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SPATIAL VARIATION IN CROP PRODUCTION ACROSS DIFFERENT AGRICULTURAL REGIONS

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ABSTRACT

The spatial variation in farming production is significant in explaining regional productivity, cropping specialization and long-term trends in food production. The aim of this study was to evaluate the spatial variation in crop production across the agricultural regions of India by employing district-level data for 311 districts of 20 states in India during 1978-2017. Descriptive statistics, regional production shares, measures of variability, and regional and temporal comparisons were used to assess cultivated area, production, and yield. Significant geographical variations were noted and Uttar Pradesh accounted for the maximum share of cumulative production followed by Punjab, Madhya Pradesh, Maharashtra and Rajasthan. Various crop-specific trends were observed such as the regional dominance of rice, wheat, maize, chickpea, soybean, groundnut and cotton. Yield ranking was different than production ranking, suggesting that yield could have been obtained from a variety of different combinations of area and productivity. District-level results also showed a high level of intra-state production specialisation. The overall production of crops rose significantly over the period 1978–2017, although with some ups and downs. Results indicate the necessity of regional strategies for enhancing agricultural productivity and resource allocation and for building agricultural region resilience.

Keywords: crop production, spatial variation, agricultural regions, crop yield, regional productivity

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1.Introduction

Agricultural production is highly geographically differentiated by variations in climate, soil fertility, water availability, cropping systems, farm management, technological adoption and resource endowments. The knowledge of this diversity plays an increasing role in food security and optimal and resilient agricultural systems. The national or state-level comparison of production figures may mask significant variation between agricultural regions, especially where there are high-yielding areas and also low-yielding areas or small acreages. The spatial distribution of agricultural production is also as significant as its total amount, as it can raise the vulnerability of food systems to geographically localized climatic and socioeconomic disruptions (Vesco et al., 2021). Therefore, spatial assessment can offer a good foundation for the identification of production centres, disadvantaged areas and regional inequalities of agricultural performances.

Crop production is the product of cultivated area and productivity, and these factors need not show the same geographical trends. On the one hand a large proportion of land is used for one crop and a high aggregate production can be obtained; on the other hand, a small proportion of land yields a high production, and the same production can be obtained in another region by using a larger proportion of land. The disparities are indicative of spatial variations in the agricultural conditions and productivity. Regional agricultural systems provide evidence that the factors affecting agricultural production efficiency are regionally variable and that general explanations of agricultural performance might miss key local processes (Ma et al., 2021). Agricultural heterogeneity can also have a wider ecological relevance as variation in crops and landscape structure can have an effect on biodiversity and ecosystem functioning across agricultural regions (Sirami et al., 2019). Thus, an assessment of area, production and yield is required to fully characterize regional agricultural variation.

Spatial differences in crop performance are an important source of climate variability. All production areas are not equally vulnerable to temperature extremes, rainfall deficits, drought or other negative weather events. There is a significant amount of evidence at the farm level showing how much yield can be lost when experience extreme weather events, with the impact varying depending on crop type and local production conditions (Schmitt et al., 2022). The shifts in drought sensitivity also highlight the space-time variability in crop responses to climatic stress which may influence known production patterns (Lobell et al., 2020 A). This spatial variation in the exposure to and responses to droughts is also evident in the regional level of evidence from the drought-prone wheat-growing regions (Theron et al., 2021). Soil salinity is expected to become another geographical limiting factor for agricultural production in areas that are susceptible to climate change (Corwin, 2021).

Spatial variation also indicates differences in the way that agriculture, nutrient management and environmental pressures are being applied. The impact of farming activities is not always the same at different sites and times, so instead of making a general assessment of agriculture, one should assess the environmental effects on a geographical basis (Fanelli, 2020). The variability in nutrient inputs and environmental carrying capacities at the regional scale also indicates that the sustainability limits of agriculture cannot be applied at any given geographical level (Schulte-Uebbing et al., 2022). The impacts of these challenges could intensify due to climate change's impacts on the suitability and productivity of key cereal growing regions, which could re-distribute agricultural benefits and risk across the regions (Farooq et al., 2023). Long-term spatial analyses are useful to check if historically prominent production areas continue to be important or if agricultural production gradually changes toward alternative areas.

