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INTERCONNECTED SYSTEMS FOR RESILIENCE IN SMALLHOLDER AGRICULTURE: CLIMATE-SMART AND VULNERABLY SMART APPROACHES

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Abstract
The fast transition of agricultural systems in response to climate change, market instability, and resource depletion has resulted in new paradigms such as Climate-Smart Agriculture (CSA) and the more recently mentioned Vulnerably Smart Agriculture (VSA). The idea of "smart agriculture" is increasingly used to describe a collection of technologies meant to improve agricultural performance, including sensor networks, autonomous machinery, AI-powered decision systems, and precise input management. However, smallholders' capacity to embrace such techniques is still unknown due to structural constraints such as low capital, low educational levels, a lack of infrastructure, and institutional neglect. These barriers are especially significant in areas sensitive to weather extremes and characterized with small scale farming, such as Bulgaria's Pazardzhik district, where this study was conducted. The publication's aim is to use factor analysis transformed into a cluster analysis. The findings are based on empirical data ot the current state of the digitalization level of the small farms in the Pazardzhik and the level of transition to smart agriculture. Examintion of their ability to adapt Vulnerably Smart Agriculture (VSA) and Climate-Smart Agriculture (CSA) are presented.
This article analyzes the main challenges faced by small farms in their transition to smart agriculture, drawing on actual field research done among 30 smallholder farms with an annual production of less than €9000. The empirical data shed light on the distinct weaknesses and technological constraints of small producers, demonstrating how smart agriculture may help to be tailored – not only technologically, but also socially and economically – to their respective environments.The incorporation of CSA and VSA into these systems provides a new theoretical and practical paradigm for developing resilience at the micro level. This includes not just lowering emissions and improving yields, but also promoting livelihood diversification, off-farm revenue creation, and locally specific adaption techniques. As global climate threats increase, understanding the circumstances under which smallholders might move to more resilient systems becomes crucial to long-term food security. This article was financially supported by the UNWE Research Programme (Research Grant No. NID NI-5/2024/A).

Keywords: resilience, smart agriculture, small farms, digitalization
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Introduction of the CSA and VSA

Agriculture is now seen as part of a broader global picture that includes environmental protection, resource-saving technologies, lowering the need for raw

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materials, economic efficiency, etc., whereas only a few years ago the agricultural sector was discussed and studied in terms of specific economic characteristics and cultivation technologies (Rose et al., 2021; Doitchinova et al., 2019). This shift reflects the increasing alignment of agriculture with the sustainability agenda, especially under the pressures of climate change and ecological degradation (FAO, 2013).

Finally, in the past ten years, the emphasis has switched to new and creative approaches, some of which are digital, with the goal of attaining sustainability at the territorial level as well as in other areas of sustainability, such as the ecological, cultural, social, and economic effects (Klerkx et al., 2019; Eastwood et al., 2017). The integration of digital tools in agriculture has enabled more precise and localized management practices, further supporting the multidimensional nature of sustainability in rural areas (Wolfert et al., 2017; Doitchinova, & Stoyanova, 2024).

The agriculture sector is frequently criticized for having less advanced technology than other economic sectors like industry. For instance, certain businesses and processes are already moving toward the 5.0 scale, whereas the agricultural sector is mostly at level 2.0 and just a tiny part has reached level 4.0 (Bacco et al., 2019). This technological lag is partly due to fragmented land ownership, aging farming populations, and limited digital infrastructure in rural areas (Zhang et al., 2021).

This calls for a new perspective on agriculture because the need to quickly adapt agricultural systems to climate change, market volatility, and resource depletion has given rise to new paradigms like Climate-Smart Agriculture (CSA). CSA emphasizes resilience, productivity, and mitigation of greenhouse gases (Lipper et al., 2014).

More and more, the term “smart agriculture” is being used to refer to a group of technologies designed to enhance agricultural performance, such as sensor networks, self-governing equipment, artificial intelligence (AI)-driven decision-making systems, and accurate input management (Kamilaris et al., 2018; Liakos et al., 2018). These technologies enable data-driven farming practices that not only increase efficiency but also contribute to environmental goals, including reduced emissions and optimized resource use.

