 2008; Marenya and Barrett 2007; Mullainathan & Shafir 2013). In the latter scenario, if the land still continues to be farmed, the corresponding decline in soil organic matter and nutrients over time would generate a self-reinforcing loop of resource degradation instigated by the initial misperceptions regarding soil quality which carry significant inertia due to the lagged, imperfect nature of information they are based on (for e.g., yields) (Barrett 2008; Moges & Holden 2007; Vigiak et. al. 2005; Desbiez et al. 2004; Murage et al. 2000). In this manner, farmers' ex-ante misperceptions about the resource base can be reinforced by their (optimal) actions under imperfect information due to the feedback loop between their actions and the ex-post changes in resource base leading to an "inertial, self-reinforcing" equilibrium which is hard to identify, and difficult to exit. (Mookherjee & Ray 2000, pp. 4; Barrett et al. 2002; Gary and Morant 2003; Barrett 2008; Marenya et al. 2008). Another explanation for these types of inertial, self-reinforcing equilibria can be inferred from the "motivated" beliefs framework proposed by Benabou and Tirole (2002). In this framework, the authors posit the presence of: (a) imperfect information about oneself (for example, imperfect information about one's ability to resist impulses); (b) imperfect willpower – one's inability to change their actions according to available information; and (c) motivated cognition – i.e., self-serving beliefs which justify a pre-conceived course of action regardless of context. Given these conditions, they argue that agents manage their *self-confidence* regarding their *ability* while deciding upon the *effort level* for a project with uncertain returns. In a scenario where the agents are trying to avoid procrastination, they could discount the value of positive observable signals about their underlying ability, or, ignore negative signals about their ability in a bid to avoid damage to their self-esteem. For example, in the context of soil perceptions, farmers may discount positive signals (such as higher yields) about their soil quality with the motive of reducing procrastination and increasing their overall effort levels throughout the crop cycle. Similarly, they may ignore negative signals about soil quality to maintain an expectation of positive profitability from cultivation especially in the face of climate uncertainty (Feng et al. 2022; Arora et al. 2019; Bénabou and Tirole 2016; Bénabou 2015; Benabou & Tirole 2002).

In general, empirical analysis of these biases in perceptions about soil quality and the underlying mechanisms for the same is impeded by: (a) the inherently non-linear dynamics of the resource base, i.e., soil quality (Barrett 2008; Sietz et al. 2017); (b) the endogeneity induced by the feedback loop whereby perceptions influence actions which in turn affect the soil quality and (hence) the perceptions regarding the same (Barrett 2008; Woodford 2020); and (c) the paucity of data which measures soil quality and the perceptions regarding the same corresponding to a common unit of analysis (Barrett 2008; Berazneva et al. 2018; Nord & Snapp 2020). A small but promising literature has attempted to analyse the drivers of farmers' soil quality perceptions and the gap between perceptions and the data-driven measurements (Berazneva et al. 2018; Wartenberg et. al. 2018; Adjaye 2008; Gruver and Weil 2007; Moges and Holden 2007; Vigiak et. al. 2005; Okoba and Graff 2005; Rainey 2005; Desbiez et. al. 2004; Barrios and Trejo 2003; Andrews et. al. 2003; Murage et. al. 2000; Corbeels et. al. 2000; Callister and Nowak 1999; Liebig and Doran 1999; Kerr and Sanghi 1992) as well as the influence of the latter on adoption of selected farm and land management practices (Delgado and Stroogovel 2022; Nord and Snapp 2020; Barrett 2008; Steiner 1998; Krogh and Laursen 1997). However, the geographical scope (and sample sizes) of this literature is generally limited, with a majority of studies spanning Sub-Saharan Africa, some corresponding to selected parts of the United States of America (USA), and two studies in selected villages in Nepal and India. Moreover, an analysis of spatial patterns in soil quality perceptions remains unexplored in the current literature. An understanding of the spatial patterns in soil quality perceptions is critical for identifying the nature and causes of behavioural norms in farm practices (such as over/under application of fertilizer (Bora 2022; Bouwman et al. 2017) or crop-residue burning (Lan et al. 2022)) - particularly those arising out of *neighbourhood* effects and *localized* patterns of information access (Feng et al. 2022; Hu et al. 2019; Mullainathan & Shafir 2013; Sutherland et al. 2012; Durlauf 2004; Holloway & Lapar 2007). In this study, we characterize soil quality perceptions of rice-growers in India with a focus on the *distance* between farmer perceptions (from primary surveys) and corresponding data-based evidence (recorded in soil maps) - thereby providing a measure for *bias* in soil perceptions. Specifically, we address *how*, if at all, soil quality perceptions deviate from corresponding data-based measurements? *What* spatial patterns might emerge in farmer *misperceptions* about soil quality given that soils typically exhibit geographic variations? We also evaluate potential drivers of soil quality misperceptions, including growers' economic status, demographic information and farming history. Finally, we evaluate linkages between soil quality misperceptions and farm-level decision making to understand whether farmers exhibit psychological motives to rationalize their farming decisions. To our best knowledge, we are the first to study spatial patterns in soil quality perceptions along with the relevant drivers and potential linkages with farm-level decisions. The next section describes the data construction and methods, followed by the discussion of results and conclusion.

2. MATERIALS AND METHODS:

2.1. Data Preparation and Summaries:

We utilize geo-referenced plot-level data for 8,327 rice-growing farmers during the 2018 *kharif* (i.e., Monsoon) season across eight Indian states of Punjab, Haryana, Bihar, Uttar Pradesh, West Bengal, Orissa, Chhattisgarh and Andhra Pradesh (see Figure 1). These data are part of primary surveys on rice production practices conducted by the International Maize and Wheat Improvement Center (CIMMYT). The average plot size is ~0.8 acres and over 75 percent of plots are less than one acre in size. Plot-level soil quality perceptions, denoted as $\tilde{S}_i$, were recorded in an ordered fashion for "fertility ($\tilde{F}_i$)" and "texture ($\tilde{T}_i$)", i.e., $\tilde{S}_i \in \{\tilde{F}_i, \tilde{T}_i\}$ where i denotes individual farmers. Specifically, $\tilde{S}_i$ =1 if farmer i perceived soils to be "Low Quality" or "Light Texture"; =2 if i perceived soils to be "Medium Quality" or "Medium Texture"; and =3 if soils are perceived to be "High Quality" or "Heavy Texture". About 4 percent of farmers (i.e., 333 farmers) in our sample perceived their soil quality to be low, 8 percent (i.e., 658 farmers) perceived their soil quality to be high, and a majority of farmers (~88 percent) perceived their soil quality to be "medium", i.e., neither low nor high. Similarly, soil texture was perceived as light by ~7 percent of farmers and heavy by ~14 percent farmers while the rest of the farmers perceived their soil texture to be medium, i.e, neither heavy nor light.

Data-based soil quality measurements denoted as $S_i \in \{F_i, T_i\}$, were obtained by matching[1] plot i's location to spatially-delineated (1km x 1km resolution) global digital soil maps provided by the International Soil Reference and Information Centre. F_i is measured as <u>organic carbon stock</u> (tonnes/hectare) and <u>nitrogen content</u> (centigram/kilogram) while T_i is measured as <u>clay content</u> (gram/kilogram) in top soil (i.e., 0-30 centimetres depth from surface). To obtain the soil quality values for soil depth ranging from 0-30 cm, all soil quality indicators values were averaged for the soil depths ranges from 0-5 cm., 5-15 cm., and 15-30 cm. The average soil nitrogen level across our sample locations is ~132 centigrams/kilogram of soil and displays significant heterogeneity with over-depletion in states like Punjab and

[1] The matching was done such that for every farm household we obtained the soil quality indicator value at the nearest point available on the soil quality map. Note that on-average the distance between the location of the farm household and the soil quality record was less than 0.1 centimeter, i.e., the points were typically coinciding). As a robustness check, we also checked the soil quality distribution using data from *five* nearest points instead of *only one* and found the distribution of soil quality to be identical in the two scenarios.

Haryana (see Figure 2). The average organic carbon stock level across our sample locations is ~35 tonnes/hectare of land and displays significant heterogeneity with states like Bihar and West Bengal having above average organic carbon stock due to the clayey texture of the soil which helps in retention of organic matter (see Figure 3). Finally, the average soil clay content is ~312 grams per kilogram of soil with heavier soils in coastal states like West Bengal & Orissa (see Figure 4).