Monitoring and spatial analytics have made significant progress in agriculture, enabling the significant advance in characterization of production heterogeneity. While ground-based measurements are necessary to assess agriculture effectively, satellite observations can supplement traditional agricultural statistics with information that is spatially explicit about crop conditions, crop areas, and yield variation (Lobell et al., 2020 B). Maize yield estimation has been successfully achieved over heterogeneous agricultural areas using remote sensing (Leroux et al., 2019), and Sentinel-2 data has been shown to have significant potential for detecting within-field yield variability, when combined with machine-learning methods (Kayad et al., 2019). High-resolution satellite observations assimilation in the crop models can also help to detect spatial yield variability early (Ziliani et al., 2022). However, the opportunities to integrate such information into more responsive and sustainable production management increase with the digital and smart-agriculture systems (Cesco et al., 2023).

In spite of these developments, the need for an understanding of long-term crop-production differences between administrative agricultural regions still exists. District level historical data offers a valuable chance to assess geographical variability with the same indicators of cultivated area, production, and yield over long time spans. This analysis can identify areas with large amounts of land planted in crops from areas with higher land productivity, and whether production is evenly spread or in specific states and districts. A multi-crop approach also allows for the identification of specialization at the regional level as well as for comparing the spatial structure of cereals, pulses, oilseeds and other commercial crops. The information can inform geographically specific agricultural planning, resource allocation, productivity enhancement, and measures to enhance the regional food-production resilience. Based on this, this study investigates the spatial variation of crop production for various agricultural regions based on the long-term agricultural observation of the districts. The specific objectives are:

1. To quantify regional differences in cultivated area, crop production, and yield across major agricultural regions and districts
2. To identify spatial patterns, production concentration, and crop-specific disparities among geographically distinct agricultural production areas
3. To assess long-term changes in regional crop production patterns and determine the persistence of spatial disparities

2. Materials and Methods

2.1 Research Design and Data Source

The quantitative observational design was used to study the spatial variations in crop production in agricultural regions of India (Hore, 2022). District level was obtained from International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) District-Level Database. This data consisted of annual observations of 311 districts in 20 states from 1978 to 2017. State-district-year was the main unit of observation. The database featured crop-specific information such as cultivated area, production and yield, and allowed for magnitude and agricultural productivity comparisons between geographical units. The long time-series was left in place to capture the regional production pattern in the long-term and to ensure an accurate representation of the spatial variability.

2.2 Crop Selection and Production Indicators

Crop variables were classified into broad crop categories, such as cereals, pulses, oilseeds and commercial crops. Crop specific analysis was conducted on major individual crops with adequate area, production and yield data. These included rice, wheat, maize, sorghum, pearl millet, chickpea, groundnut, rapeseed and mustard, sugarcane and cotton. Three main indicators were studied: cultivated area (in thousand hectares), crop production (in thousand tonnes) and yield (in kilograms per hectare). Production was used as the main outcome measure in assessing regional agricultural production; the cultivated area and yield were used to distinguish production advantages arising from increased area allocated from those arising from increased productivity.

2.3 Data Preparation and Regional Classification

Prior to analysis, the dataset was examined for data that were missing, duplicate state–district–year observations, inconsistent geographical identifier(s), and implausible numerical values. State and District names and identification codes were standardized for geographical uniformity during the study. The crop variables were standardized based on the units used for their measurement and structured around a common analysis framework. District-level observations were kept for detailed comparison and aggregated state-level estimates were taken for broader regional patterns. States were further broken down into geographical regions for broader comparisons within the larger agricultural areas. Production shares by region was determined as the percentage of production from each geographic unit to the total production. Production was complemented with crop-specific area and yield indicators to describe the structural basis of observed regional differences.

