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DIGITAL FARMING PRACTICES AND CHANGES IN AGRICULTURAL PRODUCTIVITY OVER TIME

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ABSTRACT

Digital farming is increasingly transforming agricultural production through precision technologies that support data-driven management and resource allocation. This study examined temporal changes in digital farming practices and their associations with agricultural productivity in U.S. corn production between 1996 and 2010. Precision-agriculture indicators were integrated with annual corn grain yield observations across matched years. Digital farming was characterized using precision agriculture, yield monitoring, yield mapping, GPS-based soil mapping, variable-rate technologies, and automated guidance systems. Temporal trends, Pearson and Spearman correlations, and parsimonious regression models were applied, alongside a composite Digital Farming Adoption Index. Precision-agriculture use increased from 17.29% of planted corn acres in 1997 to 72.47% in 2010, while yield-monitor use increased from 17.29% to 61.41%. Corn productivity increased by 20.1%, from 127.1 to 152.6 bu/acre. Precision-agriculture adoption was strongly associated with yield ($r = 0.953$, $p < 0.001$), while the Digital Farming Adoption Index also showed a significant positive association with productivity ($r = 0.842$, $p = 0.035$). Short-term changes in digital adoption were not significantly associated with corresponding yield changes. The findings demonstrate parallel long-term increases in agricultural digitalization and corn productivity while emphasizing the need for farm-level longitudinal evidence to establish causal effects.

Keywords: Digital farming; Precision agriculture; Agricultural productivity; Corn yield; Technology adoption

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1.Introduction

The transition towards a "digital farming system" in which data acquisition, spatial information, automation and analytical technologies become more and more present in the farm operational decisions is a progressive process on which agriculture moves. This shift has come at a time when there is still a need to enhance crop productivity and to manage land, water, energy and agriculture inputs in a more efficient and sustainable manner. Smart farming is an information-intensive approach where the vast amount of data collected in the farm and environment can be converted to farm management information for action (Wolfert et al., 2017). Digital technologies can therefore help with sustainable agricultural intensification, not only by facilitating uniform field-level management, but by assisting in more targeted and responsive production decisions (Walter et al., 2017). As more and more data is collected from machinery, sensors, field observations and production records, more and more opportunities have emerged to connect these to decision making systems (Kamilaris et al., 2017).

One of the key parts of this digital transformation is precision agriculture. Global positioning systems (GPS), yield monitors, yield mapping, remote sensing, variable-rate technology (VRT), and automated guidance are technologies that can be used to detect and control spatial and temporal variability in agricultural fields. However, their adoption is not only technically possible, but also relies on the farmers' awareness, understanding, perceived usefulness, implementation capacity (Kendall et al., 2017). The ability of precision-agriculture systems to assist in crop yield estimation and nutrient management with complex field information has been enhanced through advances in computational methods (Chlingaryan et al., 2018). In crop monitoring and grain production applications, computer vision and artificial intelligence have added other ways for automated monitoring and management (Patrício & Rieder, 2018). Other agricultural information, in the form of spatial data, has also become more available through remote-sensing systems, which can serve for monitoring and management of crops at various scales (Huang et al. 2018).

The diffusion of these technologies has nevertheless been heterogeneous. Farm characteristics, economic conditions, technical capacity, perceived benefits and institutional environments can impact the likelihood of adoption and the level of take-up of precision-agriculture technologies. There is significant variation in adoption of precision technologies across agricultural producers evident in cross regional evidence (Barnes et al., 2019). Estimates of adoption also rely heavily on the definition and measurement of precision agriculture, and on longitudinal evidence of the real trajectory of technology transfer (Lowenberg-DeBoer & Erickson, 2019). Digital agriculture is therefore moving beyond the use of individual devices and more and more towards technology, organization, and knowledge systems that are linked together. This wider transformation has been conceptualised under the terms 'smart farming' and 'Agriculture 4.0' and seen as a combination of technologies, farmers, institutions and agricultural innovation systems (Klerkx et al., 2019).