2.2. Characterizing the correlation between soil quality perceptions and data-based measures:

As discussed, farmers' perceptions of soil quality can be biased as they are often heavily influenced by production indicators like yields or weed/ pest incidence, and are generally based on lagged and imperfect measures of the underlying soil quality dynamics such as soil moisture retention and soil colour (Berazneva et al. 2018; Adjaye 2008; Gruver and Weil 2007; Moges and Holden 2007; Vigiak et. al. 2005; Desbiez et. al. 2004; Barrios and Trejo 2003; Andrews et. al. 2003; Murage et. al. 2000; Liebig and Doran 1999; Kerr and Sanghi 1992). Moreover, perception or judgement biases can also be employed as psychological strategy tools by farmers in order to maintain stable motivation (and hence effort) levels towards cultivation (Benabou & Tirole 2002; Bénabou 2015; Bénabou and Tirole 2016). In order to characterize this bias in soil quality perceptions, i.e., the distance between soil quality perceptions and the data-based measurements of the same, we employ an ordered logistic regression (McCullagh 1980; Marenya & Barrett 2007; Arora et al. 2019) to model soil quality perceptions $\tilde{S}_i$ as a function of data-based soil quality measurement S_i and a control vector $\vec{x}_i$. Specifically, under the proportional odds assumption we have:

$$\Pr(\tilde{S}_i \le j) = \log\left(\theta_{i,j} / \sum_{k>j} \theta_{i,k}\right) = \kappa_j + \beta_s S_i + \vec{x}_i \vec{\gamma} + \varepsilon_i; \text{where } \theta_{i,j} = \Pr(\tilde{S}_i = j) \text{ and } j = \{1,2\} \quad (1)$$

Note that we estimate model (1) separately for each component in $\tilde{S}_i \in \{\tilde{F}_i, \tilde{T}_i\}$ and corresponding data-based measurements $S_i \in \{F_i, T_i\}$. Here $\vec{x}_i$ contains (a) farm performance measured by crop yield (Barrett 2008); (b) farmer awareness and agency measured through education, caste, and land ownership – reflective of farm practices including participation in extension programs (Mullainathan & Shafir 2013); (c) ease of farming operations measured by the extent of insect incidence and irrigation availability (Desbiez et al. 2004; Moges and Holden 2007); (d) off-farm income availability measured by the percentage of income derived from agriculture; and (e) farming history reflective of erosion history (Gruver & Weil 2007). Parameter β_s provides a measure of the degree of consistency between plot-level soil quality perceptions and corresponding data-based evidence. The probabilities in model (1) accumulate in an ascending order meaning that a negative β_s value indicates agreement between soil perceptions and data-based evidence for an average farmer in our sample. On the other hand, a positive (and significant) estimate for β_s would reflect an on-average bias in soil quality perceptions. κ_j characterize the average log odds of perceptions $\tilde{S}_i \leq 1$ and $\tilde{S}_i \in \{1, 2\}$ for $j = 1$ and $j = 2$ respectively when all other explanatory variables are zero. Further, $\vec{\gamma}$ represents the ceterus paribus shift in the ordered log odds of being in lower perceptions category as compared with a higher category upon a marginal increase in the respective explanatory variable. Overall, using model (1) we intend to infer whether farmers' soil quality perceptions are on-average consistent with the corresponding data-based evidence and assess the role of $\vec{x}_i$ (i.e., crop yield, irrigation access, pest incidence, land ownership status, off-farm incomes, and demography – education and caste) in driving perceptions about soil fertility and texture.

On average, the crop yield is ~19 tonnes per acre with a standard deviation of ~6 tonnes per acre, and households derive slightly more than half of their incomes from agricultural activities. About 60 percent of farmers have less than 10 years of formal education while ~83 percent own the land they cultivate on. An overwhelming majority of households (~95 percent) face weed incidence pressure. At the same time, close to 90 percent of farmers have access to irrigation on the plot. The prior cropping season history consists majorly of cereal (~ 60 percent of farms), and pulses (~12 percent farms). The detailed summary statistics for all the variables are provided in Table 1 and Tables 2(A & B).

2.3 Identifying the biases in soil quality perceptions:

As a next step we characterize potential biases in soil quality perceptions compared with the data-based records. To do this, we utilize cross-tabulations between each soil quality metric in S_i and the corresponding soil quality perceptions in $\tilde{S}_i$. In particular, soil quality measurements are categorized as: $S_i \leq Q(0.25)$, $S_i \in [Q(0.25), Q(0.75)], S_i \geq Q(0.75)$ (where $Q(\tau) = \inf\{s_i : F_S(s_i) \geq \tau\}$ represents the respective quantiles of the soil quality distribution in our sample), to match the soil perception categories $\tilde{S}_i \in \{1, 2, 3\}$, i.e., “Low Quality” or “Light Texture”; “Medium Quality” or “Medium Texture”; and “High Quality” or “Heavy Texture” about $\tilde{F}_i$ (fertility) and $\tilde{T}$ (texture) respectively. The cross-tabulations provide a pairwise count of farmers with respect to the soil quality and soil perceptions categories. So, if the categories coincide as in the case of diagonal elements, then perceptions are reflected as consistent with data-based measurements. On the contrary, off-diagonal elements represent inconsistencies soil quality perceptions and the corresponding data-based records, i.e., the *bias* in soil quality perceptions. Tables 18-20 shows that the diagonal elements provide a count of *consistent* soil quality perceptions, i.e., better quality (heavier) soils are perceived when nitrogen content/ soil organic carbon (clay content) is high. On the other hand, off-diagonal elements provide a count of *inconsistent* soil quality perceptions, i.e., off-diagonal entries represent farmers who perceived higher/heavier (lower/lighter) quality soils when nitrogen/ soil organic carbon/clay content was relatively lower (higher).

2.4 Linking soil quality perceptions with nutrient application and residue burning decisions:

Finally, we posit that soil quality misperceptions are likely endogenous to farm-level decisions based on the concept of inertial self-reinforcement and motivated reasoning (Benabou & Tirole 2002; Benabou 2015; Feng et al. 2022). We test the proposition that survey-based soil fertility[2] misperceptions are independent of plot-level decisions (i.e., frequency of fertilizer and irrigation application, and crop residue burning) by employing a Chi-squared (χ^2) test of independence between fertilizer use and irrigation use frequency categories – i.e., "High" or "Low" and the soil quality perceptions mapping described earlier. In particular, the soil quality perception is denoted by $p_i^H \in \{H \to L, H \to M, H \to H\}$ where $H \to L$ denotes a scenario whereby High Quality soil (i.e., soils with Nitrogen content strictly greater than 144 centigram/kilogram or soils with Organic Carbon stock strictly greater than 42 tonnes/hectare) is perceived as Low Quality soil (i.e., soils with Nitrogen content strictly lower than 113 centigram/kilogram or soils with Organic Carbon stock strictly lower than 32 tonnes/hectare); $H \to M$ denotes a situation where High Quality soil is perceived as Medium Quality soil (i.e., soils with Nitrogen content in the range of 113-144 centigram/kilogram or soils with Organic Carbon stock in the range 32-42 tonnes/hectare); and finally $H \to H$ denotes the scenario of consistent perceptions whereby High Quality soils are indeed perceived as High Quality. Similarly, we can define p_i^L and p_i^M . Further, fertilizer use frequency per acre is categorized into $f_i = \{\text{High,Low}\}$ corresponding to nitrogen application strictly more than thrice per hectare and vice versa. Similarly, irrigation

[2] For soil fertility, we present results for both types of measures – i.e., soil nitrogen levels, and soil organic carbon stock. But, we have kept soil texture out of this analysis because the link between soil clay content and nutrient application is not clear.

frequency is categorized into $w_i = \{\text{High,Low}\}$ corresponding to irrigation application strictly more than five times per hectare and vice versa. Lastly, crop residue burning decision has two categories: $r_i = \{\text{Yes,No}\}$.