2.4 Statistical Analysis of Regional Variation

The following descriptive statistics were used: mean, median, standard deviation, minimum, maximum, and coefficient of variance for cultivated area, production and yield. States and districts were estimated for production totals and relative shares in order to determine which states and districts were the dominant production areas. The coefficients of variance were calculated to quantify the regional heterogeneity, the higher the coefficient of variance, the larger the geographical dispersion. After studying the distribution and variance properties of the data, the differences between agricultural regions were assessed on the basis of production and yield. When the parametric assumptions were met, the analysis of variance was applied and when it was not, the Kruskal–Wallis test was used. There were significant overall differences followed by appropriate pairwise comparisons. In addition to testing for significance, effect sizes were calculated to provide information on the size of regional differences, and not just the probability value. Significance was determined as $p < 0.05$.

2.5 Spatial and Temporal Pattern Analysis

Spatial patterns were determined at state and district levels using indicators of crop production, cropped area, yield, production shares and production variability across geographical units. Regions were ranked based on their production contribution, both overall and per crops, with the aim of locating regions of persistent production and low production. The geographical units were compared in terms of crop-production profiles in order to describe regional specialization and geographical concentration. If available, administrative boundary data was merged with production data to create areas for choropleth visualization. Temporal analysis was used as a complementary analysis to determine if observed spatial patterns remained stable or shifted during 1978-2017. The study period was split into similar time periods and changes in production contribution, area cultivated, and yield were assessed over these time periods. Wherever applicable, percentage changes were calculated for the long term and compound annual growth rates were calculated. Changes in geographical distribution of production were the key temporal feature of the study, which was interpreted mainly in relation to this change.

3. Results

3.1 Overall Characteristics of Crop Production

The analytical data consisted of 12,418, district-year observations, from 311 districts, in 20 Indian states between 1978 and 2017. There was a significant crop difference among the major crops analyzed. Cumulative produce of rice, wheat and sugarcane was at 3.163 billion tonnes, 2.676 billion tonnes and 1.060 billion tonnes respectively. Production of maize was 515.78 million tonnes, sorghum was 349.06 million tonnes and pearl millet was 294.24 million tonnes. The production of the groundnut amounted to 289.07 million tonnes, while the production of chickpea was 233.20 million tonnes, showing the production of groundnut is significantly higher than that of the chickpea (Table 1).

Table 1. Overall Production of Major Crops, 1978–2017

Crop	Cumulative Production (million tonnes)	Rank
Rice	3,163.00	1
Wheat	2,676.00	2
Sugarcane	1,060.00	3
Maize	515.78	4
Sorghum	349.06	5
Pearl millet	294.24	6

Groundnut	289.07	7
Chickpea	233.20	8

3.2 Regional Variation in Crop Production

There were significant geographical variations in cumulative production between the 20 States. The total production of the selected crops in Uttar Pradesh was the highest at 1.905 billion tonnes accounting for 20.94% of total production. Punjab was second with 915.78 million tonnes and 10.06% followed by Madhya Pradesh with 742.75 million tonnes (8.16%). Maharashtra made a 694.38 million tonne contribution (7.63%) and Rajasthan contributed 585.73 million tonnes (6.44%). The other two states, West Bengal and Haryana, contributed 5.90% and 5.75%, respectively. The results showed that there was high level of spatial variability within the states during the study period (Table 2) (Figure 1).

Table 2. State-Level Variation in Total Crop Production

State	Cumulative Production (million tonnes)	Share of Total Production (%)	Rank
Uttar Pradesh	1,905.00	20.94	1
Punjab	915.78	10.06	2
Madhya Pradesh	742.75	8.16	3
Maharashtra	694.38	7.63	4
Rajasthan	585.73	6.44	5
West Bengal	536.90	5.90	6
Haryana	523.20	5.75	7

