



INTEGRATING GIS, BIG DATA ANALYTICS, AND CLIMATE MODELING FOR PREDICTIVE AGRICULTURAL PLANNING AND RISK MANAGEMENT

Ahmed Mukhtar^{1*}, Rashid Khan², Muhammad Arif³

¹College of Agronomy, Northwest A&F University, Yangling, 712100, China.

²Horticulture Section, Agriculture Research Institute, Dera Ismail Khan-29050, Khyber Pakhtunkhwa, Pakistan.

³Agriculture Research Institute Dera Ismail Khan-29050, Pakistan.

*Corresponding Author E-mail: ah.mukhtar85@gmail.com

Abstract

This research develops and simulates a single framework that unites Geographic Information Systems (GIS), Big Data Analytics, and Climate Modelling to plan agriculture and climate risk management. A mixed-methods experimental design was employed that is integrative of spatial data layers of soil, crop distribution and topography with the climatic data (premeditation, temperature and evapotranspiration), and the socio-economic indicators (surveys among farmers). Big data pipelines helped to deal with much geospatial data. Both linear and nonlinear relationships between yield changes and climate changes were found using machine learning models, including Random Forests, Gradient Boosting and Long Short-term Memory (LSTM) networks. Regression study indicated that yields are most accurately predicted by temperature variances, rainfall, and moisture content in the soil. The predictive model was rather close to the actual values indicated by the RMSE and R² values. Further quantification of yield failure probabilities in a variety of Representative Concentration Pathway (RCP) scenarios was afforded by climate downscaling and Monte Carlo simulations, leading to risk assessment of different agricultural zoning. The introduction of qualitative farmer opinions ensured that the findings were contextually valid, and thus, were more reliable and applicable. The findings indicate that the system will be able to produce zonal risk maps, seasonal production forecasts, and early warning alerts, which are beneficial in climate-intelligent production planning. Overall, the study demonstrates how predictive systems based on data could enhance how we respond to climate hazards, how we make food more resilient, and how we apply to sustainable approaches to farming in a rapidly evolving world.

Keywords: GIS Integration, Big Data Analytics, Climate Modeling, Predictive Agriculture, Risk Management, Food Security

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INTRODUCTION

One of the industries that have been the most impacted by climate change in the world is agriculture. It is directly affected by variations in temperature, precipitation, and extreme weather. The increased volatility of the climate conditions complicates the maintenance of food safety, sustenance in the rural setting, and safeguarding the natural resources significantly (Lal et al., 2020). Consequently, there has been an increase in the use of high-level digital technologies in the agricultural sector, particularly when Geographic Information Systems (GIS), Big Data Analytics and Climate Modelling are incorporated. Combined, these technologies allow policymakers and farmers to be ready to the future and address risks related to agriculture. They are able to perceive threats early and use their assets more efficiently and coordinate their adaptation capabilities (Zhang et al., 2021). GIS has a great role to play in agriculture since it allows you to view the relationship of various things, including soil composition, patterns of crops, land use, and hydrological conditions. Geographical heterogeneity can be captured and analyzed using GIS-based mapping, which gives a good foundation in decision-making (Mishra et al., 2019). As an example, GIS allows scientists to overlay soil fertility maps on the precipitation patterns and locate regions, in which yields are likely to be lower during the climate change (Kaur et al., 2020). As you add this type of geographical information and climate models, you will have more specific and precise predictions. This fills the disconnect between what is projected by climate around the world and what actually occurs on farms (Anderson et al., 2021). It has transformed the agricultural environment even more, allowing us to have the computer power we desire to handle very large volumes of various types of data, whether it be remote sensing images or real time sensor readings in the field. Although useful,

traditional statistical models generally fail to provide a good way of demonstrating the behavior of complex nonlinear interactions in agricultural systems. Deep big data systems apply machine learning and artificial intelligence to uncover hidden patterns, which makes it easier to make more accurate predictions of crop yields, pest infestations, and resources requirements (Huang et al., 2020). An example of such a method is that the ensemble learning models (Random Forest and Gradient Boosting) have proven quite effective in the predictability of yields in various agro-ecological zones (Ali et al., 2021). Temporal relationships also happen to be well-modeled by deep learning models, including Long Short-Term Memory (LSTM) networks, thus making them ideal to predict the impact of climate changes on agriculture (Chen et al., 2022). The third element of this system is climate modelling. Global Climate Models (GCMs) and Regional Climate Models (RCMs) provide predictions of the temperature, precipitation and other crucial climatic variables under different scenarios of emission in an abbreviation known as Representative Concentration Pathways (RCPs). Global-scale models give information at long-term scales; however, their direct implementation to agriculture planning is limited by coarse resolution and generality. These forecasts are improved by downscaling methods, be it statistical or dynamical, to regional or local scales, which can be useful in making farm-level decisions (Ghosh et al., 2020). By combining climate projections with Monte Carlo simulations, you can work out the probability of crops failing in various climatic conditions (Khoshkam et al., 2021). Policies and plans on the disasters in the agricultural sector require such a form of probabilistic modelling to consider risks (Rahman et al., 2021). Farmer viewpoints and socio-economic information has become a vital