To construct the χ^2 test statistic for each decision, the unique categories of each of the cropping decisions are cross tabulated with p_i^L and p_i^H in a contingency table (see Table 3 – Table 14) where each cell entry represents the count of farmers[3]. Let us look at the method for statistic construction with a stylized example pertaining to High Quality soil perceptions, i.e., $p_i^H \in \{H \to L, H \to M, H \to H\}$ and crop residue burning decision (i.e., $r_i = \{\text{Yes,No}\}$). Here, the first two categories can effectively be understood as under-perceptions, i.e., cases where the soil quality is perceived to be poorer than it is (according to data-based measures). Based on this, we can construct a 2 - by – 2 contingency table as in Table 16 where $N_{\text{Row}(k)\,;\,\text{Column}(j)}$ is the number of farmers who belong to category $k:1,2,...K$ of decision-making and category $j:1,2,...J$ of perceptions. For example, N_{11} is the number of farmers who burn crop residue and under-perceive their (high) soil quality. Similarly, N_{12} is the number of farmers who burn crop residue but correctly perceive the soil quality on their plot to be high and so on. Here, $N = \sum_{\text{Row}(k)} \sum_{\text{Column}(j)} N_{\text{Row}(k),\text{Column}(j)}$ is the total number of farms where the data-based measure of soil fertility is High. The joint distribution of soil fertility perceptions and crop residue burning decision is represented by Table 17. We further define $N_{1*} = N_{11} + N_{12}$ as the frequency of crop residue burning; $N_{2*} = N_{21} + N_{22}$ as the frequency of <u>no</u> crop residue burning; $N_{*1} = N_{11} + N_{21}$ as the frequency of soil quality being under-perceived (when measured soil quality is high); and $N_{*2} = N_{12} + N_{22}$ as the frequency of soil quality being correctly perceived (when measured soil quality is high). To understand the

[3] The figures in brackets are explained later in this section.

basis of the χ^2 test of independence, note that random variables r_i and p_i^H would be independent (by definition) if $\Pr(r_i = \mathrm{r}, p_i^H = p) = \Pr(r_i = \mathrm{r})^*\Pr(p_i^H = p)$. This testable implication can be written as follows:

$$\begin{aligned} &H_0 : \rho_{11} = \rho_{1*} * \rho_{*1} \wedge \rho_{12} = \rho_{1*} * \rho_{*2} \wedge \rho_{21} = \rho_{2*} * \rho_{*1} \wedge \rho_{22} = \rho_{2*} * \rho_{*2} \\ &H_A : \rho_{11} \neq \rho_{1*} * \rho_{*1} \vee \rho_{12} \neq \rho_{1*} * \rho_{*2} \vee \rho_{21} \neq \rho_{2*} * \rho_{*1} \vee \rho_{22} \neq \rho_{2*} * \rho_{*2} \end{aligned} \tag{2}$$

Under H_0, we can write the cell-wise expected frequencies as $\hat{N}_{11} = N_{1*} * N_{*1}/N$; $\hat{N}_{12} = N_{1*} * N_{*2}/N$; $\hat{N}_{21} = N_{2*} * N_{*1}/N$; and $\hat{N}_{22} = N_{2*} * N_{*2}/N$. These are the numbers in brackets in Table 3 – Table 14. The comparison of these expected and observed frequencies (and hence, the expected and observed probabilities) gives a measure of independence between the variables. Finally, the test statistic is defined as:

$\chi^2 = \sum_{\mathrm{Row}(k)} \sum_{\mathrm{Column}(j)} \frac{(N_{kj} - \hat{N}_{kj})^2}{\hat{N}_{kj}} \sim \chi_d^{\ 2}$ where $d = (K-1)(J-1)$ is the degrees of freedom. Based on this statistic and the critical values for the χ^2 distribution, we can formulate the decision rule.

3. RESULTS AND DISCUSSION:

We find that a majority of farmers in our sample (~53 percent) *consistently perceived soil texture* but generally *inconsistently perceived soil fertility* on their farms <u>relative to the respective data-based measurements</u>. In particular, while soil organic carbon levels were inconsistently perceived by just over half of the sample, soil nitrogen levels were inconsistently perceived by over 53 percent of farmers (see Tables 18-20). Further, estimation of model (1) revealed that $\hat{\beta}_T < 0$ and was statistically significant whereas $\hat{\beta}_F$ exhibited ambiguity in its sign as well as statistical significance depending on the model specification. Moreover, while soil nitrogen levels were *on-average* perceived consistently, the relationship with soil organic carbon stock was not significant. Further, we found that farmers who reported greater irrigation access and higher yields were more likely to perceive better soil quality on their farms when compared with those who reported reliance on rainfall and/or lower yields. This aligns with a significant section of the literature which posits that better levels of observable indicators like yields and ease of farming are associated with higher perceptions of soil quality (Berazneva et al. 2018; Adjaye 2008; Gruver and Weil 2007; Moges and Holden 2007; Vigiak et. al. 2005; Desbiez et. al. 2004; Barrios and Trejo 2003; Andrews et. al. 2003; Murage et. al. 2000; Liebig and Doran 1999; Kerr and Sanghi 1992). Further, we found that educated farmers and those belonging to forward castes were more likely to perceive higher soil quality when compared with farmers having lower education from backward castes. An explanation for this could stem from upper caste farmers, and farmers with higher education levels owning better quality lands. However, this does not seem to be the case in our data. Indeed, we find that on-average nitrogen levels were *higher* for lands belonging to farmers of relatively lower castes and those with lower education levels when compared with the upper caste (and more educated) counterparts. Hence, the results are suggestive of a negative linkage between education levels and soil quality mis-perceptions.

On the other hand, landowners on-average exhibited perceptions of lower quality soils relative to landless or renter farmers. Again, a comparison of mean nitrogen levels between lands which are owned by the farmers versus lands which are leased, shows that the leased lands have higher nitrogen content on-average while the difference in soil organic carbon stock is insignificant. This is suggestive of mis-perceptions in soil quality by land ownership which may be explained by the fact that land-owners are likely to have worked on the same piece of land for a longer period of time and hence the inertia in their (mis)perceptions of soil quality is relatively higher (Barrett 2008). Greater weed incidence is found to be associated with better soil quality perceptions – this is reflective of the understanding that weeds are not inherently bad and are often indicative of overall higher soil quality and nutrient balance (Altieri 1995; Schnobeck 2007; Milberg & Hallgren 2004; Colbach et al. 2020). Lastly, we found that farmers who cultivated cereal crops in the season prior to rice were more likely to perceive poorer soil quality – this is expected because cereal crops are generally nutrient depleting (Berge at al. 2019).

A visual map of *bias* in soil quality and soil texture perceptions (Figure 5 – Figure 7) shows *consistent* perceptions (star-marker) and *biased* perceptions (green triangle and red circle markers) that are spatially clustered with a Moran's-I value of 0.43 (p<0.001), 0.34 (p<0.001), and 0.48 (p<0.001) for soil quality measured by Organic Carbon stock and Nitrogen content respectively, and soil texture measured by Clay content. Moreover, soil quality misperceptions are spatially heterogeneous, e.g., higher farm revenues (concentrated in Punjab and Andhra Pradesh) were associated with greater incidence of *over-perceptions* of soil quality relative to the regions that reported lower farm revenues.

Lastly, we rejected the null hypothesis (in (2)) for all cases of over-perception in soil quality[4], i.e., when the farmers' perceived soil quality was Low, to conclude that farmers' soil quality perceptions were generally <u>not independent</u> of farm-level input application and residue burning decisions. In particular, over-perceptions of soil quality were associated with lower incidence of residue burning, and lower fertilizer application. The results were not conclusive for irrigation application. However, under-perceptions of soil quality were not always associated with farm-level decisions, except in case of residue burning where we found that farmers who *under-perceived* soil quality were more likely to engage in end-of-season residue burning.

[4] The results hold for both measures of soil fertility – nitrogen content and organic carbon stock.

4. CONCLUSION:

Farm-level decisions about crop choice, input application, nutrient supplementation, and land management necessarily stem from farmers' perceptions regarding the soil quality of their lands – i.e., the quality of their primary resource base. Policy efforts to improve soil fertility tend to inform these farm-level decisions but the adoption of these measures is naturally linked to the perception of the soil quality itself. However, this linkage between soil quality and farmers' perceptions regarding the same remains understudied in the literature, particularly for India. Our study focuses on filling this gap by studying the *bias* in soil quality perceptions for rice-growing farmers in India during Kharif, 2018. We find that a majority of farmers in our sample consistently perceived soil texture but generally inconsistently perceived soil fertility on their farms relative to the respective data-based measurements. Further, as expected from the literature, higher levels of economic indicators of soil quality (such as crop yield) were associated with better soil quality perceptions. Interestingly, an exploration of the linkage between soil quality perceptions and farm-level decisions revealed that under-perceived soil quality was less likely to affect (and be affected by) farm decisions. In contrast, over-perceptions of soil quality were associated with lower nutrient supplementation, and lower incidence of end of season crop residue burning. In conclusion, we find that an assessment of soil quality perceptions varies by soil quality parameters, i.e., texture or fertility, in terms of consistency with objective data as well as in relation with farmer decisions. These results, (we hope) will aid in devising more effective land management policy.