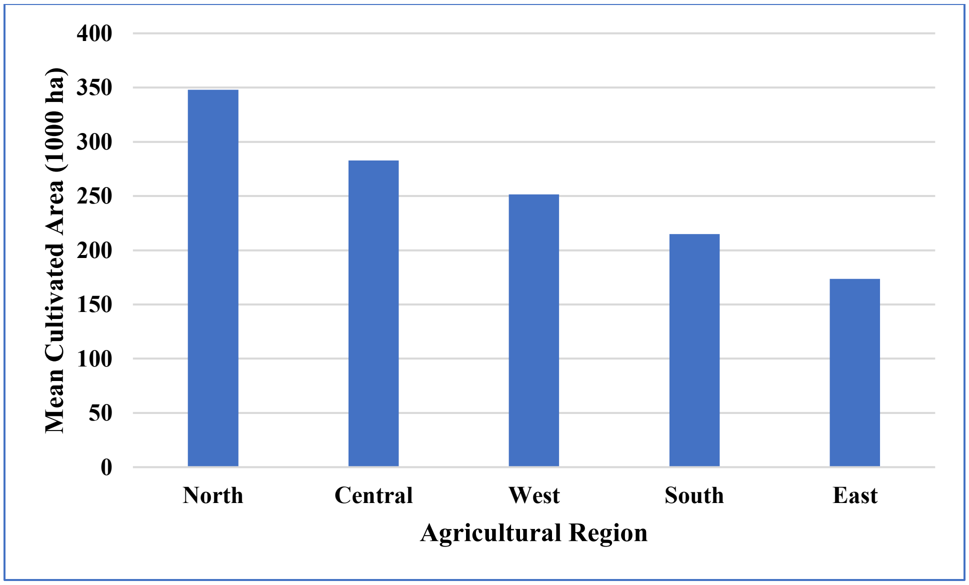

Figure 1. Regional Distribution of Cultivated Area

3.3 Crop-Specific Spatial Patterns

Production of the different crops was found to be geographically distributed. In both rice and wheat production, West Bengal had recorded the highest cumulative production of 477.25 million tonnes and Uttar Pradesh had the bulk of wheat production at 890.22 million tonnes respectively. Karnataka accounted for the highest maize production of 72.95 million tonnes and Maharashtra had the largest production of sorghum at 164.98 million tonnes. Pearl millet production was led by Rajasthan with 103.59 million tonnes while in the case of rapeseed-mustard it was led by Rajasthan with 84.47 million tonnes. Madhya Pradesh accounted for the highest production of chickpeas and soybeans with 86.57 million tonnes and 136.01 million tonnes respectively. The highest groundnut production was recorded in Gujarat at 82.15 MTs while cotton production was recorded highest as 27.64 MTs (Table 3) (Figure 2).

Table 3. Leading States for Major Crop Production

Crop	Leading State	Cumulative Production (million tonnes)
Rice	West Bengal	477.25
Wheat	Uttar Pradesh	890.22
Maize	Karnataka	72.95
Sorghum	Maharashtra	164.98

Pearl millet	Rajasthan	103.59
Chickpea	Madhya Pradesh	86.57
Rapeseed and mustard	Rajasthan	84.47
Soybean	Madhya Pradesh	136.01
Groundnut	Gujarat	82.15
Cotton	Gujarat	27.64

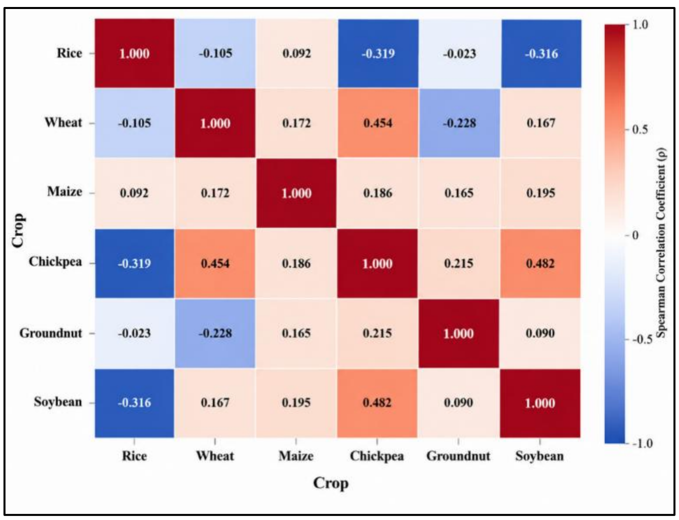

Figure 3. Spearman Correlation Matrix of Major Crop Production Variables

3.4 Spatial Variation in Crop Yield

The geographical distribution of total production was very different from the yield pattern. The highest aggregated rice and wheat productivity was observed in Punjab with area weighted productivity of around 3,586 kg/ha and 4,042 kg/ha, respectively. The highest yield of maize was recorded in AP (5,878kg/ha) and the highest yield of sugarcane recorded in TN (10,560kg/ha). Rape seeds productivity in Gujarat was about 1304 kg/ha and in Haryana was about 1303 kg/ha.The productivity of rape seeds in Gujarat (1304 kg/ha) was similar to that of Haryana (1303 kg/ha). High production and high yield were not necessarily experienced in the same state, highlighting the distinct geographical spreads between overall agricultural output and productivity of land under individual crops (Table 4) (Figure 3).