The publication's main goal is to analyze the main challenges that small farms in the Pazardzhik region face when transitioning to smart agriculture, including their adaptability to the concepts of Climate-Smart Agriculture (CSA) and Vulnerably Smart Agriculture (VSA), using empirical data and factor analysis.

Smart Agriculture is most commonly connected with the usage of the Internet of Things (IoT), precision agriculture (PA), artificial intelligence (AI), drones, sensors, blockchain, and cloud databases. Researchers in the area underline that this will result in optimized resource usage and enhanced tolerance to climate change (Wolfert et al. 2017). According to Klerkx et al. (2019), smart agriculture is more than simply a technology package; it is also a socio-technical system that includes connections between farmers, ICT businesses, service providers, and politicians. The primary advantages are focused at lowering resource costs (water and fertilizers), boosting yields, improving decision-making, implementing sustainable risk management, and others. In addition to the previously mentioned theory, Carolan (2020) argues that digitization in agriculture has two aspects: on the one hand, it creates opportunities for sustainable production; on the other hand, by expanding its reach geographically, it can exacerbate the digital divide. In rural areas with low levels of educational attainment, restricted Internet access, and insufficient institutional support, this disparity will be especially noticeable.In addition to this idea, the new notion of Vulnerably Smart Agriculture is developed, which is based on unrealistic assumptions about digitization. It refers to instances in which digital advances fail to address social, institutional, and geographical realities, and in certain cases, exacerbate inequality (Santos and Neves, 2022; Paycheva, 2022 Harizanova–Metodieva, & Metodiev, 2013). Eastwood et al. (2021) and their colleagues identify four major shortcomings that also serve as indicators of vulnerability: technological vulnerability, economic vulnerability, social vulnerability (digital illiteracy), and ecological vulnerability. According to Fraser et al. (2022), in their publication, the implementation of "smart" technologies in rural areas is highly unbalanced between farmers with high investment opportunities and access to expert support, and small and elderly farmers remain on the periphery of the digital transition. This deepens inequality and problems in rural areas. In this setting, the Vulnerably Smart Agriculture Index (VSAI) becomes a multifaceted, composite diagnostic tool. It seeks to quantify the extent of farm integration into smart agricultural systems while paying close attention to structural constraints, risk exposure, and gaps in adaptation. Digital divide theory (van Dijk, 2005), climate-smart agriculture (FAO, 2013), innovation systems theory (Hall et al., 2001), and agricultural vulnerability assessment frameworks (Turner et al., 2003; IPCC, 2014) are some of the theoretical approaches that provide the conceptual foundation of the VSAI.

Main methods and data

The publication's aim is to use factor analysis transformed into a cluster analysis based on empirical data to examine the current state of the digitalization level of the small farms. The goal is to track the degree of smart agriculture adoption, including their capacity to adopt the concepts of Climate-Smart Agriculture (CSA) and Vulnerably Smart Agriculture (VSA).The research was conducted in December 2024 among small farms in the Pazardzhik municipality with the aim of assessing the digital vulnerability of farms with different levels of digitalization. With an emphasis on smallholder farms with an annual production value of less than €9000, which is the legal definition of small farms in Bulgaria, the sample of 30 farms was selected at random from the Pazardzhik municipality.The region's present agricultural structure, where most farms are fragmented, family-owned, and have low levels of capitalization, is reflected in the tiny sample size.The statistics are based on an assessment of Likert-based criteria on the main elements of vulnerable agriculture, which include production efficiency, market connection, technical equipment, and environmental monitoring, in accordance with the theoretical framework. This study employed the Principal Component Analysis (PCA) method, which transforms the original variables into new, uncorrelated linear combinations (components) that explain the greatest amount of variance. The number of factors was determined using Kaiser's criteria, which stipulate that only factors with eigenvalues greater than one are retained (Kaiser, 1960). When the chosen components account for more than 40–50% of the total variation, the model is considered reasonable. According to the data, the follow assumption after proceeding factor analysis is made in table 1.