Sensing, communication, data processing, machinery and decision-support technologies have gradually been integrated into agricultural production systems in a way that has progressively connected them (Bacco et al., 2019). On a higher level of development, digital technologies have also been identified as possible tools for enhancing the flow of information, production management, market connections and rural development (Trendov et al., 2019). The transition towards Agriculture 5.0 continues to emphasize on the increasing integration of data management, automation and intelligent decision-making throughout the crop production processes (Saiz-Rubio & Rovira-Más, 2020). The developments indicate that digital farming is not a binary concept and cannot be understood as an either/or situation between adopters and non-adopters, but rather a developing technological system.

The ability to effectively use the technologies and information also relies on the knowledge structures in which they are explained and utilized. Digital platforms have the potential to transform farmer-adviser, farmer-researcher, farmer-technology provider and farmer-Farmers interaction and subsequently agricultural knowledge and advisory networks (Fielke et al., 2020). These shifts would have consequences for the production and dissemination, as well as the uptake of agricultural knowledge, and their role in farm management decisions (Ingram & Maye, 2020). Incorporating Agriculture 4.0 will pose challenges to technological diversity, accessibility, responsibility, and pathways of transition, meaning that digital transformation can be understood not only as a matter of technological availability (Klerkx & Rose, 2020).

Although significant research efforts have been dedicated to digital agriculture, there is still a lack of empirical understanding of how digital farming practices are expanding and relate to the time series evolution of agricultural productivity. There has been a focus in much of the literature on individual technologies, adoption determinants, technological capabilities or on differences between cross sections. There are few analyses that combine repeated measures of multiple precision-agriculture practices with corresponding long-term productivity observations. The analysis of these trajectories together could offer insights on whether agricultural digitalisation has taken place alongside a measurable increase in productivity of crops, without assuming causal links between them and temporal association. Corn is appropriate because the use of precision technologies has been incrementally adopted in its production practices and its productivity is easily measured by grain yield per unit area. Accordingly, this study integrated historical indicators of precision-agriculture adoption with corresponding annual corn-yield observations to examine the temporal relationship between agricultural digitalization and productivity. The specific objectives were:

1. To examine temporal changes in the adoption of major digital farming practices.
2. To quantify changes in agricultural productivity across corresponding observation years.
3. To assess associations between digital farming adoption and agricultural productivity over time.

2. Materials and Methods

2.1 Study Design

Changes in agricultural productivity and digital farming practices over time were analyzed using a quantitative ecological design approach. The integration of precision-agriculture practice records with the annual observations of corn productivity was accomplished by mapping the records to the calendar year. Analysis encompassed observations from 1996 through 2010, and matched years were selected based on the availability of the individual digital farming indicators (U.S. Department of Agriculture, Economic Research Service, 2023; U.S. Department of Agriculture, National Agricultural Statistics Service, 2022). The digital-practice estimates were assigned to percent of acres planted based on the precision-agriculture technologies implemented on the planted acreage, and agricultural productivity was represented with annual corn grain yield estimates. Data were harmonized through standardizing the year fields, checking the format of variables, removing non-analytical data points, and matching productivity observations to the years of technology adoption. The resulting dataset was thus treated as a time series dataset at national level rather than a panel dataset of farms.

2.2 Digital Farming Indicators

Digital farming was characterized using indicators representing the adoption and intensity of precision-agriculture technologies in corn production. The principal indicators included overall precision agriculture use, yield-monitor use, yield-map creation, GPS-based soil-property mapping, aerial or satellite imagery, variable-rate technology (VRT), VRT fertilization, VRT seeding, VRT pesticide application, and guidance or AutoSteering systems. Adoption was expressed as the percentage of planted corn acres associated with each practice. Indicators with insufficient temporal observations were excluded from inferential models where appropriate but retained for descriptive analysis. For integrated analysis, eight sufficiently observed indicators—precision agriculture, yield monitoring, yield mapping, GPS soil mapping, overall VRT, VRT fertilization, VRT seeding, and VRT pesticide application—were standardized. Their standardized values were combined and rescaled to a 0–100 Digital Farming Adoption Index, where higher values represented greater overall digital-farming intensity.