Table 4. Highest Area-Weighted Crop Yields Across States

Crop	State with Highest Yield	Area-Weighted Yield (kg/ha)
Rice	Punjab	3,586
Wheat	Punjab	4,042
Maize	Andhra Pradesh	5,878
Sugarcane	Tamil Nadu	10,560
Rapeseed and mustard	Gujarat	1,304
Rapeseed and mustard	Haryana	1,303

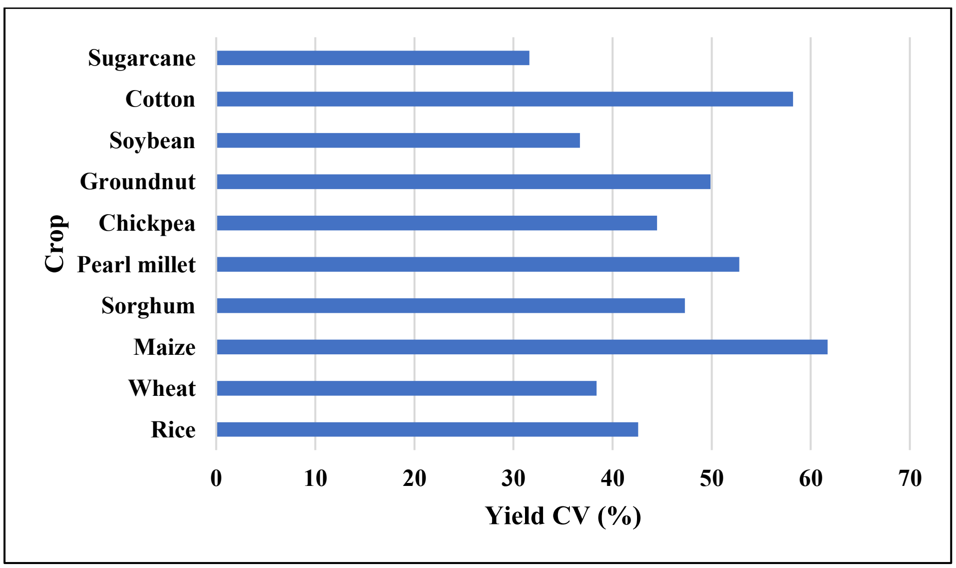

Figure 3. Interregional Variability in Crop Yield

3.5 Spatial Concentration of Crop Production

The aggregation at the district level showed good spatial delineation of the state level production pattern. Ferozpur, Punjab reported the maximum production of selected crops in the combined format, totaling 184.39 million tonnes. Haryana's Hissar and Karnal districts trailed with the 147.32 and 136.72 million tonnes, respectively. Sangrur in Punjab and Bhatinda had production of around 121.35 and 112.87 million tonnes respectively and Patiala had production of 98.39 million tonnes. The figures of Meerut in Uttar Pradesh (94.62 million tonnes) and Amritsar in Punjab (93.02 million tonnes) are the highest. The district rankings showed significant within-state variability and focus in agricultural production in a fairly small number of districts (Table 5).

Table 5. District-Level Production Concentration

Rank	District	State	Cumulative Combined Production (million tonnes)
1	Ferozpur	Punjab	184.39
2	Hissar	Haryana	147.32
3	Karnal	Haryana	136.72
4	Sangrur	Punjab	121.35
5	Bhatinda	Punjab	112.87
6	Patiala	Punjab	98.39
7	Meerut	Uttar Pradesh	94.62
8	Amritsar	Punjab	93.02

3.6 Temporal Evolution of Spatial Production Patterns

Production of selected crops increased significantly over the 40 year observation period. The overall increase was about 160.0% with combined annual production growing from about 137.34 million tonnes in 1978 to 357.08 million tonnes in 2017. This equated to a compound annual growth rate of 2.48% over the period. Production was still variable annually, and in 2016 was 349.45 million tonnes, compared to 273.25 million tonnes in 2008, 333.41 million tonnes in 2013 and 290.86 million tonnes in 2015. But spatial production patterns were embedded in a longer-term growth in agricultural production (Figure 4).