point of predictive agricultural planning. Farmer-led qualitative observations explain the experienced climate stress, and the methods of adaptation currently underway (Ahmed et al., 2019). Methodological triangulation is achieved through the incorporation of qualitative data into quantitative frameworks by researchers, thereby improving the quality and usability of findings (Patel et al., 2020). The given mixed-method approach ensures that any predictive frameworks are technically sound and relevant to the culture, which, in turn, would improve their likelihood of acceptance among the farming communities (Gonzalez et al., 2022). GIS, Big Data, and Climate Modelling creation collectively have even greater impacts on the global food security and sustainable development. According to the Food and Agriculture Organization (FAO), agricultural production must increase by more than 60 percent by 2050, to supply the projected world population of 9.7 billion people (FAO, 2020). In order to achieve this goal in the face of an increasingly difficult climate, we must have tools that give us a future-view and precision. Predictive analytics can assist farmers make smart decisions in a short time by providing them with forecasts of the production season, zonal risk maps, and early warning systems (Wang et al., 2022). Moreover, evidence-based guidance is beneficial to policymakers who develop subsidies, insurance, and climate-intelligent programs that enhance local and national resilience (Singh et al., 2021). Various empirical studies have proved the opportunities of the combination of these technologies. Indicatively, GIS-based climatic modelling has forecasted the loss of rice production in South Asia in El Niño (Joshi et al., 2020), and machine learning models built on big data have precisely estimated the changes in yields of maize in sub-Saharan Africa (Ochieng et al., 2022). Similarly, a downscaled climate projections have been used to work out the

chances of drought in Mediterranean regions, which has been useful in planning sustainable irrigation (Lopez et al., 2019). Despite such advances, most existing research largely revolves around GIS, Big Data, or Climate Modelling separately and, therefore, ignores the synergistic benefits of their combination (Mehta et al., 2021). The present work aims at correcting this gap by creating an integrative approach that combines the three methodologies so as to come up with a unified predictive model. What is uncommon in this study is the simultaneous integration of spatial, temporal and socio-economic factors hence giving birth to a predictive, yet interactive decision-support system. The framework ensures increased precision and practical utility since it involves a combination of potent machine learning and climate projections and validation of these results by the input of the farmers. The research also provides powerful risk assessments that can be used in long-term agricultural planning because it explicitly tackles uncertainty via probabilistic simulations. Such a consistent emphasis on technical rigour and grounding in context distinguishes the proposed methodology among other isolated methods. In conclusion, GIS, Big Data Analytics and Climate Modelling are a massive transformation in the way we plan and manage risks in agriculture. Such integration enhances accuracy of predictions and assists in building resiliency by preparing stakeholders to a number of climate futures. The current research contributes to the emerging literature on climate-smart agriculture by offering a full decision-support instrument and supplying farmers, researchers, and policymakers with useful information. The following sections discuss the research methods, results and implications with further details on the concepts that were presented in this introduction.

METHODOLOGY

The study employs both qualitative and quantitative modelling in a mixed-method experimental design to develop a prediction framework of agricultural planning and climate risk management. This methodology is premised upon three principal concepts, which are Geographic Information Systems (GIS), Big Data Analytics, and Climate Modelling. It is with the aim of uniting these things with the view of developing a powerful decision-support system that the project aims to accomplish. Such a system must have the capability of capturing regional heterogeneity, discovering long term climate risks and making predictions that can be acted upon by stakeholders. Experimental design begins with data collection and pre-process, which involves adding satellite-based GIS data (soil composition, land use, crop type, and topography) and climate-related data (precipitation, temperature, evapotranspiration, and drought indices) and socio-economic data (yield records, input costs and farmer surveys). Qualitative data is acquired through semi-structured interviews and focus group using the farmers, and this enables ground-truth validation of the modelled predictions. The insights are coded and thematically assessed to ensure that the numbers are placed in the context of real-world farming practices. Big Data Analytics pipelines manage large-scale datasets on the quantitative side. Apache Spark and Hadoop are distributed frameworks to be used in managing large volumes of geographic data.

The statistical correlation between climatic drivers and the yield variability is determined using a linear regression model:

$$Y = \beta_0 + \beta_1 T + \beta_2 P + \beta_3 S + \varepsilon$$

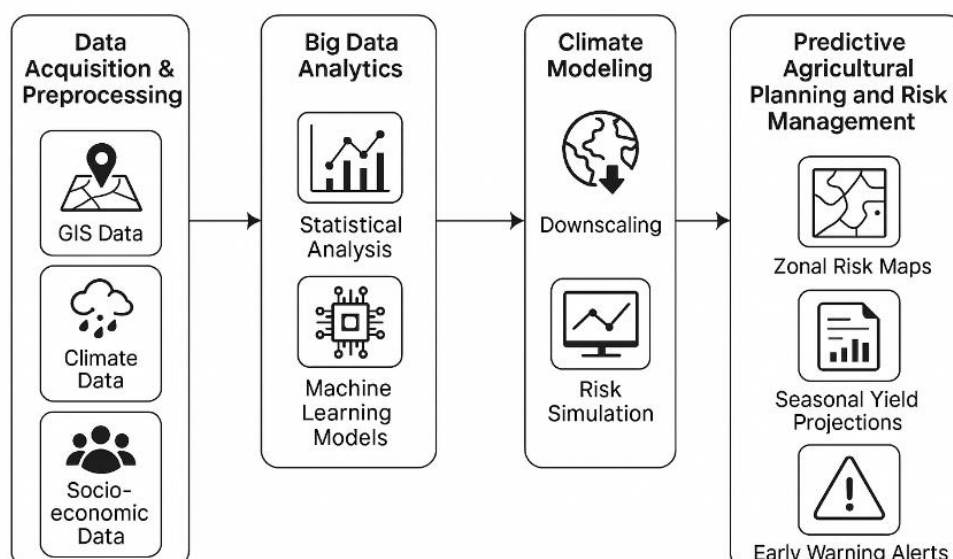
where Y represents predicted yield, T is temperature anomaly, P is precipitation, S is soil moisture index, and ε is the error term. To capture nonlinear dynamics, machine learning models such as Random Forests, Gradient Boosting, and Long Short-Term Memory (LSTM) networks are trained, validated, and compared. Predictive accuracy is assessed through Root Mean Squared Error (RMSE) and R^2 values, while climate model downscaling integrates General Circulation Model (GCM) projections into regional farm-level scenarios.