Table 1. Loadings of factors

Factor	Explanations	Loadings
PC1	General digital activity – efficiency, automation, market	**33.5%**
PC2	Puts ecology against market Puts automation against ecology	**27.0%**
PC3	Puts automation against ecology Remaining specific information	**25.1%**
PC4	Remaining specific information	**14.3%**

Source: own calculations

Together, the first two variables (PC1 and PC2) account for 60.5% of the total appearance. Thus, more than half of the variations across farms may be explained by two primary axes of difference (such as “digital progress” and “ecology vs. market”). Factors loadings are summarized in the following table 2.

Table 2. Cross measurement of factors

Cross meassurements	PC1	PC2	PC3	PC4
Digital Productivity & Resource Optimization	0.572	–0.231	–0.730	–0.302
Technological Enablement for Automation	0.556	–0.341	0.634	–0.415
Market Access & Value Chain Enhancement	0.377	0.897	0.068	0.221
Sustainability & Environmental Monitoring	0.481	–0.124	–0.234	0.829

Source: own calculations

Based on the factor analysis, four main dimensions were identified that describe the differences between the surveyed farms in terms of digitalization. The first dimension covers efficiency and resource optimization, the second dimension is based on automation and technological equipment, the third dimension describes access to markets and digital trade, including online platforms and logistics. The last dimension focuses on sustainability and environmental monitoring, through resource-saving and environmental protection practices. Each of these factors is the result of grouping similar survey questions and explains a different aspect of the digital vulnerability of farms. Once the factor analysis has been conducted, we will use the data from it for the 4 factors to calculate the respondent's responsiveness index using the following formula:

$$VSAI_i = \frac{1}{4}\left(Factor_1 + Factor_2 + Factor_3 + Factor_4\right)$$

This index shows (table 3) the level of digitalization and the higher the number, the more digitalized the farm is. It is understood, it is clarified that the data is based on the responses of 30 managers of small farms, randomly selected by random sampling.

Table 3. VASI

Farms 1–10	Farms 11–20	Farms 21–30
–1.068	–0.316	0.489
–0.715	–0.499	0.622
–0.662	–0.431	0.722
–0.723	–0.387	0.775
–0.736	–0.710	0.713
–0.809	–0.403	1.053
–0.582	–0.873	1.899
–0.709	–0.509	1.821
–0.548	–0.194	1.760
–0.412	–0.445	1.926

Source: own calculations

According to the data of the VASI index of each farm was conducted cluster analysis (K-means method), which will devide the respondents into 3 groups- low digitalization, medium and high. Each VASI result is related with the closest centroid and divides the respondents into following groups, validated by Elbow method: Low: VSAI < 0; Medium: 0.0–1.0; High: > 1.7.
The clusters are shown by their names in the table 4.

Table 4. Distribution of cluster analysis

Farms 1–10	Farms 11–20	Farms 21–30
–1.068 [Low]	–0.316 [Low]	0.489 [Medium]
–0.715 [Low]	–0.499 [Low]	0.622 [Medium]
–0.662 [Low]	–0.431 [Low]	0.722 [Medium]
–0.723 [Low]	–0.387 [Low]	0.775 [Medium]
–0.736 [Low]	–0.710 [Low]	0.713 [Medium]
–0.809 [Low]	–0.403 [Low]	1.053 [Medium]
–0.582 [Low]	–0.873 [Low]	1.899 [High]
–0.709 [Low]	–0.509 [Low]	1.821 [High]
–0.548 [Low]	–0.194 [Low]	1.760 [High]
–0.412 [Low]	–0.445 [Low]	1.926 [High]

Source: own calculations

Analysis of interconnected systems for resilience in smallholder agriculture: climate-smart and vulnerably smart approaches is shown in table 5.

Results and discussion

The results of the factor analysis show that the digital vulnerability of smallholder farms in the Pazardzhik region has a unique structure. The Principal Component Analysis (PCA) method was used to identify four major components, which collectively account for the overall variation in the dataset. The first two factors alone can explain over 60% of the total variability, indicating that over half of the differences between farms can be explained by two prominent patterns of digital behavior: the degree of overall digital advancement and the tension between market orientation and environmental sustainability.