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Tables:

Variable	N	Mean	SD	Minimum	P25	P50	P75	P90	Maximum
Soil Clay Content (gram/kilogram)	8327	312.68	51.74	211	276	299	348	394	480
Soil Nitrogen Content (centigram/kilogram)	8327	132.60	30.31	77	113	128	144	165	380
Soil Organic Carbon Stock (tonnes/hectare)	8327	35.38	9.39	0	32	38	42	44	69
Crop Yield (quintal/acre)	8327	18.72	6.00	1.5	14.93	18.06	22	27	45.05
Percentage of Income Derived from Agriculture	8327	52.53	30.37	0	30	50	80	100	100

Table 1: Summary Statistics for Continuous Variables

Variable	Count of Households (Percentage)	
	0	**1**
Land Ownership (=1 if plot is owned, 0 otherwise)	1477 (17.74)	6850 (82.26)
Lack of Education (= 1 if Education is less than Secondary/Senior Secondary, i.e., class Xth/XIIth, and 0 otherwise).	3254 (39.08)	5073 (60.92)
Irrigation Availability (Yes = 1, 0 otherwise)	968 (11.62)	7359 (88.38)
Weed Incidence (Yes = 1, 0 otherwise)	441 (5.30)	7886 (94.70)
Farming History: Crop Grown in Previous Season = Cereal (Yes = 1, 0 otherwise)	3318 (39.85)	5009 (60.15)
Farming History: Crop Grown in Previous Season = Pulses (Yes = 1, 0 otherwise)	7399 (88.86)	928 (11.14)

Table 2A: Summary Statistics for Categorical Variables

Variable	Count of Households (Percentage)		
	0	**1**	**2**
Caste (= 0 for SC/ST, = 1 for OBC, = 2 for General Caste)	1622 (19.49)	3502 (42.09)	3197 (38.42)

Table 3B: Summary Statistics for Caste

Residue Burning	Soil Quality = Low (Soil Nitrogen Content < 113 centigram/kilogram)	
	Consistent Perceptions	Over-Perceptions
No	63 (54.76)	1735 (1743.24)
Yes	3 (11.24)	366 (357.76)
Chi-Squared Statistic = 7.5***		

*: p-value<0.10; **: p-value<0.05; ***: p-value<0.01

Table 3: Cross-Tabulation of p_i^L and Residue Burning Decision. (Measure of Soil Quality: Nitrogen (centigram/kilogram))

Fertilizer Application Frequency	Soil Quality = Low (Soil Nitrogen Content < 113 centigram/kilogram)	
	Consistent Perceptions	Over-Perceptions
Low	2 (0.55)	16 (17.45)
High	64 (65.45)	2085 (2083.55)
Chi-Squared Statistic = 3.99***		

*: p-value<0.10; **: p-value<0.05; ***: p-value<0.01

Table 4: Cross-Tabulation of p_i^L and Fertilizer Application Decision. (Measure of Soil Quality: Nitrogen (centigram/kilogram))

Irrigation Application Frequency	Soil Quality = Low (Soil Nitrogen Content < 113 centigram/kilogram)	
	Consistent Perceptions	Over-Perceptions
High	35 (35.3)	1124 (1123.7)
Low	31 (30.7)	977 (977.3)
Chi-Squared Statistic = 0.005		

*: p-value<0.10; **: p-value<0.05; ***: p-value<0.01

Table 5: Cross-Tabulation of p_i^L and Irrigation Application Decision. (Measure of Soil Quality: Nitrogen (centigram/kilogram))

Residue Burning	Soil Quality = High (Soil Nitrogen Content > 144 centigram/kilogram)	
	Consistent Perceptions	Under-Perceptions
No	220 (205.69)	1645 (1591.32)
Yes	19 (24.59)	204 (190.28)
Chi-Squared Statistic = 2.1		

*: p-value<0.10; **: p-value<0.05; ***: p-value<0.01

Table 6: Cross-Tabulation of p_i^H and Residue Burning Decision. (Measure of Soil Quality: Nitrogen (centigram/kilogram))

Fertilizer Application Frequency	Soil Quality = High (Soil Nitrogen Content > 144 centigram/kilogram)	
	Consistent Perceptions	Under-Perceptions
Low	5 (9.49)	81 (73.38)
High	234 (220.8)	1768 (1708.21)
Chi-Squared Statistic = 2.8*		

*: p-value<0.10; **: p-value<0.05; ***: p-value<0.01

Table 7: Cross-Tabulation of p_i^H and Fertilizer Application Decision. (Measure of Soil Quality: Nitrogen (centigram/kilogram))

Irrigation Application Frequency	Soil Quality = High (Soil Nitrogen Content > 144 centigram/kilogram)	
	Consistent Perceptions	Under-Perceptions
High	161 (137.75)	1088 (1065.71)
Low	78 (92.53)	761 (715.88)
Chi-Squared Statistic = 6.39***		

*: p-value<0.10; **: p-value<0.05; ***: p-value<0.01

Table 8: Cross-Tabulation of p_i^H and Irrigation Application Decision. (Measure of Soil Quality: Nitrogen (centigram/kilogram))

Residue Burning	Soil Quality = Low (Soil Organic Carbon Stock < 32 tonnes/hectare)	
	Consistent Perceptions	Over-Perceptions
No	56 (47.1)	1674 (1802.65)
Yes	3 (15.98)	584 (611.65)
Chi-Squared Statistic = 13.12***		

*: p-value<0.10; **: p-value<0.05; ***: p-value<0.01

Table 9: Cross-Tabulation of p_i^L and Residue Burning Decision. (Measure of Soil Quality: Organic Carbon Stock (tonnes/hectare))

Fertilizer Application Frequency	Soil Quality = Low (Soil Organic Carbon Stock < 32 tonnes/hectare)	
	Consistent Perceptions	Over-Perceptions
Low	4 (1.09)	36 (41.68)
High	55 (61.99)	2222 (2372.62)
Chi-Squared Statistic = 9.11***		

*: p-value<0.10; **: p-value<0.05; ***: p-value<0.01

Table 10: Cross-Tabulation of p_i^L and Fertilizer Application Decision. (Measure of Soil Quality: Organic Carbon Stock (tonnes/hectare))

Irrigation Application Frequency	Soil Quality = Low (Soil Organic Carbon Stock < 32 tonnes/hectare)	
	Consistent Perceptions	Over-Perceptions
High	38 (48.71)	1751 (1864.13)
Low	21 (14.38)	507 (550.17)
Chi-Squared Statistic = 5.64***		

*: p-value<0.10; **: p-value<0.05; ***: p-value<0.01

Table 11: Cross-Tabulation of p_i^L and Irrigation Application Decision. (Measure of Soil Quality: Organic Carbon Stock (tonnes/hectare))

Residue Burning	Soil Quality = High (Soil Organic Carbon Stock > 42 tonnes/hectare)	
	Consistent Perceptions	Under-Perceptions
No	147 (107.18)	1381 (1004.9)
Yes	5 (3.37)	43 (31.54)
Chi-Squared Statistic = 0.03		

*: p-value<0.10; **: p-value<0.05; ***: p-value<0.01

Table 12: Cross-Tabulation of p_i^H and Residue Burning Decision. (Measure of Soil Quality: Organic Carbon Stock (tonnes/hectare))

Fertilizer Application Frequency	Soil Quality = High (Soil Organic Carbon Stock > 42 tonnes/hectare)	
	Consistent Perceptions	Under-Perceptions
Low	5 (3.65)	47 (34.17)
High	147 (106.9)	1377 (1001.47)
Chi-Squared Statistic = 0.01		

*: p-value<0.10; **: p-value<0.05; ***: p-value<0.01

Table 13: Cross-Tabulation of p_i^H and Fertilizer Application Decision. (Measure of Soil Quality: Organic Carbon Stock (tonnes/hectare))