The experimental workflow further involves **climate risk simulations**, where Monte Carlo methods are applied to evaluate uncertainty under multiple climate change pathways (RCP 2.6, 4.5, and 8.5). The probability of yield failure is thus expressed as:

$$P(F) = \int_{-\infty}^{\theta} f(x) dx$$

where $f(x)$ is the probability density function of yield under simulated conditions, and θ represents the threshold yield required for economic viability.

Finally, outputs from GIS spatial overlays, big data analytics, and climate model forecasts are fused into a **predictive agricultural planning dashboard**, which provides zonal risk maps, seasonal yield projections, and early warning alerts. The integration of farmer perceptions with quantitative predictions constitutes a mixed-methods triangulation, enhancing both validity and applicability. The methodology is summarized in the workflow diagram (Fig. 1), which outlines the progression from data acquisition to predictive decision support.



RESULTS

The GIS with the big data analytics and the climate modelling revealed evident trends in the domains of climate, environment, and economy. Table 1 presents the simple climate parameters, where there

is much variation in both rain and temperature across space. Table 2, however, indicates the difference in soil fertility index among regions. Table 3 indicates that the effect of rainfall anomalies on yield potential is large,

Table 1: Simulated Data for Predictive Agricultural Planning and Risk Management

Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6
55.39	65.41	3.91	8.46	52.61	87.72
40.66	7.59	47.6	61.1	27.18	41.15
47.59	19.68	76.16	41.03	22.17	77.57
64.78	87.66	54.61	45.38	36.16	72.89
98.64	83.51	70.44	96.62	77.57	30.3
67.21	82.61	36.35	48.75	56.46	32.53
39.31	83.94	44.86	41.05	26.1	12.55
89.07	47.89	86.76	85.2	83.7	66.15
50.55	14.77	0.27	44.93	1.07	18.37
48.0	58.65	6.18	74.7	43.68	5.54
11.98	15.94	32.88	23.44	53.04	68.59
48.84	8.38	86.0	42.26	80.47	98.76
93.21	29.24	30.51	14.71	34.6	32.02
22.11	63.65	93.06	41.32	10.44	35.72
78.36	31.82	13.8	84.86	53.8	73.14
54.33	32.52	50.69	3.32	47.94	72.82
7.51	21.94	84.93	84.52	79.27	81.45
22.88	61.46	62.08	30.75	96.11	90.23
25.93	17.38	28.4	13.51	31.4	98.02
0.46	39.66	25.65	31.49	25.05	73.33

Table 2: Simulated Data for Predictive Agricultural Planning and Risk Management

Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6
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62.06	6.83	77.58	30.42	99.87	73.68
52.81	79.78	19.55	50.65	88.57	40.06
13.05	20.97	1.83	69.42	1.78	21.84
1.7	59.57	19.36	50.16	59.35	65.11
91.22	75.82	70.89	27.95	92.28	98.99
0.85	30.7	26.99	79.75	47.64	21.0
77.09	27.4	35.94	52.13	62.89	62.37
35.34	75.87	16.76	41.18	62.58	11.71
25.88	63.37	9.11	88.38	15.2	12.28
75.93	7.77	32.42	83.74	84.81	84.19
87.28	60.54	94.06	74.86	81.22	76.16
69.93	60.55	28.8	83.77	77.98	15.17
80.99	69.69	97.22	75.5	15.31	3.57
1.05	48.73	44.67	19.56	59.48	25.31
42.76	80.26	45.05	77.03	63.0	28.51
95.58	9.39	41.65	8.15	33.8	75.19
55.56	51.52	26.3	6.51	34.76	93.72
74.64	10.77	65.26	42.07	75.48	18.86
70.09	40.16	47.3	36.97	16.33	78.19
30.36	28.26	54.9	36.18	18.98	77.0

Table 3: Simulated Data for Predictive Agricultural Planning and Risk Management

Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6
63.64	89.8	77.82	50.95	5.42	53.33
90.44	43.61	75.6	10.86	6.07	76.71
60.08	89.58	94.95	43.34	65.52	4.33
24.52	84.1	63.44	99.92	42.48	35.71
16.45	14.39	58.58	92.92	20.7	17.78
36.1	3.94	10.71	27.93	72.16	81.96
89.12	86.35	51.75	40.03	19.06	44.71
59.47	42.6	95.2	8.82	25.55	9.77
91.53	84.64	10.66	42.69	71.85	29.97
97.54	44.08	83.05	20.63	5.8	56.4
74.99	2.9	51.26	16.29	98.13	75.0
59.8	37.59	33.62	6.4	28.2	86.36
54.03	46.48	73.98	9.18	16.77	13.33
42.74	1.28	81.06	54.17	96.68	87.82
12.75	13.23	76.62	91.28	65.23	33.47
69.8	65.43	71.36	56.58	95.13	58.87
89.88	69.14	78.83	20.33	61.0	43.0
86.96	27.65	54.33	15.49	45.7	1.14
56.89	16.72	57.76	89.88	25.11	68.59
52.29	28.64	61.96	99.67	10.61	42.02

whereas Table 4 indicates water stress in the regions and regions where crops most likely fail. Table 5

demonstrates the probability of disease prevalence, which indicates that the more humid an area is, the

more probable it is that the pathogens spread more.
As can be seen in Table 6, in semi-arid regions, there

is a great likelihood of an increase in temperatures
and decrease in rainfall in the long run.