2.3 Productivity Measures

Productivity was defined as the productivity of agricultural crops, in this case measured as bushels per acre (bu/acre) of corn grain. Forecast observations were kept only for the final year of each season, to ensure temporal comparability, within-year forecast observations were not retained. The productivity data was harmonised with the digital farming records for the years of observation. Descriptive measures used were: mean yield, standard deviation, absolute change, and percentage change between successive observations. Changes in productivity were determined between the first and the last observations. An index of temporal trends was retained that quantified the direction and magnitude of long-term productivity change, using calendar year as the temporal scale. Sensitivities were calculated for intervals between matched observations that differed in year and were annualized.

2.4 Statistical Analysis

The data was processed and the statistical analysis was carried out in Python, using the following libraries: pandas, NumPy, SciPy, and statsmodels. Means, standard deviations, ranges and temporal changes of continuous variables were reported. Descriptive trend analysis was used to evaluate digital-practice trajectories and corn productivity for each observation year. The temporal productivity trend was estimated using a simple linear regression of corn yield on calendar year. Since the number of temporal observations was small and linearity was a possibility, both Pearson correlation coefficients (r) and Spearman rank correlation coefficients (ρ) were used to examine the association between digital farming indicators and corn yield. Overall precision-agriculture adoption and the Digital Farming Adoption Index were later used as separate inputs for fitting parsimonious ordinary least-squares regression models of corn yield. The regression coefficients, 95% confidence intervals, coefficient of determination (R^2) and p-values were reported. The statistical significance was determined by $p< 0.05$ and the results were considered in the light of the limited temporal sample.

2.5 Robustness Analysis

To ensure data comparability, data completeness was evaluated separately for each digital farming indicator, as data on technologies were not consistently reported throughout the survey years. All observations were used in descriptive analyses, while complete observations are available for the composite Digital Farming Adoption Index across the eight indicators for which data was available and were limited to 1998, 1999, 2000, 2001, 2005, and 2010. Model estimates were only made for years with both adoption and productivity observations. A sensitivity analysis was performed to assess the relationship between changes in the Digital Farming Adoption Index (DFAI) and changes in corn yield at the annual level to see if there were any relationships between successive years as well. Cross checking has been done with the Pearson and Spearman estimates of correlation, and model residuals and influential observations have been examined when sample size permitted. Temporal clustering of data was taken into account, and statistical relationships were established as associations and not as causal effects.

3. Results

3.1 Digital Farming Trends

Digital farming adoption increased across the observation period. Precision agriculture use increased from 17.29% of planted corn acres in 1997 to 72.47% in 2010, an absolute increase of 55.18 percentage points. Yield-monitor use increased from 17.29% to 61.41%, while yield mapping increased from 7.67% to 33.94%. GPS-based soil mapping increased from 13.10% in 1998 to 22.27% in 2010.

Variable-rate technology (VRT) for any purpose increased from 8.04% in 1998 to 22.45% in 2010. VRT fertilization increased from 7.62% to 19.29%, VRT seeding from 1.98% to 7.20%, and VRT pesticide application from 1.35% to 4.95%. Guidance or AutoSteering increased from 5.34% in 2001 to 45.17% in 2010. Table 1 summarizes the temporal characteristics of the digital farming indicators, while Figure 1 presents their adoption trajectories.

Table 1. Temporal characteristics of major digital farming indicators

Digital farming indicator	Available years (n)	Mean (%)	SD	Earliest (%)	Latest (%)	Change (pp)
Precision agriculture used	7	40.04	17.60	17.29	72.47	+55.18
Yield monitor used	7	30.93	15.70	17.29	61.41	+44.12

Yield map created	7	14.15	9.68	7.67	33.94	+26.27
GPS soil mapping	6	18.43	4.10	13.10	22.27	+9.17
VRT, any purpose	6	12.68	5.09	8.04	22.45	+14.40
VRT fertilization	6	11.05	4.23	7.62	19.29	+11.67
VRT seeding	6	3.24	2.07	1.98	7.20	+5.22
VRT pesticide application	6	2.53	1.36	1.35	4.95	+3.60
Guidance/AutoSteering	3	21.85	20.77	5.34	45.17	+39.83

Note: pp = percentage points.