Irrigation Application Frequency	Soil Quality = High (Soil Organic Carbon Stock > 42 tonnes/hectare)	
	Consistent Perceptions	Under-Perceptions
High	161 (52.89)	1088 (495.48)
Low	78 (57.66)	761 (540.16)
Chi-Squared Statistic = 0.4		

*: p-value<0.10; **: p-value<0.05; ***: p-value<0.01

Table 14: Cross-Tabulation of p_i^H and Irrigation Application Decision. (Measure of Soil Quality: Organic Carbon Stock (tonnes/hectare))

Table Number	Test Statistic	p-value	Endogeneity
3	7.5	0.006	Yes
4	3.99	0.04	Yes
5	0.005	0.94	No
6	2.1	0.14	No
7	2.8	0.09	Yes
8	6.39	0.01	Yes
9	13.12	0	Yes
10	9.11	0.003	Yes
11	5.64	0.01	Yes
12	0.03	0.85	No
13	0.01	0.99	No
14	0.4	0.52	No

Table 15: Cross-Tabulation of p_i^H and Irrigation Application Decision. (Measure of Soil Quality: Organic Carbon Stock (tonnes/hectare))

Decision Categories	**Soil Fertility Perception (when measured Soil Fertility is High)**	
	(1) Under-Perceived (i.e., $H \to L, H \to M$)	**(2) Correctly Perceived (i.e., $H \to H$)**
(1) Crop Residue Burning - Yes	N_{11}	N_{12}
(2) No Residue Burning	N_{21}	N_{22}

Table 16: Stylized cross-tabulation between p_i^H and Crop Residue Burning decision.

Decision Categories	**Soil Fertility Perception (when measured Soil Fertility is High)**	
	(1) Under-Perceived (i.e., $H \to L, H \to M$)	**(2) Correctly Perceived (i.e., $H \to H$)**
(1) Crop Residue Burning - Yes	$\rho_{11} = \Pr(r_i = \text{Yes}, p_i^H \in \{H \to L, H \to M\})$	$\rho_{12} = \Pr(r_i = \text{Yes}, p_i^H = H \to H)$
(2) No Residue Burning	$\rho_{21} = \Pr(r_i = \text{No}, p_i^H \in \{H \to L, H \to M\})$	$\rho_{12} = \Pr(r_i = \text{No}, p_i^H = H \to H)$

Table 17: Stylized joint probability distribution of p_i^H and Crop Residue Burning decision.

Organic Carbon Stock / Soil Quality Perception	Low	Medium	High
Low	59	184	95
Medium	2,024	4,004	1,329
High	234	274	152

Table 18: Cross-Tabulation of Soil Fertility Categories (as measured by Organic Carbon Stock) and Soil Fertility Perceptions.

Nitrogen Content / Soil Quality Perception	Low	Medium	High
Low	66	156	116
Medium	1,989	3,635	1,733
High	112	309	239

Table 19: Cross-Tabulation of Soil Fertility Categories (as measured by Nitrogen Content) and Soil Fertility Perceptions.

Clay Content / Self-Reported Soil Texture	Low	Medium	High
Light	114	436	68
Medium	1,875	4,022	700
Heavy	174	750	216

Table 20: Cross-Tabulation of Soil Texture Categories (as measured by Clay Content) and Soil Texture Perceptions.

Independent Variables	Dependent Variable: Soil Quality Perception (1: Low | 2: Medium | 3: High)	Dependent Variable: Soil Texture Perception (1: Light | 2: Medium | 3: Heavy)
	Log Likelihood = -3533.433 N = 8321	**Log Likelihood = -5291.77 N = 8321**
Soil Organic Carbon Stock (Tonnes/Hectare) (Between soil depth 0-30 cm.)	0.004 (0.004)	.
Soil Nitrogen Content (Centigram/Kilogram) (Between soil depth 0-30 cm.)	**-0.007*** (0.001)**	.
Soil Clay Content (Grams/Kilogram) (Between soil depth 0-30 cm.)	.	**-0.003*** (0.0006)**
Yield (Quintal/Acre)	**-0.07*** (0.007)**	**-0.03*** (0.005)**
Land Ownership (=1 if plot is owned, 0 otherwise)	**0.2** (0.09)**	**0.38** (0.07)**
Caste (= 0 for SC/ST, = 1 for OBS, = 2 for General Caste)	**-0.13** (0.05)**	**-0.07* (0.04)**
Lack of Education (= 1 if Education is less than Secondary/Senior Secondary, i.e., class Xth/XIIth, and 0 otherwise).	**0.14* (0.07)**	**0.06 (0.06)**
Irrigation Availability (Yes = 1, 0 otherwise)	**-0.62*** (0.14)**	**-0.38*** (0.11)**
Weed Incidence (Yes = 1, 0 otherwise)	**-0.31** (0.13)**	**-0.36*** (0.10)**
Extent of Farm-Diversification: Percentage of Income Derived from Agriculture	**-0.01*** (0.001)**	**-0.003*** (0.009)**
Farming History: Crop Grown in Previous Season = Cereal (Yes = 1, 0 otherwise)	**0.41*** (0.09)**	**0.18** (0.08)**
Farming History: Crop Grown in Previous Season = Pulses/Legumes (Yes = 1, 0 otherwise)	0.18 (0.14)	0.003 (0.10)

Table 21: Regression Results for Model (1) for Soil Quality and Soil Texture.

Figures:

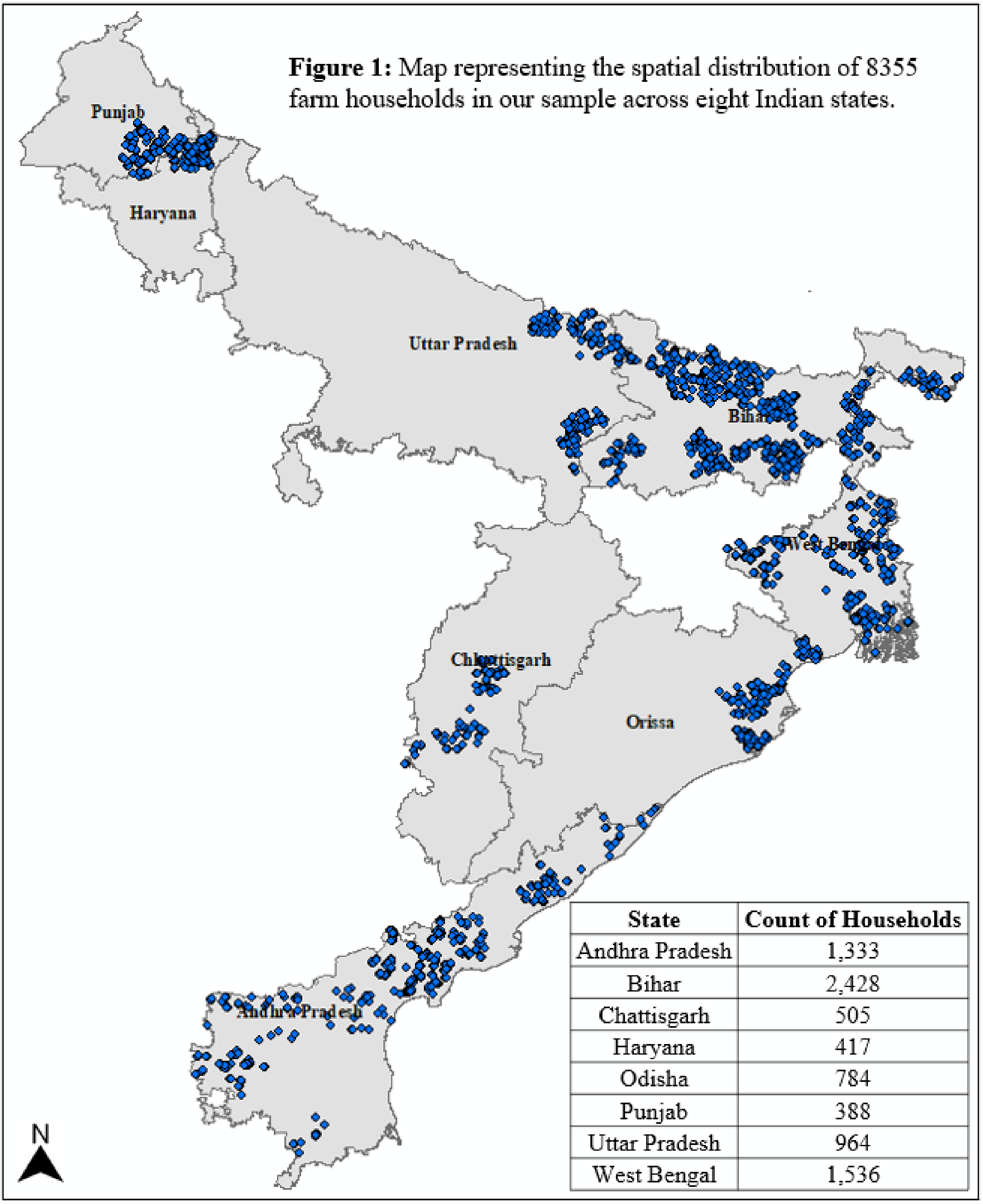

Figure 1: Map representing the spatial distribution of 8355 farm households in our sample across eight Indian states.