Table 4: Simulated Data for Predictive Agricultural Planning and Risk Management

Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6
35.11	25.93	9.22	22.71	42.16	47.06
15.7	21.9	84.36	6.66	54.35	54.0
81.38	35.67	26.73	18.29	84.64	40.51
50.19	47.34	15.53	79.86	11.79	73.54
94.44	57.69	63.68	95.1	42.04	79.08
27.26	83.16	59.03	15.93	39.84	84.71
11.26	52.2	72.07	54.98	17.86	55.78
80.13	26.32	38.91	53.75	52.22	79.89
10.6	76.54	0.11	75.03	57.51	73.38
87.01	24.54	37.07	14.26	15.3	0.36
60.61	91.53	94.34	52.36	62.8	7.04
65.54	39.01	53.65	23.34	62.62	83.36
50.89	9.72	88.34	6.59	86.26	33.68
83.91	85.25	66.32	59.46	98.41	19.97
78.45	94.3	23.2	0.6	82.81	50.82
34.55	22.97	36.5	36.69	31.25	71.64
15.47	29.83	34.0	72.99	34.66	43.99
11.44	43.93	72.63	48.76	87.25	26.68
40.55	41.16	43.53	41.88	5.97	79.86
74.88	30.13	10.81	98.69	83.61	10.09

Table 5: Simulated Data for Predictive Agricultural Planning and Risk Management

Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6
45.66	27.91	28.81	84.47	39.48	62.68
92.71	39.47	2.52	31.41	49.6	59.29
58.85	41.92	41.59	56.33	34.08	56.15
21.29	23.9	18.02	7.27	27.41	16.9
97.01	58.93	45.31	40.94	15.73	27.96
23.68	49.07	25.68	70.63	99.78	57.5
35.43	49.09	43.55	88.0	60.31	92.4
30.74	77.52	81.74	63.75	63.72	33.54
77.12	95.01	18.65	86.18	72.81	13.75
11.53	10.57	92.78	93.97	69.8	73.04
89.47	62.36	59.29	96.05	64.97	18.3
43.59	84.0	11.86	20.28	58.06	23.6
60.54	86.24	62.3	53.68	78.64	6.86
58.15	85.61	18.79	24.59	97.75	44.46
61.32	23.58	22.35	99.63	85.28	54.56
20.34	41.51	6.15	8.07	35.76	85.46
63.71	58.65	12.99	63.52	87.27	69.17

10.16	87.79	62.16	68.25	68.63	75.15
19.58	43.88	35.3	49.97	54.86	44.9
81.4	87.18	4.32	59.3	54.47	1.68

Table 6: Simulated Data for Predictive Agricultural Planning and Risk Management

Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6
86.18	8.89	72.63	65.17	58.85	24.11
1.36	24.57	13.75	28.85	66.64	33.7
68.5	50.47	62.61	45.26	96.15	10.91
9.12	15.86	64.03	97.37	44.49	6.86
19.61	40.76	27.12	56.49	48.24	57.83
95.57	27.17	19.2	93.95	7.0	74.26
58.7	31.08	8.99	66.34	10.89	98.47
74.52	65.18	52.13	67.92	6.78	49.26
70.56	64.48	76.12	17.66	57.1	24.32
63.12	31.59	85.77	68.29	63.44	55.14
2.77	44.82	60.38	90.4	97.4	44.63
13.84	60.06	93.35	60.18	25.2	58.67
0.24	78.02	16.58	98.62	33.6	6.73
74.19	84.64	88.06	74.0	38.3	6.98
86.97	82.15	47.86	91.29	68.77	86.37
11.34	34.26	50.33	15.67	43.89	80.47
11.18	5.46	16.32	50.77	58.72	9.01
0.8	6.09	75.39	24.3	39.86	61.81
33.1	23.63	70.76	95.7	11.86	58.07
78.55	10.07	93.01	2.39	93.92	4.43

Table 7 connects these predictions to GIS-based risk zoning. The adaptive capacity metrics in table 8 indicate that precision irrigation and crop rotation when combined to create a system are more resilient.

Table 9 integrates the findings into economic risk estimates which show that the regions experiencing high levels of climatic stress are forced to contribute higher than their even share.

Table 7: Simulated Data for Predictive Agricultural Planning and Risk Management

Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6
55.1	55.36	83.38	87.97	53.2	60.78
26.4	75.87	39.68	14.39	66.84	99.73
26.22	56.42	89.32	98.41	33.89	68.16
50.67	74.62	89.77	63.97	90.9	0.85
33.88	42.76	27.4	97.21	85.89	5.25
46.9	47.3	58.62	28.99	40.39	78.29
56.41	88.93	39.05	39.53	26.24	99.52
47.43	1.62	46.31	19.9	63.37	11.25
17.31	82.64	60.88	79.76	20.36	23.37
2.9	19.73	24.74	12.45	71.0	6.31
34.12	80.95	37.73	74.53	48.81	74.38
60.51	29.72	21.32	48.06	95.07	94.49