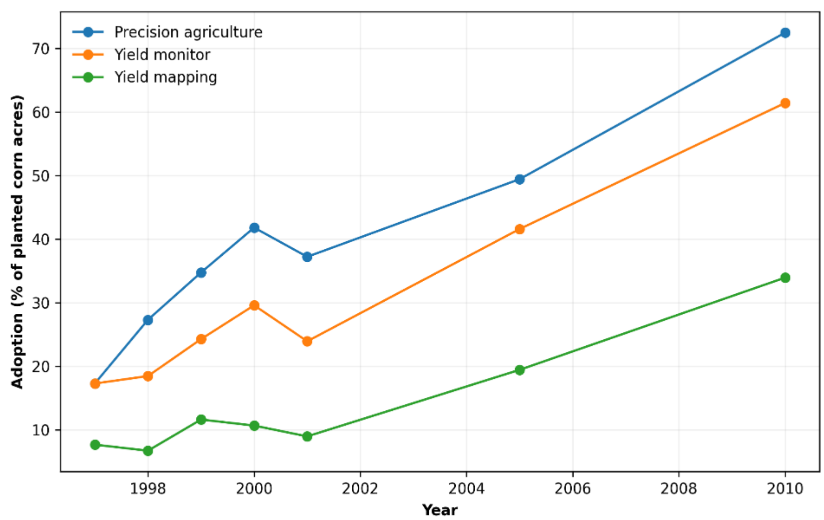

Figure 1. Temporal trends in the adoption of major digital farming practices in U.S. corn production.

3.2 Productivity Trends

Corn grain yield increased from 127.1 bu/acre in 1996 to 152.6 bu/acre in 2010, corresponding to an absolute increase of 25.5 bu/acre (20.1%). Mean yield across the eight matched years was 137.2 ± 9.14 bu/acre. Yield decreased slightly between 1996 and 1997 and between 1998 and 1999, while increases were recorded during the remaining matched intervals. The linear temporal model estimated an increase of 1.91 bu/acre per year (95% CI: 1.45–2.37, $p < 0.001$; $R^2 = 0.946$). Table 2 presents annual productivity values and changes between successive observations, and Figure 2 shows the temporal yield pattern.

Table 2. Corn productivity across matched observation years

Year	Yield (bu/acre)	Change (bu/acre)	Change (%)
1996	127.1	—	—
1997	126.7	−0.4	−0.31
1998	134.4	+7.7	+6.08
1999	133.8	−0.6	−0.45
2000	136.9	+3.1	+2.32
2001	138.2	+1.3	+0.95
2005	147.9	+9.7	+7.02
2010	152.6	+4.7	+3.18

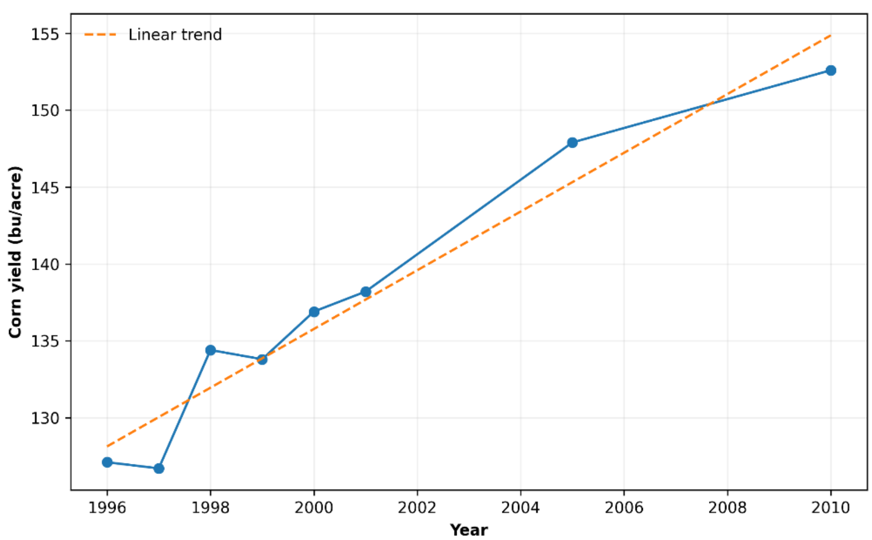

Figure 2. Temporal changes in U.S. corn grain yield from 1996 to 2010.