State	Count of Households
Andhra Pradesh	1,333
Bihar	2,428
Chattisgarh	505
Haryana	417
Odisha	784
Punjab	388
Uttar Pradesh	964
West Bengal	1,536

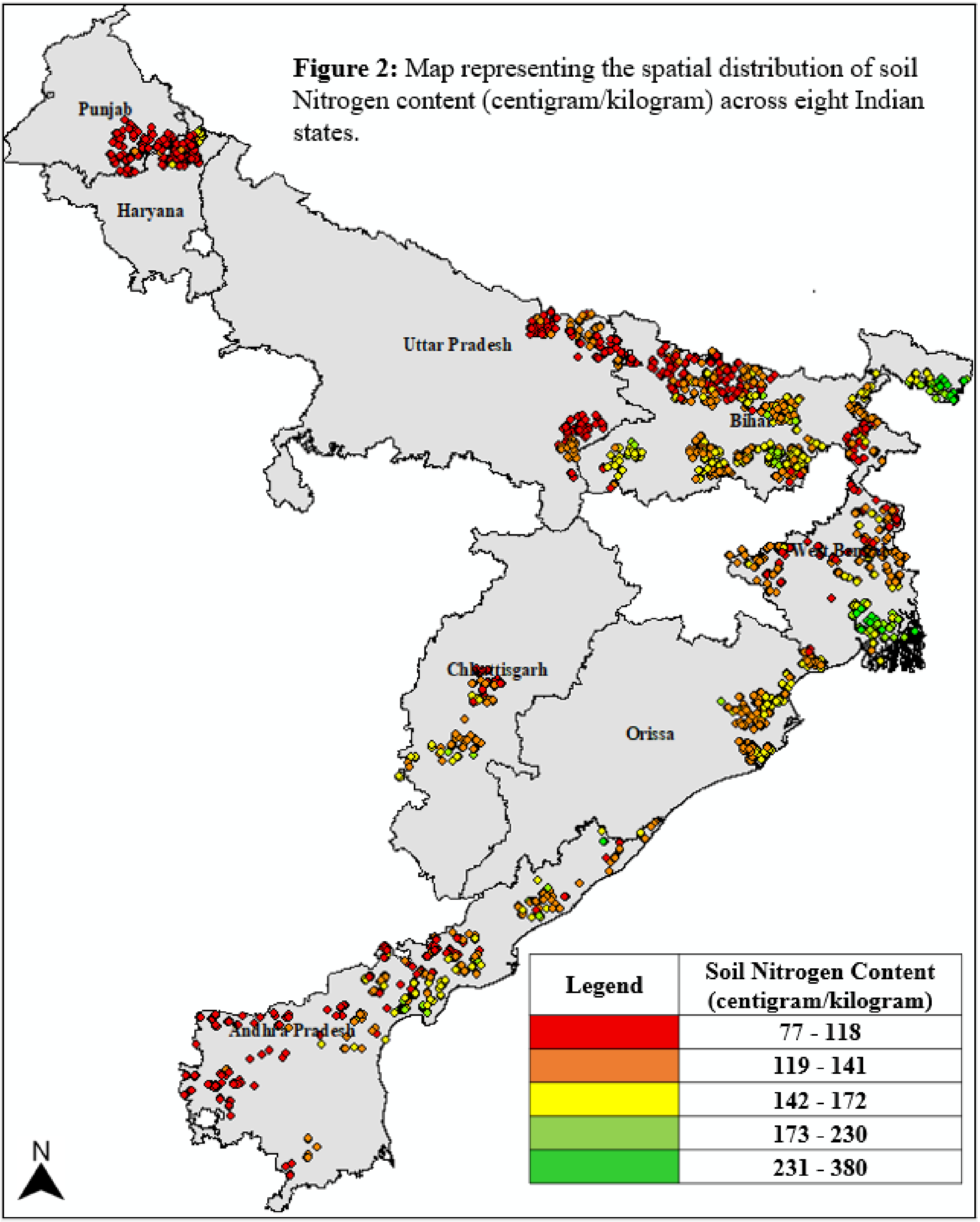

Figure 2: Map representing the spatial distribution of soil Nitrogen content (centigram/kilogram) across eight Indian states.

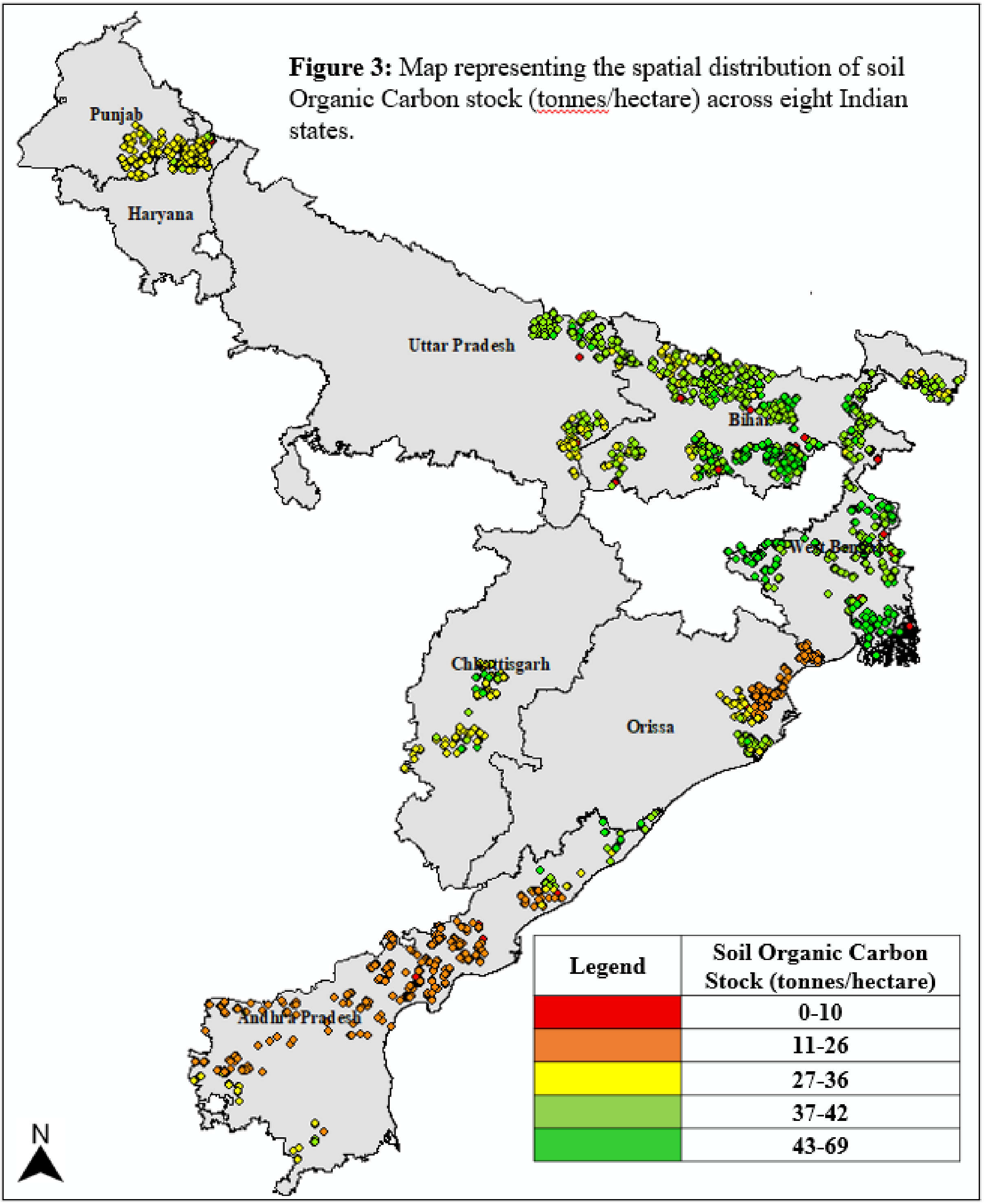

Figure 3: Map representing the spatial distribution of soil Organic Carbon stock (tonnes/hectare) across eight Indian states.