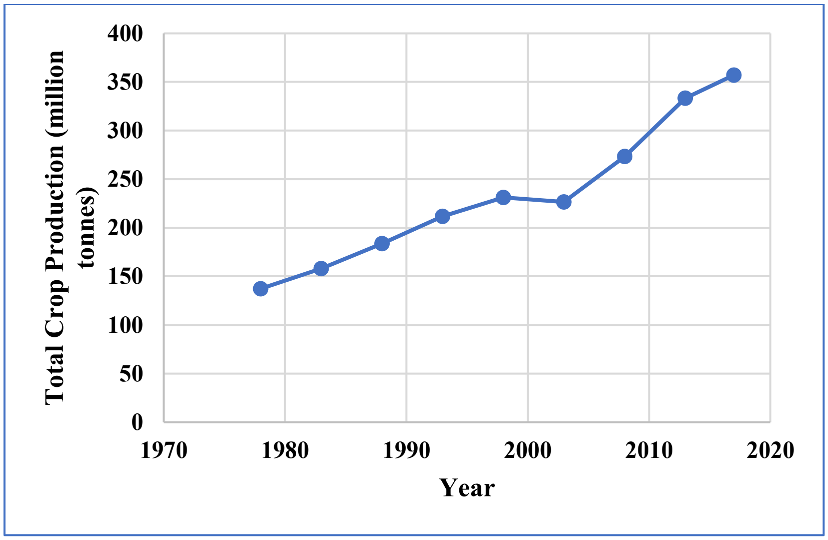

Figure 4. Change in Total Crop Production Across Selected Years

4. Discussion

Crop production illustrate an uneven distribution of agricultural production in the regions studied. The cumulative production of Uttar Pradesh was about 20.94% followed by Punjab, Madhya Pradesh, Maharashtra and Rajasthan, which shows significant concentration in a few small states. This is in line with the general knowledge that the performance of agriculture is spatially heterogeneous due to the interplay of environmental and management factors. The importance of spatially explicit assessments lies in the fact that in the agricultural landscape, not only the spatial variation of soil properties can be significant, but also individual properties can vary significantly, affecting productive potential of cultivated land (Guo et al., 2021). The national-level differences noted here thus highlight the fact that there can be substantial sub-national variation in agricultural production indicators.

Results by crop also showed high geographical specialization. Rice production was the most strongly represented in the state of West Bengal; wheat production was most strongly represented in the state of Uttar Pradesh; Karnataka was prominent in production of maize; Maharashtra was prominent in production of sorghum. Rajasthan led pearl millet, Madhya Pradesh led soybean and chickpea while Rajasthan and Madhya Pradesh led in rape seed mustard. Gujarat was of special significance for groundnut and cotton. These opposing distributions suggest that the production geography of different crops are different, not all following the same spatial pattern. Specialization in agriculture may arise from variations in growing-season conditions, land characteristics, and crop systems already in place, as well as rainfall regime. Spatial and temporal variability of precipitation is pertinent as it is because the spatial distribution of rainfall may significantly vary from place to place and time to time, which makes the agricultural opportunities and constraints equally variable across the different spaces and times (Alemu & Bawoke, 2020). The landscapes may then be heterogeneous, leading to long-lasting regional variation in agricultural outcomes (Evans et al., 2019).

Yield patterns also reinforced the idea that the size of production and land productivity are two aspects of the performance of agriculture in a region. The area weighted rice and wheat yields were highest in Punjab, the maize productivity was highest in Andhra Pradesh and the sugarcane yield was highest in Tamil Nadu. The places did not always match the highest accumulated states. The high production of aggregates can thus result from a high cultivated area, a high productivity, or both. Spatial variability of soil conditions could account for some of these productivity differences because agricultural soils can have significant geographical variation in chemical properties and related soil environmental constraints (Shi et al., 2019). To conclude and in general terms, the landscape and land-use configurations can generate differentiated environmental conditions across space, which adds to the importance of conducting spatial analysis of agricultural outcomes beyond the assumption of uniformity of production environment (Nafi'Shehab et al., 2021).