The first part factor analysis related with the smart agriculture brings factors related to market access, automation, and production efficiency. This statement fits with the modern view of smart agriculture as a socio-technical system that combines advances in organizations, economics, and technology, not just a bunch of technologies (Klerkx et al., 2019). It also points out that farms with more resources and stable economies are more likely to get more digital skills.

Table 5. Explanation of factors

Factor	What is measuring	Main implementations
General digital activity – efficiency, automation, market	Production, savings, productivity	Water sensors, lower costs, higher yields
Puts ecology against market Puts automation against ecology	Technological equipment and management	Drones, IoT, automatic irrigation
Puts automation against ecology Remaining specific information	Market presence, trade	Online sales, digital logistics
Remaining specific information	Environmentally friendly practices and monitoring	Reduced fertilizers, digital soil and water monitoring

Source: own calculations

The second part makes clear the conflict between market integration and sustainability. Some farms focus on environmental practices and monitoring, but as well part of them focus on digital logistics and business channels. This statement is similar to what Carolan (2020) found, where he pointed out that digitalization in agriculture makes existing socioeconomic gaps worse, especially in rural areas with poor infrastructure, little institutional support, and low levels of digital literacy. This exacerbation of inequality can hinder the overall development of these communities, limiting their access to essential resources and opportunities for growth. As a result, targeted interventions are necessary to ensure that all farmers can benefit from technological advancements. In fragile agricultural systems, these kinds of dynamics are common because farmers' strategies, skills, and environments affect how they choose to use technology.

The next part makes this difference by showing that automation and sustainability are not linked in a positive direction. This is explained by the fact that even though some farms have made technical progress, they haven't included environmentally friendly practices in their digital transformation. Santos and Neves (2022) say that many digital innovations make people more vulnerable by not taking into account the institutional and ecological context.

Despite having a lower explanatory power, the fourth component is linked to resource sustainability and environmental monitoring. The three pillars of the Climate-Smart Agriculture (CSA) framework – productivity, resilience, and the preservation of natural resources – are represented in this component (FAO, 2013; Lipper et al., 2014).

All things considered, the factor analysis demonstrates that technology access by itself is insufficient to adequately explain the complex nature of digital vulnerability in agriculture. Different socioeconomic contexts, different levels of adaptive ability, and different development strategies all have an impact on it.

After the factor analysis, based on VSAI was performed a cluster analysis which will help to show the level of digtalization of the farmers by actually seeing their current status. On the figure 1 is shown the actual distribution according to the data.

