

Complex Dynamical Study of ESG Factors and Crop Price Volatility in India

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Motivation: Agricultural markets are a prime example of complex adaptive systems. Farmers, traders, climate, government policies, and global supply chains all interact through feedback loops that make price behaviour hard to predict from any single factor alone¹. In India, where agriculture supports nearly half the population, understanding these dynamics matters deeply. Climate variability is one key driver: even small changes in temperature or rainfall can ripple through supply chains and cause sharp swings in crop prices, threatening food security and farmer incomes². But weather is not the only factor at play. Environmental, Social, and Governance (ESG) considerations also shape how agricultural markets function. At the district level, governance capacity like irrigation infrastructure, electricity access, agricultural labour, and cultivated land affects how well markets operate and how effectively price support policies reach farmers. Districts with better infrastructure may absorb climate shocks more smoothly, while those with weaker governance may see them amplified. This multi-layered interplay of climate, governance, and national policy calls for a computational social science approach combining econometric modelling, machine learning, and spatial analysis. We ask two related questions: (i) How do meteorological variables influence crop price volatility, and can we forecast that influence? (ii) Does district-level socio-governance capacity affect crop prices once we account for national price policy and price volatility?

Approach and Methodology: The study has two complementary parts, connected by a complex systems perspective. In Part I, we look at how meteorological variables affect the price volatility of two Indian crops³: soybean in Madhya Pradesh (an export-oriented *kharif* oilseed) and brinjal (eggplant) in Odisha (a domestically consumed vegetable grown year-round). We use monthly district-level price and weather data from 2012 to 2024. First, we fit EGARCH models⁴ to estimate conditional volatility from log returns. We then use cross-correlation analysis and Granger-causality tests to check whether precipitation and maximum temperature have a causal effect on that volatility. Next, we build statistical (SARIMAX) and deep learning (LSTM) forecasting models with meteorological factors as exogenous inputs. Finally, we apply the statistical method, Conditional Autoregressive (CAR), to construct

monthly volatility surfaces across districts, capturing how price risk varies geographically. In Part II, we turn to the social and governance side. We construct a composite Socio-Governance (SG) Index using PCA on four structural indicators namely, agricultural labour population, per capita electricity consumption, net irrigated area, and net cropped area for five districts in Madhya Pradesh over 2006–2020. To link monthly volatility estimates to annual crop prices, we use the Mixed Data Sampling (MIDAS) framework⁵ with Exponential Almon lag polynomials⁵. This approach lets the data decide which months matter most, rather than simply averaging across the year. We then run panel regressions, using Hausman tests to choose between fixed and random effects, to test whether the SG Index affects, e.g. wheat and soybean prices after controlling for MSP and MIDAS-weighted volatility.

Results: On research question (i), from Part I: Brinjal shows persistent volatility throughout the year, driven by its perishability and local supply-demand swings, while soybean volatility spikes mainly around harvest time, with a sharp surge in late 2021 tied to COVID-19 disruptions. Cross-correlations between meteorological variables and price volatility show cyclical seasonal patterns for both crops, but are modest in magnitude. Granger-causality tests reveal that precipitation significantly influences brinjal price volatility at lags of 6-7 months, but no such relationship exists for soybean. These results are consistent with brinjal being locally consumed and climate-sensitive, while soybean prices are shaped more by global trade. For forecasting, LSTM outperforms SARIMAX on both crops (MAPE: soybean 0.33 vs. 0.48; brinjal 0.25 vs. 0.28). The CAR-based volatility surfaces show clear spatial differences in price risk across districts. On research question (ii), from Part II: MSP dominates price determination for both wheat and soybean, with pass-through coefficients close to one. The SG Index is not significant for either crop, suggesting that the uniformity of national MSP policy may crowd out local governance effects on prices. MIDAS-weighted conditional volatility, however, is significant for both crops. For wheat, the unequal seasonal weighting is statistically significant ($p=0.009$), with the heaviest weights falling in the post-harvest marketing months of November and December. For soybean, MIDAS volatility is also significant, but the seasonal weighting does not improve on a simple annual average ($p=0.153$), suggesting that volatility timing matters less for soybean price determination.

Conclusions and Outlook: These findings show that agricultural price volatility in India is shaped by the interaction of climate, local governance, and centralized policy, exactly the kind of multi-scale feedback that characterizes complex adaptive systems. The dominance of MSP over local governance in determining prices is itself an important result: it suggests that India's MSP policy may be masking the role of district-level institutional capacity. We demonstrate the empirical linkage between ESG factors and crop price volatility.

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