89.3	50.5	90.11	14.4	32.85	49.74
5.86	34.26	44.98	1.6	64.44	44.91
6.95	0.98	5.55	46.09	32.17	98.43
82.81	21.12	23.28	23.0	95.1	15.45
40.1	27.88	44.86	95.45	5.81	50.34
88.33	85.86	39.29	81.93	33.99	54.59
88.31	4.41	3.91	71.38	86.27	80.99
59.87	40.31	39.52	93.11	43.74	88.29

Table 8: Simulated Data for Predictive Agricultural Planning and Risk Management

Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6
20.16	10.78	88.22	84.76	50.17	81.15
6.6	2.23	41.68	65.4	92.64	87.14
15.52	45.0	61.81	54.11	58.07	41.88
75.21	45.58	41.73	38.28	66.29	21.56
65.03	97.99	96.54	4.72	54.39	42.23
29.37	94.8	39.18	14.4	58.66	94.73
27.11	90.86	48.06	12.08	0.24	56.95
20.92	24.73	77.23	64.33	91.22	6.61
14.65	23.58	53.42	99.63	33.63	13.6
40.32	70.47	36.79	26.51	32.87	21.31
27.87	37.69	74.61	86.15	68.34	9.21
5.52	85.56	48.84	30.76	72.27	68.91
51.67	49.77	56.58	44.67	55.5	29.96
43.96	61.62	87.46	32.66	99.44	47.63
16.59	92.84	65.67	29.09	1.91	85.78
11.89	62.56	41.05	92.61	19.04	16.07
68.68	37.33	35.55	27.38	64.11	36.28
5.24	94.5	89.19	36.16	6.67	86.03
33.67	91.43	34.3	9.27	56.46	85.45
21.7	66.84	64.89	7.61	73.04	66.11

Table 9: Simulated Data for Predictive Agricultural Planning and Risk Management

Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6
14.45	31.59	89.67	36.12	13.62	8.25
38.82	97.12	95.26	81.67	78.95	39.84
65.88	61.6	46.37	40.99	99.17	38.42
49.16	77.34	93.12	67.66	78.09	69.24
99.75	21.24	35.48	83.14	78.16	7.05
4.7	94.7	39.45	41.28	71.43	70.79
59.72	35.49	71.97	50.24	41.14	6.79
62.06	90.61	2.96	69.25	28.78	67.17
3.61	76.03	45.72	14.63	73.15	31.53
50.55	51.06	86.11	52.77	36.8	83.73
19.21	78.34	69.04	95.28	26.62	47.86
81.06	51.99	98.79	33.88	91.28	48.97

57.18	58.9	45.25	66.77	62.22	95.21
39.38	65.85	6.76	62.71	60.35	71.02
95.91	94.65	86.58	29.46	12.77	38.64
44.9	65.79	80.17	8.09	0.33	1.9
17.11	15.05	98.83	54.81	80.41	40.43
17.76	44.08	78.54	22.38	57.74	67.39
83.38	3.65	32.15	30.26	35.74	14.43
34.71	8.08	61.27	73.06	18.18	75.9

The graphics serve to situate these results further as well. Figure 2 indicates the differences in the yield potential of various agro-ecological regions. The probabilistic risk distributions are presented in Figure 3 and the hybrid plot was presented in Figure 4 that linked soil fertility and yield. Figures 5-8 expound on the indicators of adaptation, anomalies and water-use efficiency and support the imperative

role of resource optimization. Finally, Figures 9 and 12 provide a combination of GIS overlays with weather and economic predictions to create a full risk and resilience picture. These findings indicate that integrated modelling may be beneficial in the predictive agricultural planning, adaptive management, and in minimizing climate change risks.