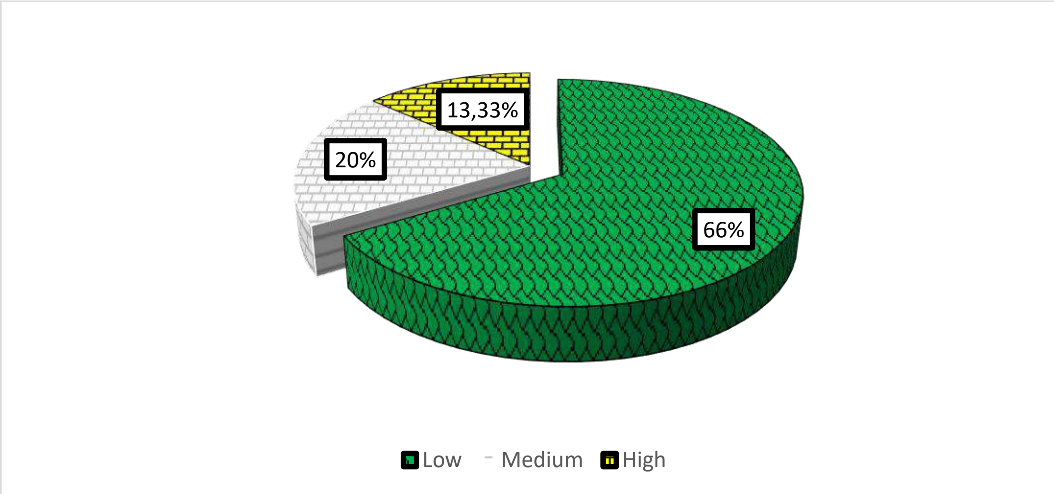

Figure 1. Cluster distribution

The data confirms that only a small part of the farms are digitally well developed and they apply and use a digital technology in agricultural activities. The major group is 66% of the sample and they are not using digital technologies. The transitional group is showing that 20% of the respondents have a real chance to transform into a higher group. Cluster 1 (low digitalization, 66%) is distinguished by consistently low scores for each of the four elements. Low use of automation, digital productivity tools, and market linkage was indicated by these farms' low PC1 scores. Their lack of use of digital technology for environmental monitoring and sustainability is further supported by their weak link with PC4. The productivity and automation loadings in PC2 and PC3 are negative, which indicates that smart solutions are not sufficiently integrated and are fragmented. This organization supports the idea of Vulnerably Smart Agriculture, which holds that structural impediments prevent technology access from converting into resilience. Cluster 2 (moderate Digitalization: 20%) has modest results, showing a partial integration of digital instruments for productivity and market access, especially in PC1 and PC2. However, their relatively lesser loadings on PC3 and PC4 suggest that automation and ecological digitization are still in their early stages. These farms are about to undergo a digital transition; they are ready for more advanced, intelligent methods, but they are still limited by infrastructure or capacity (Carolan, 2020). The trade-off between ecological attention and market connectedness that PC2 highlights is especially relevant to this group, as they seek to balance sustainability and competitiveness. Automation, digital efficiency, and environmental monitoring are significantly integrated, as indicated by the significant alignment between Cluster 3 (Highly Digitalized, 14%) and PC1 and PC4. These farms actively use integrated smart farming systems and are prime examples of Climate-Smart Agriculture (FAO, 2013; Lipper et al., 2014). Furthermore, the notable positive loadings on PC3 suggest that automation is not isolated but rather incorporated into a broader digital strategy. This group serves as an example of how comprehensive and context-aware digital transformation can enhance sustainability and resilience in rural areas.

Conclusion

The study illustrates how the unequal digital transformation of Pazardzhik's smallholder farms is significantly impacted by structural limitations. Using PCA, four key characteristics were identified, and two main factors – the trade-off between ecological practices and market orientation and overall digital participation – accounted for over 60% of farm variance. According to the article, while some farms have complex digital tools, most are either environmentally conscious or technologically isolated without digital integration. This illustrates how, if local contexts are neglected, digitalization may worsen inequality, which is in line with the concept of Vulnerably Smart Agriculture. According to a cluster analysis, 66% of farms are categorized as low to medium digitalized, while only 13% of farms are highly technologically advanced.

References

Bacco, M., Bertoncini, M., Gotta, A., & Zoppi, T. (2019). Smart farming: Opportunities, challenges and technology enablers. Internet Technology Letters, 2(1), e113. https://doi.org/10.1002/itl2.113

Branzova, P. (2024). Прецизното земеделие: Технологични иновации за устойчиво селско стопанство. Икономическа мисъл, (1), 24-36.

Carolan, M. (2020). A sociology of technology-in-practice: A reconceptualization of agricultural technology and its use. Sociologia Ruralis, 60(2), 267–290. https://doi.org/10.1111/soru.12295

Doitchinova, J., & Stoyanova, Z. (2024). Regional Aspects of Transformations in Agriculture: The Case of the Republic of Bulgaria. Sustainability, 16(23), 10711.

Doitchinova, J., Miteva, A., & Zaimova, D. (2019). Determinants and directions of the transition from traditional to sustainable agriculture: the Bulgarian case. In CBU International Conference Proceedings (Vol. 7, pp. 75–80).