3.3 Digitalization–Productivity Association

Precision agriculture use showed a strong positive association with corn yield (Spearman $\rho = 0.929$, $p = 0.003$; Pearson $r = 0.953$, $p < 0.001$). Yield-monitor use was also positively associated with yield ($\rho =$

0.821, $p = 0.023$; $r = 0.935$, $p = 0.002$). Yield mapping produced $\rho = 0.679$ ($p = 0.094$) and $r = 0.887$ ($p = 0.008$).

GPS soil mapping showed weaker associations with yield ($\rho = 0.543$, $p = 0.266$; $r = 0.268$, $p = 0.608$). Overall VRT use produced $\rho = 0.371$ ($p = 0.468$) and $r = 0.758$ ($p = 0.081$). Guidance/AutoSteering had only three matched observations and yielded $r = 0.884$ ($p = 0.309$). The complete association estimates are reported in Table 3, while Figure 3 displays the correlation structure.

Table 3. Associations between digital farming indicators and corn productivity

Indicator	n	Spearman ρ	p	Pearson r	p
Precision agriculture used	7	0.929	0.003	0.953	<0.001
Yield monitor used	7	0.821	0.023	0.935	0.002
Yield map created	7	0.679	0.094	0.887	0.008
GPS soil mapping	6	0.543	0.266	0.268	0.608
VRT, any purpose	6	0.371	0.468	0.758	0.081
Guidance/AutoSteering	3	1.000	—	0.884	0.309

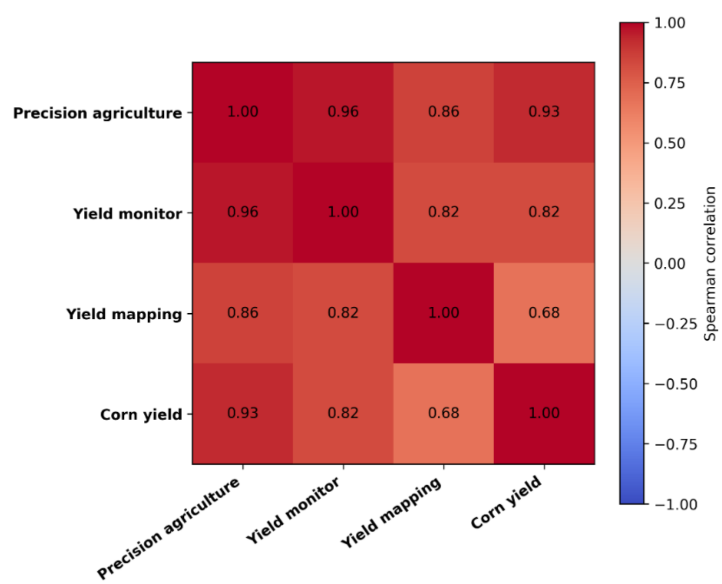

Figure 3. Correlation heatmap of digital farming indicators and corn productivity.

3.4 Integrated Model

The Digital Farming Adoption Index was calculated for the six years with complete observations across the selected indicators: 1998, 1999, 2000, 2001, 2005, and 2010. The standardized index ranged from 0 to 100, with the highest value occurring in 2010. The index was positively correlated with corn yield (Pearson $r = 0.842$, $p = 0.035$; Spearman $\rho = 0.771$, $p = 0.072$). In the bivariate regression model, a one-point increase in the Digital Farming Adoption Index corresponded to a 0.189 bu/acre increase in yield (95% CI: 0.021–0.358, $p = 0.035$; $R^2 = 0.709$).

Overall precision-agriculture adoption produced a coefficient of 0.478 bu/acre per percentage-point increase (95% CI: 0.304–0.652, $p < 0.001$; $R^2 = 0.909$). In the annualized-change sensitivity analysis, the relationship between changes in the Digital Farming Adoption Index and changes in yield was $r = -0.137$ ($p = 0.827$). Table 4 reports the model estimates, and Figure 4 presents the relationship between the Digital Farming Adoption Index and corn yield.