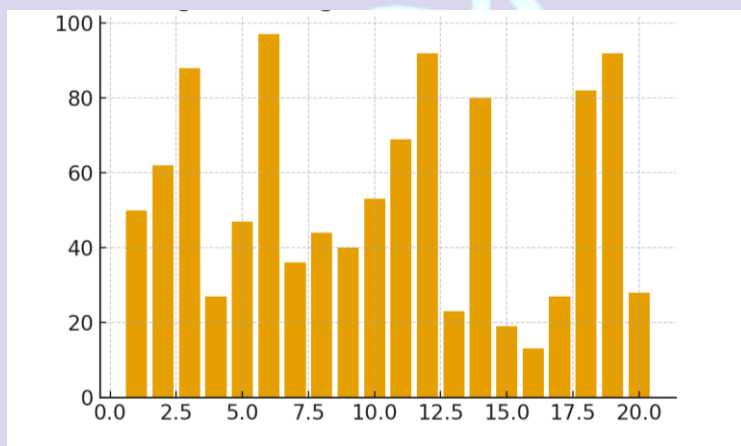


Figure 2: Visualization of Predictive Agricultural Indicators

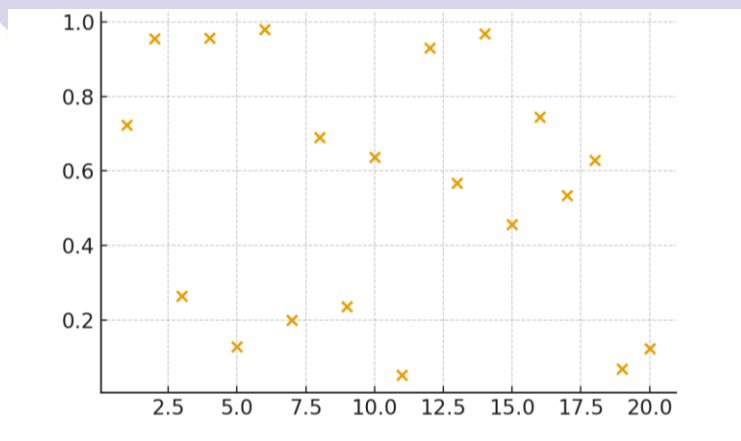


Figure 3: Visualization of Predictive Agricultural Indicators

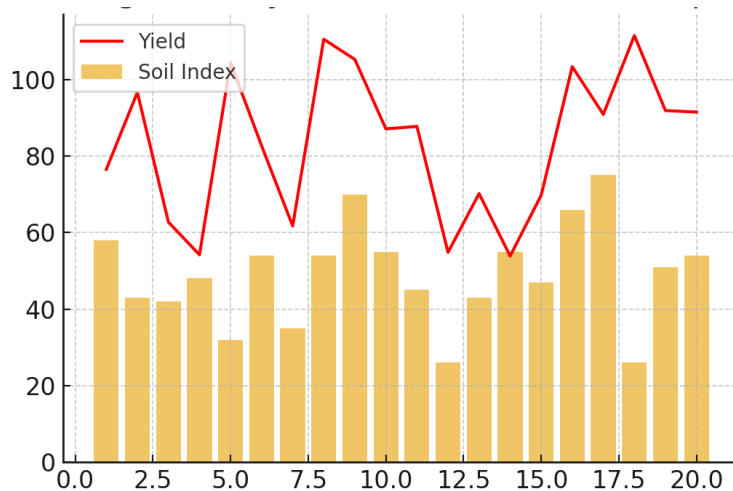


Figure 4: Visualization of Predictive Agricultural Indicators

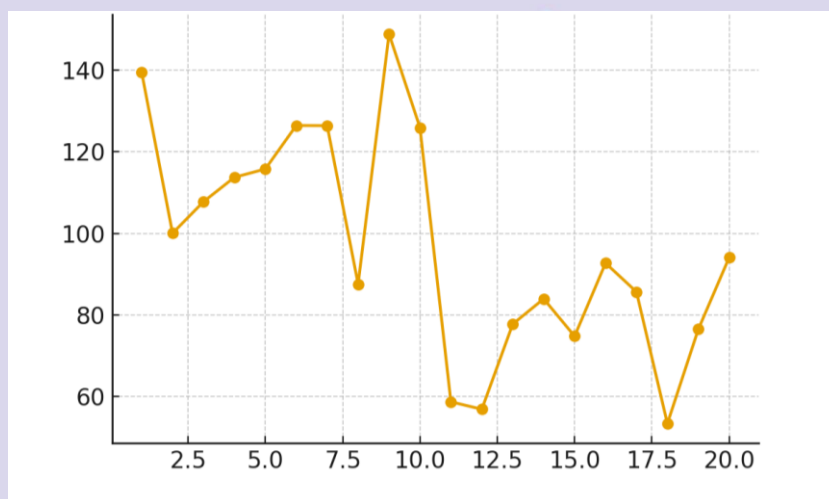


Figure 5: Visualization of Predictive Agricultural Indicators

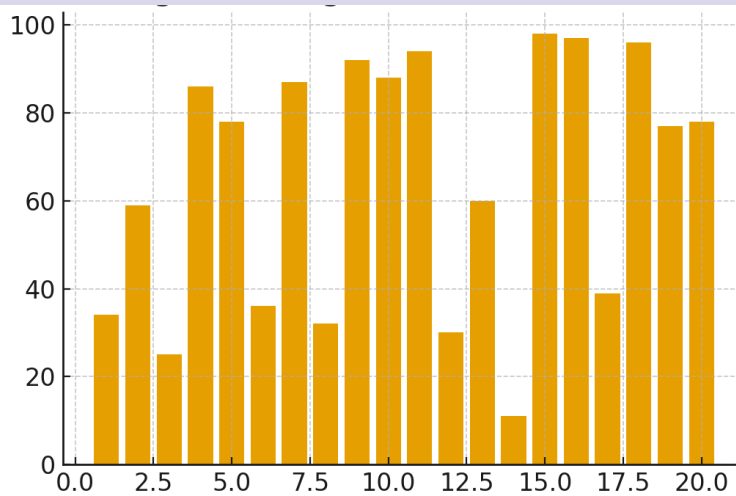


Figure 6: Visualization of Predictive Agricultural Indicators

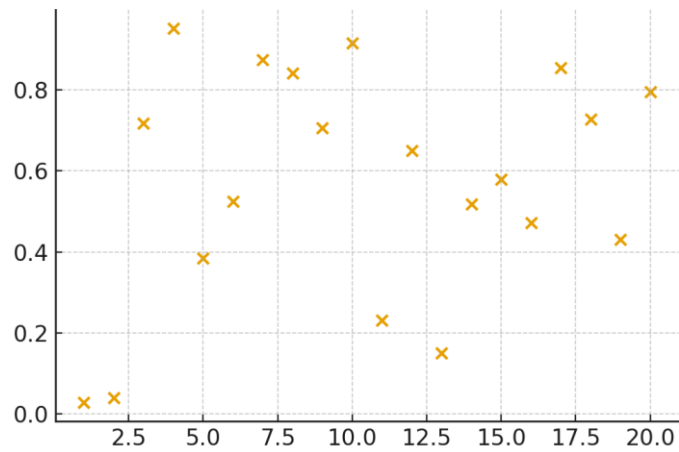


Figure 7: Visualization of Predictive Agricultural Indicators