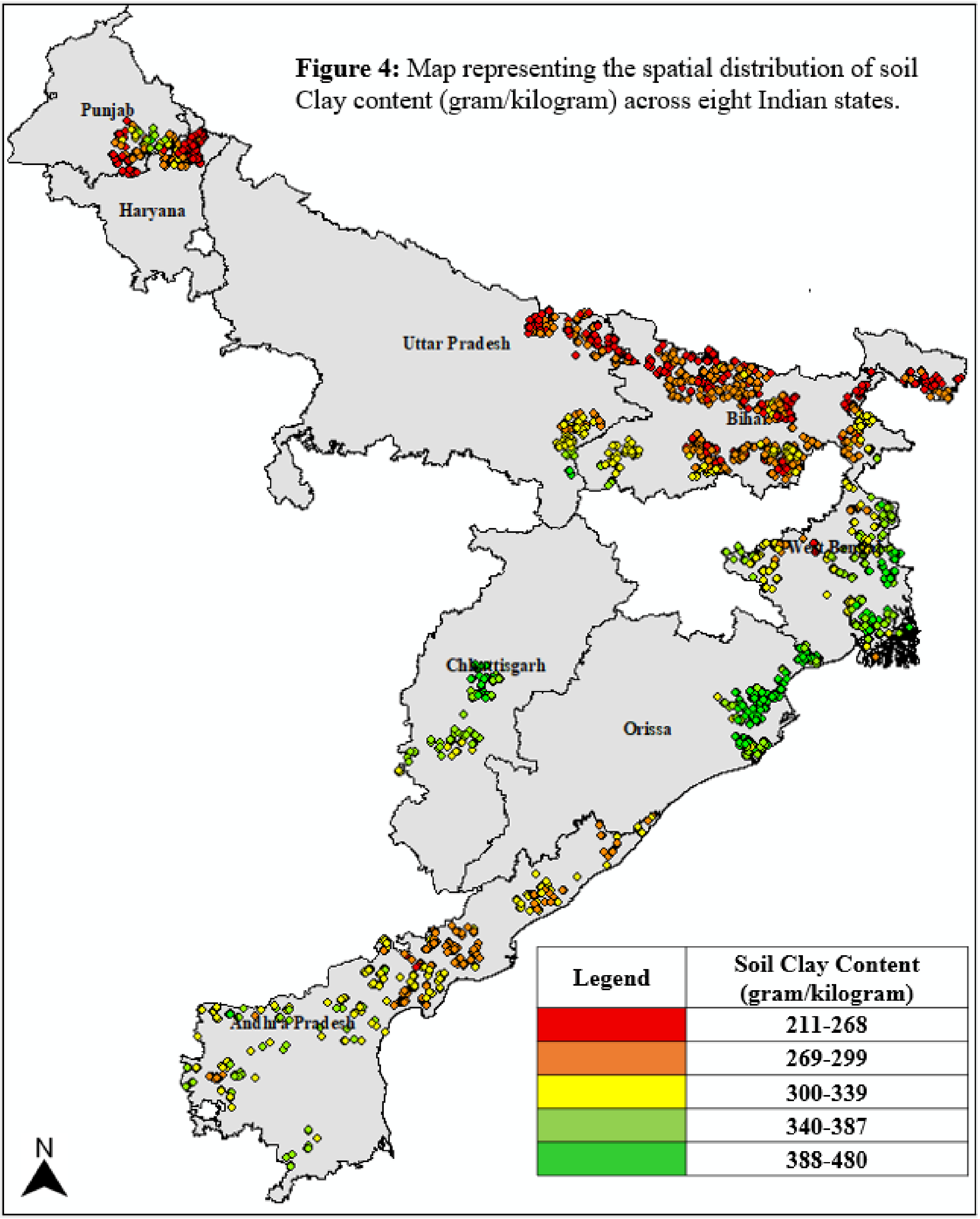

Figure 4: Map representing the spatial distribution of soil Clay content (gram/kilogram) across eight Indian states.

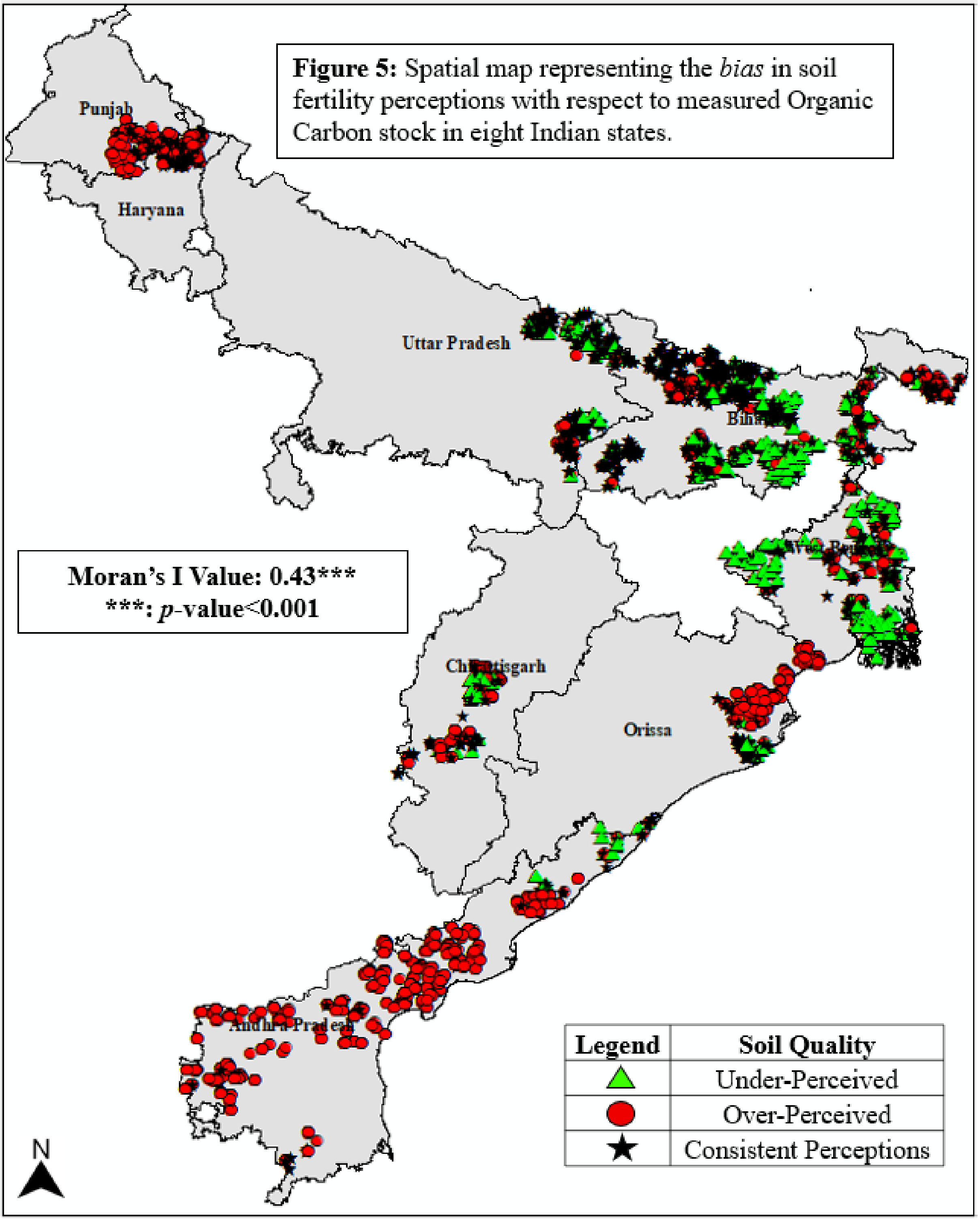
Figure 5: Spatial map representing the bias in soil fertility perceptions with respect to measured Organic Carbon stock in eight Indian states.
Punjab
Haryana
Uttar Pradesh
Bihar
West Bengal
Chhattisgarh
Orissa
Andhra Pradesh
Moran's I Value: 0.43***
***: p-value<0.001
Legend
Soil Quality
Under-Perceived
Over-Perceived
Consistent Perceptions
N