Table 4. Statistical models of digital farming and corn productivity

Model	Predictor	n	Estimate	95% CI	R^2	p
Temporal trend	Calendar year	8	1.910 bu/acre/year	1.454–2.366	0.946	<0.001
Digital adoption	Precision agriculture (%)	7	0.478 bu/acre/pp	0.304–0.652	0.909	<0.001
Integrated model	Digital Farming Adoption Index	6	0.189 bu/acre/index point	0.021–0.358	0.709	0.035
Change sensitivity	Annualized index change	5 intervals	$r = -0.137$	—	—	0.827

Note: pp = percentage point.

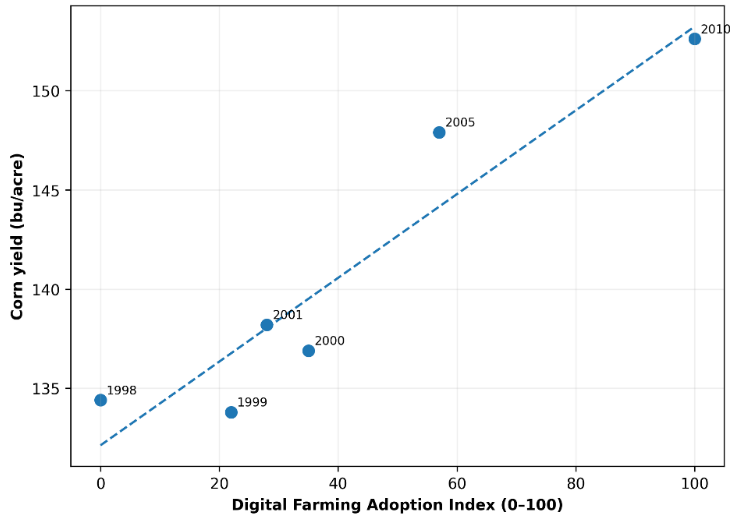

Figure 4. Association between the Digital Farming Adoption Index and corn productivity across matched observation years.

4. Discussion

The results show significant changes and growth in digital farming activities over time and with agricultural productivity in corn production in the USA. The total acreage of corn planted with precision agriculture rose from 17.29% in 1997 to 72.47% in 2010, and the acreage of corn planted with yield monitors rose from 17.29% to 61.41%. Production of corn grew by 127.1 bu/acre in 1996 to 152.6 bu/acre in 2010, a total increase of 20.1%. Overall precision-agriculture use and yield monitoring showed the strongest productivity associations, and the integrated Digital Farming Adoption Index was a positive association with corn yield. The patterns align with empirical evidence that the adoption of precision-agriculture technology can help develop technical efficiency by increasing the knowledge available for management decision making and resource allocation (DeLay et al., 2022). The correlation between the annualized percentage change in digital adoption and annualized percentage change in yield is weak, but within longer time periods, the correlation is much stronger than between consecutive time periods.

Additionally, the results of the adoption patterns show significant variation between the different digital technologies. Yield monitoring and general precision agriculture application increased rapidly, and specialized applications like VRT seeding and pesticide application were less common. Increased adoption of automated field operations for corn production was observed for Guidance and AutoSteering as both technologies demonstrated very high growth rates in the later observation period. Variations between technologies might be associated with variation in capital requirements, technical complexity, compatibility with existing machinery, expected economic returns and applicability of specific technologies to farm management needs. Other evaluations of precision-agriculture implementation have also found that there is a significant variability in the functions, maturity and practical use of precision-agriculture technologies across agricultural production systems (Cisternas et al., 2020). Digital transformation should instead be considered as a journey rather than a single technology wave spreading out at once. The observed trajectories, on the contrary, show how the technological layers are developed, progressing over time from monitoring and information generation tools to increasingly automated and site specific management systems. These trajectories might also be influenced by supply-side factors, as technology manufacturers, service providers, infrastructure, investment needs, and institutional arrangements determine the availability and accessibility of agricultural digital innovations (ADI) (Birner et al., 2021).

The positive relationship between the use of precision-agriculture and yield-monitor and corn productivity is also important in understanding the potential for agricultural digitalization to be associated with increases in production performance. The spatially explicit information about the performance of the crop that can be obtained from the yield monitors can be linked with the locations in the field and with the management history of the field using mapping and GPS technologies. VRT can then be used to deliver this information in a way which can differentiate the use of fertiliser, seed or crop protection inputs. These functions can enhance the accuracy and/or timeliness of management, instead of treating spatially heterogeneous fields as the same. In the past, precision-agriculture technologies have been associated with potential enhancement of farm productivity and economic results by optimizing the use of inputs and farm management (Balafoutis et al., 2017). The positive correlation found for the composite Digital Farming Adoption Index also suggested that the overall digitalization of agriculture was linked with productivity, not only the empirical pattern described for individual technological practice was limited to that technology.