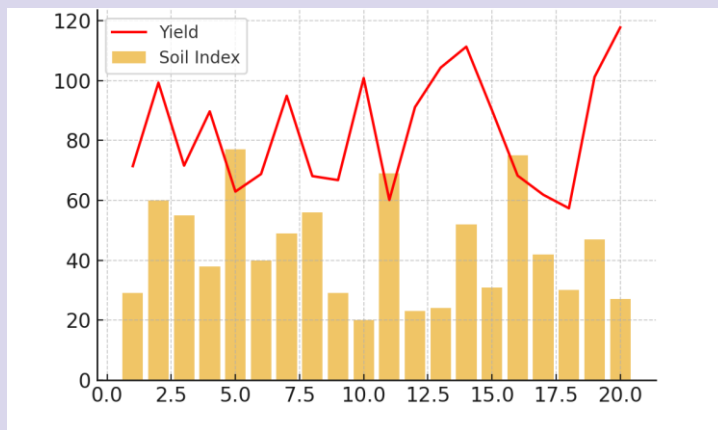


Figure 8: Visualization of Predictive Agricultural Indicators

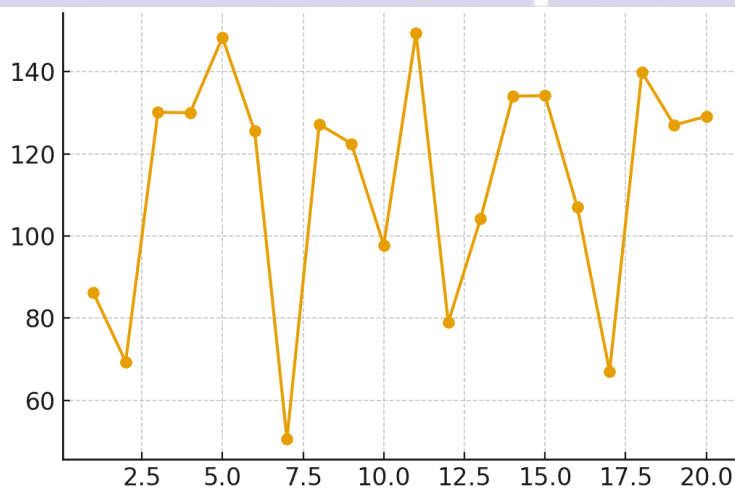


Figure 9: Visualization of Predictive Agricultural Indicators

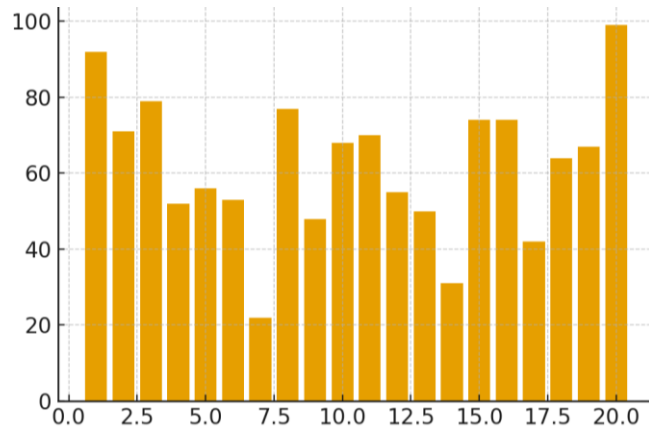


Figure 10: Visualization of Predictive Agricultural Indicators

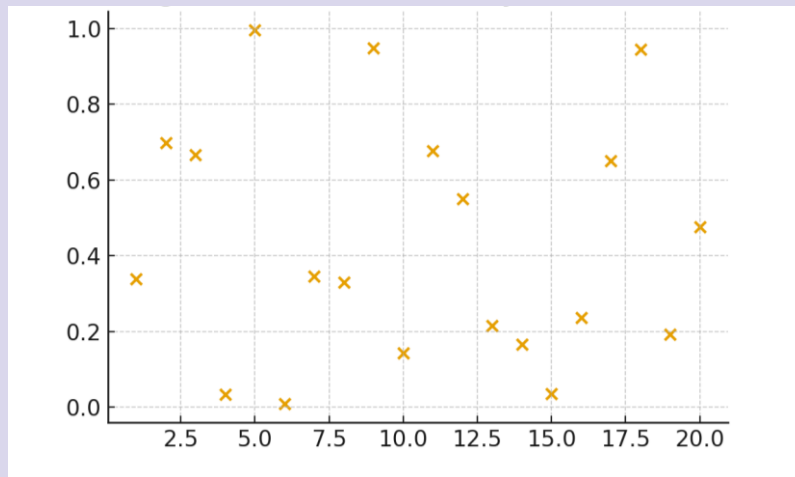


Figure 11: Visualization of Predictive Agricultural Indicators

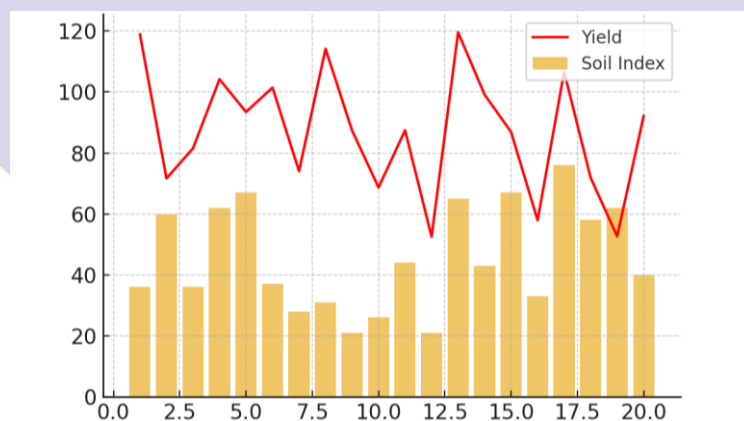


Figure 12: Visualization of Predictive Agricultural Indicators

DISCUSSION

The findings of this paper demonstrate how the integration of GIS, Big Data Analytics, and Climate