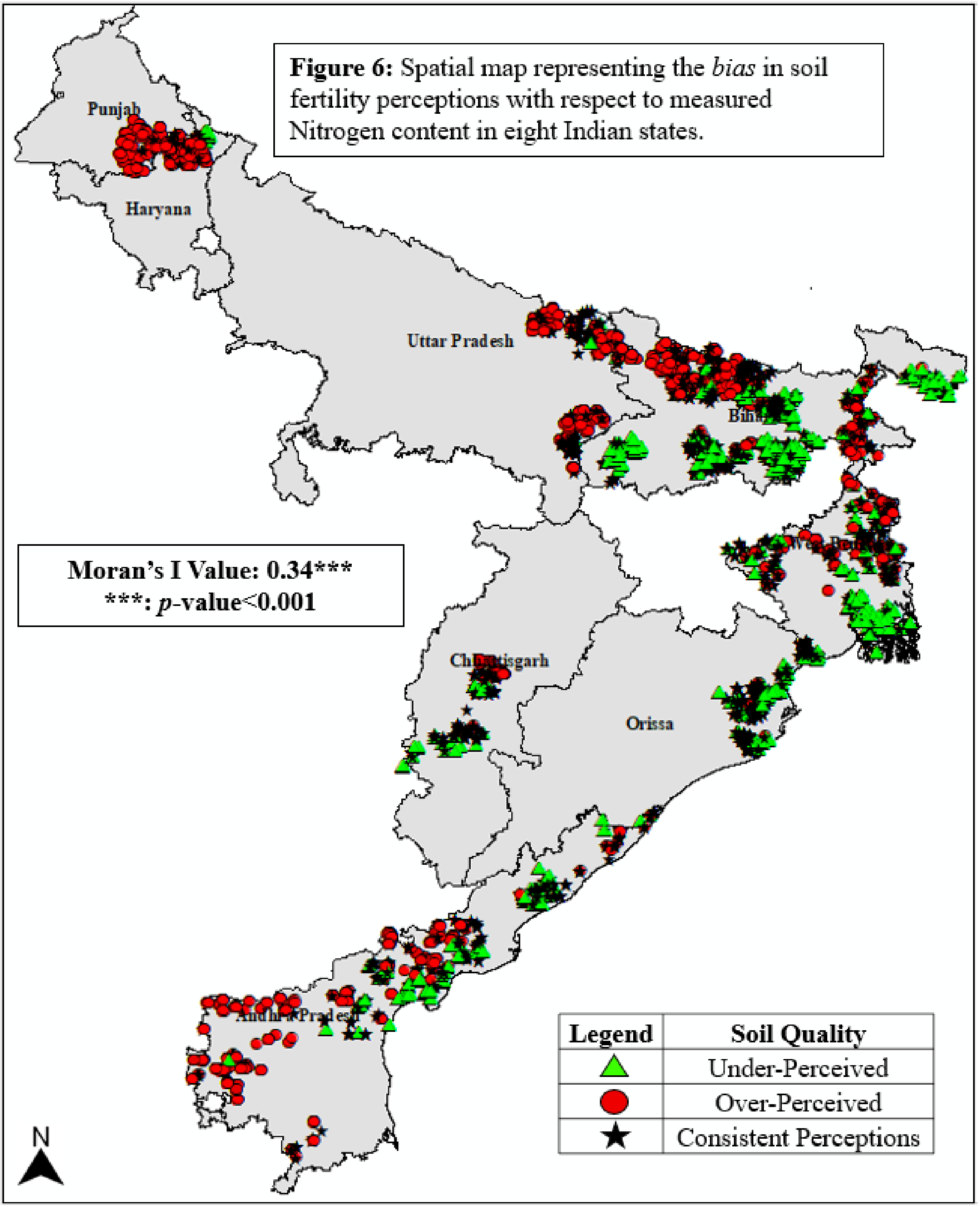

Figure 6: Spatial map representing the *bias* in soil fertility perceptions with respect to measured Nitrogen content in eight Indian states.

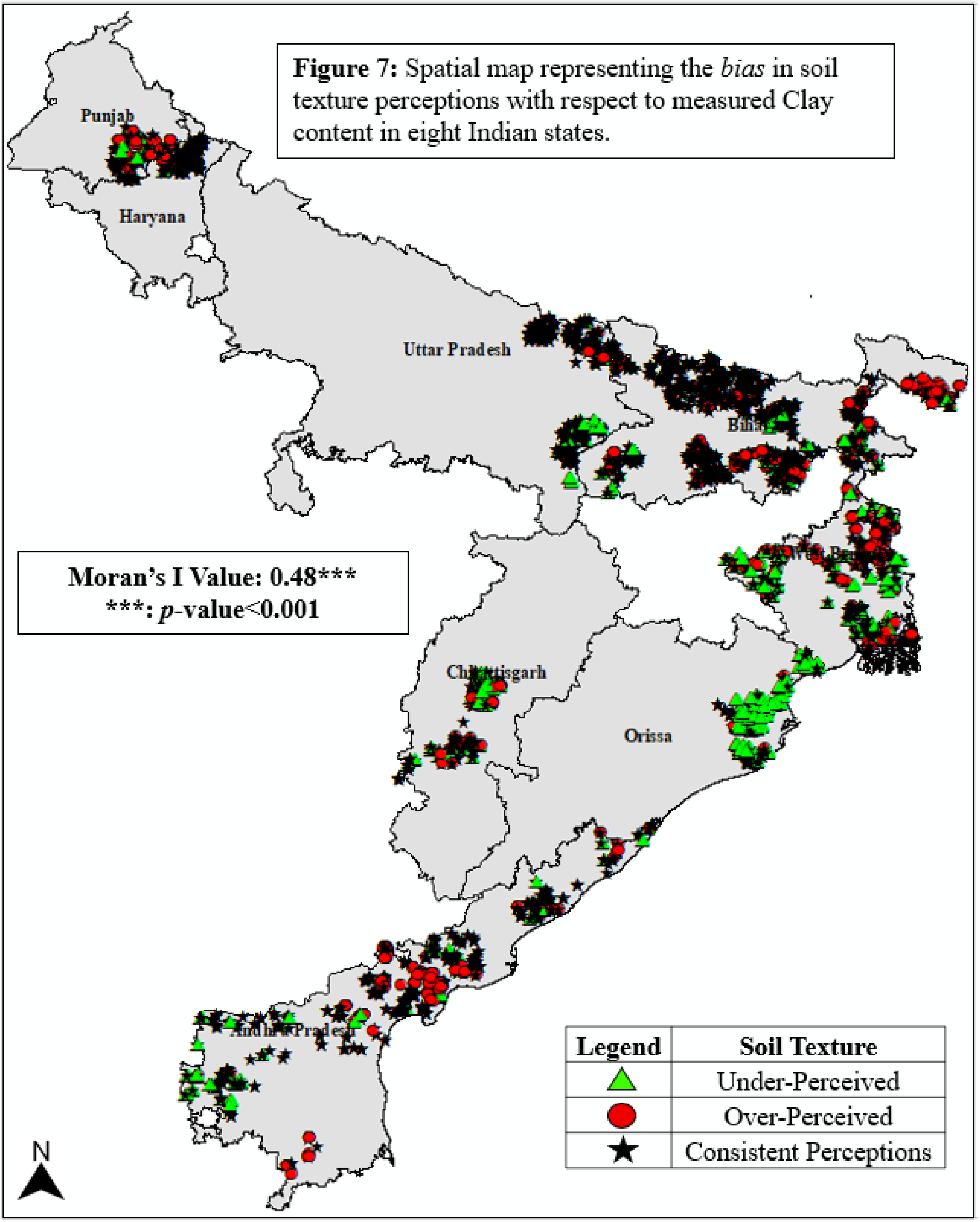

Figure 7: Spatial map representing the *bias* in soil texture perceptions with respect to measured Clay content in eight Indian states.