This relationship is qualified by the findings of temporal sensitivity. The Digital Farming Adoption Index was strongly correlated with the level of adoption and yield, whereas there was no strong correlation between annual changes in digital adoption and short-term productivity changes. This did not lead to a proportional response from agricultural productivity at every incremental increase in digital adoption measured. Yield is a reflection of the effect of weather, crop genetics, soil characteristics, fertilizer use, pest and disease levels, irrigation, machinery management and other agronomic advances. These are the conditions that digital technologies are working in and can affect efficiency but otherwise do not drive variations in annual yield. Precision farming has thus been placed in the crossroads between agricultural production and environmental management, where the technological performance is closely related to the integration of precision farming with broader production system (Finger et al., 2019). The results thus offer more evidence for the long-term evolution of parallel trajectories than for short-term productivity gains resulting from year-over-year variations in digitalization. This distinction is important, because the influence of the technological development may be different from other developments that happened during the same period at the same time.

The findings also have implications for agricultural technology strategies. Yield monitoring, precision agriculture and automated guidance are all technologies that have shown high growth rates, suggesting that digital technologies will move from a comparatively small position to a more significant place in large-scale crop production systems. Future adoption may require the ability to produce information that can be used to make decision for managing the farm, and the potential for a range of digital tools to be integrated into a production system. Precision-agriculture applications can aid in the management of crop and resource utilization, input management and operational efficiency if properly integrated into farming practices (Monteiro et al., 2021). Investment strategies should therefore go beyond the acquisition of equipment to connectivity, digital skills, advisory support, data interpretation, interoperability and the farmers' capacity to interpret the data to make decisions in the field. The relatively low number of VRT applications adopted also suggests significant potential for further diffusion where agronomic value and economic viability warrant adoption.

There are some constraints to be taken into account. The analysis was based on a small number of national observations matched, and some digital technologies were not available for each year of the survey. Individual farm, regional, production scale and environmental differences could not be assessed due to national aggregation. It was not possible to completely control important time-varying factors affecting corn productivity such as weather, genetic development, soil conditions, irrigation and input management. The associations should not, therefore, be considered as causal estimates of productivity gains due solely to digital farming. Further research is needed to integrate farm-level longitudinal technology-adoption data with yield, weather, soil, input, economic and management data. Longer and more frequent time series would allow for more robust panel, time-series and causal-inference analysis and differentiation of the impact of digital technologies from the impact of other concurrent agronomic and technological advances.

5. Conclusion

This study showed a clear long-term expansion in the use of digital farming, as well as an increase in productivity on the farm in U.S. corn production from 1996 to 2010. Precision-agriculture use, yield monitoring, yield mapping, GPS-based applications, variable-rate technologies and automated guidance generally grew during the observation period, albeit at varying levels and rates of adoption across technologies. Corn grain yield rose by 20.1% (127.1 to 152.6 bu/acre) and was a significant improvement in productivity during the same general time period. The overall precision-agriculture adoption and yield-monitor use indicated the strongest positive associations with corn yield and the composite Digital Farming Adoption Index was significantly associated with productivity. These results suggest that digitalization of agriculture went hand-in-hand with an increase in crop yields. The absence of a significant relationship between the short-term change in the digital adoption index and the yield changes indicates, however, that the gains in productivity are also related to other factors beyond digital farming. Farm performance depends on the interplay of technological, agronomic, environmental and genetic factors. The data are also aggregated over time, which also hinders causal interpretation. These limitations aside, the results offer empirical support for two parallel long-term trends: an increase in precision-agriculture adoption and in corn productivity. Continuing research at the farm level should also combine the adoption of digital technology with weather, soil, input use, management, and economic characteristics to separate out technology-specific productivity impacts. The information contained in such evidence will be crucial to inform investment, extension and policy approaches to productive, efficient, and increasingly data-rich agricultural systems.

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