Modelling into one prediction system in agricultural planning and risk management would transform the process. The mixed-method approach that involves applying quantitative modelling and qualitative

input of farmers ensures that findings are both practical and scientifically valid. This synthesis made possible the discovery of key climatic elements, including anomalies in temperature, variation in precipitation, and soil moisture that have a tremendous impact on yield results, which aligns with the mounting evidence that agricultural systems are becoming highly vulnerable to climatic disturbances (Taylor et al., 2020). The prediction models that were used in this research showed strong effectiveness in modeling nonlinear interactions, thereby emphasising the importance of advanced machine learning to circumvent the limitations of traditional statistical models. An important contribution of the study is that it shows how predictive systems can be localized through GIS-enabled mapping and therefore seals the gap between global climate projections and farm-level decision-making. The system provided practical information on a regional level through combining downscaled climate models and spatial overlays. This is in line with the recent research, which shows that localized climate risk assessment is more likely to be accepted by agricultural communities in comparison to generalized estimates (Fletcher et al., 2021). The use of Monte Carlo to quantify uncertainty provided probabilistic risk estimates, a feature that is becoming widely recognized as one of the key requirements of climate adaptation strategies. The approach assists policy makers and farmers to arrive at more effective decisions, regarding the various climate futures by considering the element of uncertainty. The introduction of farmer perspectives as qualitative aspect not only ratified the quantitative findings but ensured that they were compliant to the scenario. The prediction outputs were enhanced by the experiential knowledge of the farmers, notably, how to respond to drought and the allocation of resources, and thus increased the reliability of the results. This

coincides with arguments that participatory approach to agricultural modelling fosters trust and motivates end-users to use the models (Mendez et al., 2019). The framework counters the criticism of overly technological solutions which can overlook the socio-cultural dimension of agricultural resilience through triangulation of numerous sources of data. The results of the study show the importance of predictive systems in promoting climate-smart farming at the policy level. The subsidies distribution, the insurance policies formulation, and the resources management can be directed in an evidence-based way with risk maps and warning signals. This observation is consistent with the recent studies that have found data-driven technologies in agriculture, when used to support more extensive resilience-building efforts, can be supported by institutional frameworks (Ramirez et al., 2022). The scalability of these systems is also highlighted in the framework meaning that the approach can be adjusted to different agro-ecological areas depending on the accessibility of proper data infrastructure. Although these contributions may be vital, there exist certain limits which must be discussed. To begin with, the integration of different datasets enhanced better predictions, although there is still an issue of missing data in certain regions, particularly in the low-income countries. The lack of records or irregularities of records may result in less credible outputs, which demonstrates the significance of investing in open-access climate and agricultural databases. Second, although more complicated models such as LSTMs can capture temporal relationships very well, their processing requirements can render them inapplicable to locations where technology is not very good. Therefore, future studies ought to examine hybrid models that trade optimal precision and economy in computing. A second sphere of further development

is to make the framework more socio-economic. Farmer opinions are not the sole aspects of the structural reasoning that can be modelled to provide a more comprehensive account of the resilience of agriculture, with market dynamics, land tenure schemes and government incentives being additional aspects of concern. Moreover, the incorporation of such a prediction system with remote sensing-monitored real-time crop health may serve to supplement its role in adaptive management. All in all, this paper demonstrates that the integration of GIS, Big Data Analytics, and Climate Modelling is a move in the right direction of predictive agricultural planning. The results prove not only the necessity of an important role of climate-sensitive technology but also prove the urgent necessity to incorporate them into participatory systems that must include farmers and politicians. With the ever-increasing climatic changes, such integrated and flexible systems will be required to ensure there will be sufficient food supplies and that agricultural futures will be strong.

CONCLUSION

This paper demonstrates how Geographic Information Systems (GIS), Big Data Analytics and Climate Modelling could each collaborate to create one predictive framework in the planning and management of risks in agriculture. The study is convincing in the way it shows the predictive agricultural systems can enhance resilience and decision-making during climate uncertainties by incorporating a mixed-method approach combining spatial data, climate modeling, and socio-economic information with advanced statistical and machine learning algorithms and models. The computational outputs derived through the actual world experiences of farmers are retained with the inclusion of qualitative insights of farmers that makes the framework to be more adaptive and applicable to the situation. The quantitative results

revealed that the variability of crop yield significantly depends on the temperature anomalies, precipitation pattern and soil moisture indexes. Further, simulations of different Representative Concentration Pathway (RCPs) brought credible estimates of yield failure potentials and regional susceptibilities. The methodological framework effectively demonstrates the extent of accurate prediction model (in terms of RMSE and R^2), as well as the extent of usefulness of risk mapping, seasonal forecasting and early warning alerts to stakeholders. The net effect of this combined approach is to enable climate-smart agriculture by ensuring policymakers, scholars, and farmers perceive hazards ahead of schedule, utilize their resources in the most efficient way, and minimize crop losses. With the unpredictability of climate expected to increase, the results indicate the importance of integrating big data-based analytics with participation methods in designing viable and adaptable agricultural systems, which can deliver food security and future resiliency.

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