There was also a good amount of concentration within the districts. There was even significant variation within the big agricultural states as the highest cumulative production districts were: Ferozpur, Hissar, Karnal, Sangrur, Bhatinda and Patiala. This discovery highlights the importance of district-level observations in analyzing the analytical content of the district-level findings, as state averages can mask key subregional production clusters. This scale is important for forecasting because crop yields are also spatially and temporally variable, and sometimes a single modeller will not adequately capture the spatial variability (Leng & Hall, 2020). Spatialized assessments of agriculture can also detect variations in the availability and distribution of resources derived from crops at a level of geographical aggregation that is too wide to capture them (Scarlat et al., 2019). There is therefore a need for district-level information for prioritization of areas for productivity improvement and agricultural investments.

The temporal results indicated that the combined production of crops grew from around 137.34 million tonnes in 1978 to 357.08 million tonnes in 2017, a rise of about 160% or an average annual growth rate of 2.48%. This growth was accompanied by significant annual variation, indicating that the production growth over the long term did not remove the temporal instability. As water availability is likely to be a key issue in regions of high production, the water resources of the Indo Gangetic Plain are important for agriculture as a significant source of water for irrigation comes from snow and glacier melt. Thus, the observed long term changes emphasise the need to consider spatial patterns of production in a temporal perspective, and to not assume regional dominance in agriculture as a permanent fact.

The results are applied to spatial planning of agriculture. The regions with high production volumes and moderate yields may consider interventions to increase productivity, while the highly productive, but spatially concentrated regions may need resilience building and lower production risks for localized regions. The introduction of multi-layer agricultural datasets and predictive modelling offer the potential of predicting crop performance in heterogeneous farming contexts (Filippi et al., 2019). In addition, multi-source and multi-temporal remote sensing can be used to enhance crop identification and spatial agricultural monitoring (Sun et al., 2019), and machine-learning techniques can be adopted with proximal sensing to further boost the yield prediction and management decisions. The use of these technologies with district long-term statistics could lead to significant improvement in region-specific production assessment.

Some caveats should be noted. This study did not directly account for climatic, soil, and irrigation data, and socioeconomic and farm-management data were not included because they were not available to explain the spatial differences identified. Furthermore, there were no geographic coordinates or administrative boundary geometries in the core dataset, which hindered advanced spatial dependence analysis. Future studies could synthesize district production records and soil, climate, irrigation, remote-sensing and socioeconomic data and use spatial econometric or geostatistical techniques. This integration would be useful for overcoming the current limitation of identifying the locations of production gaps and moving towards understanding what drives the persistence of gaps and variation in production across agricultural regions.

5. Conclusion

Crop production exhibited a significant geographical variation in the agricultural regions and between different states and districts during 1978-2017. The production was limited to few States with Uttar Pradesh as the highest overall production State, followed by Punjab, Madhya Pradesh, Maharashtra and Rajasthan. The crop-specific patterns revealed significant regional specializations, with West Bengal having a strong presence of rice, Uttar Pradesh of wheat, Karnataka of maize, Madhya Pradesh of chickpea and soybean and Gujarat of groundnut and cotton. Relationships between yields and production were not consistent; that is, high production can be achieved through increased land size or land productivity or a combination of both. There was also a high concentration of districts in certain areas, suggesting key spatial variations at the district level, which are not captured in the wider regional level. In long term, the aggregate production shows a significant increase from 1978 to 2017, although there are significant fluctuations in the range of years. The results highlight the importance of spatial (district level) evaluation in the identification of production centres, productivity gaps, and geographical specialization of crops. Agricultural strategies regionally should thus take into account both production size and yield performance. The incorporation of historical production data with information on climate, soil, irrigation, socioeconomic, and remote-sensing data could further benefit in supporting targeted resource allocation, productivity improvement, and resilient agricultural planning.

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