Eastwood, C., Ayre, M., Nettle, R., & Reed, M. (2021). Knowledge politics and the framing of smart farming: A case for examining the role of power in digitalization. Sociologia Ruralis, 61(2), 311–334. https://doi.org/10.1111/soru.12268

Eastwood, C., Klerkx, L., Ayre, M., & Dela Rue, B. (2017). Managing socio-ethical challenges in the development of smart farming: From a fragmented to a comprehensive approach for responsible research and innovation. Journal of Agricultural and Environmental Ethics, 30, 643–668. https://doi.org/10.1007/s10806-017-9704-5

FAO. (2013). Climate-smart agriculture sourcebook. Food and Agriculture Organization of the United Nations. https://www.fao.org/3/i3325e/i3325e.pdf

Fraser, E. D. G., Legwegoh, A., Krishna, K. C., CoDyre, M., Dias, G., Hazen, S., Johnson, R., Martin, R., Ohberg, L., Sethuratnam, S., & Sneyd, A. (2022). A call for equitable access to agricultural innovation. Nature Food, 3, 322–324. https://doi.org/10.1038/s43016-022-00478-4

Hall, A., Mytelka, L., & Oyeyinka, B. (2001). An innovation systems perspective on development and the challenges of agriculture in Africa. UNU-INTECH Discussion Paper No. 2001-3.

Harizanova–Metodieva, T., & Metodiev, N. (2013). Social characteristic of farmers according to different factors. Agricultural science, 46(3-4), 26-31.

IPCC. (2014). Climate Change 2014: Impacts, adaptation, and vulnerability. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

Kaiser, H. F. (1960). The application of electronic computers to factor analysis. Educational and Psychological Measurement, 20(1), 141–151. https://doi.org/10.1177/00131644 6002000116

Kamilaris, A., Kartakoullis, A., & Prenafeta-Boldú, F. X. (2018). A review on the practice of big data analysis in agriculture. Computers and Electronics in Agriculture, 143, 23–37. https://doi.org/10.1016/j.compag.2017.09.037

Klerkx, L., Jakku, E., & Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. NJAS – Wageningen Journal of Life Sciences, 90–91, 100315. https://doi.org/10.1016/j.njas.2019.100315

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674. https://doi.org/10.3390/s18082674

Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., Bwalya, M., Caron, P., Cattaneo, A., Garrity, D., Henry, K., Hottle, R., Jackson, L., Jarvis, A., Kossam, F., Mann, W., McCarthy, N., Meybeck, A., Neufeldt, H., Remington, T., ... & Vermeulen, S. (2014). Climate-smart agriculture for food security. Nature Climate Change, 4(12), 1068–1072. https://doi.org/10.1038/nclimate2437

Peicheva, M. (2022). A Model for Implementing Innovations in Training. Journal "Човешки ресурси & Технологии= HR & Technologies", Creative Space Association, 1, 5–17.

Rose, D. C., Wheeler, R., Winter, M., Lobley, M., & Chivers, C. A. (2021). Agricultural policy in post-Brexit UK: Defining a progressive direction for the future. Food Policy, 101, 102014. https://doi.org/10.1016/j.foodpol.2021.102014

Santos, J., & Neves, J. A. (2022). Vulnerably smart agriculture: Exploring the unintended consequences of digitalization. Technology in Society, 70, 102013. https://doi.org/10.1016/j.techsoc.2022.102013

Turner, B. L., Kasperson, R. E., Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., Eckley, N., Kasperson, J. X., Luers, A., Martello, M. L., Polsky, C., Pulsipher, A., & Schiller, A. (2003). A framework for vulnerability analysis in sustainability science. Proceedings of the National Academy of Sciences, 100(14), 8074–8079. https://doi.org/10.1073/pnas.1231335100

van Dijk, J. A. G. M. (2005). The deepening divide: Inequality in the information society. Sage Publications.

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017). Big data in smart farming–A review. Agricultural Systems, 153, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023

Zhang, Y., Wang, G., Zhang, W., & Li, Y. (2021). Agriculture 5.0: Mechanization and digitalization of agriculture in China. Journal of Integrative Agriculture, 20(4), 867–874. https://doi.org/10.1016/S2095-3119(20)63462-1