BILINGUAL PUBLISHING GROUP

Research on World Agricultural Economy

https://journals.nasspublishing.com/index.php/rwae

RESEARCH ARTICLE

Portfolio Agriculture: A Model for Resilient Regional Agricultural Planning

Boyang Lu*[*], *Garrick E. Louis

Department of Systems and Information Engineering, University of Virginia, Charlottesville, VA 22901, USA

ABSTRACT

Food security is threatened by climate change worldwide; consequently, agriculture and farming livelihoods must adapt to new and unpredictable conditions. These conditions vary along spatial scales, and since agricultural yields are sensitive to microclimate conditions, a locally tailored data-driven approach may be helpful. Furthermore, limited agricultural resources like water and labor increasingly constrain food production. This research proposes a regional portfolio model for identifying crop choices and regional portfolio compositions that align with known and forecasted microclimate variation in temperature and humidity. The model will enable farmers to assess tradeoffs between the financial returns and agricultural production risks. The goal of this work is to provide new insights into agricultural planning in the face of climate risk and limited access to water and labor resources. Three steps are taken. Firstly, regional agricultural land is divided into farming subunits, with each representing a terroir characterized by temperature and humidity. Then a simulated yield coefficient is used to assess the effect of microclimate variables on the yield of the different crops in the portfolio of each subunit. Secondly, farming resource allocation, represented by water and labor, across crops and farming subunits is optimized to maximize the yield and associated financial return from farming across the agricultural region. Finally, a resilient agricultural planning model is developed based on the assumed data for regional microclimate and agricultural resources. The results of this research can be used by regional farmers as a reference for selecting crop portfolios and resource allocations to maximize overall profit.

*CORRESPONDING AUTHOR:

Boyang Lu, Department of Systems and Information Engineering, University of Virginia, Charlottesville, VA 22901, USA; Email: bl2ab@virginia.edu

ARTICLE INFO

Received: 28 July 2024 | Revised: 26 August 2024 | Accepted: 5 September 2024 | Published Online: 8 October 2024

DOI: https://doi.org/10.36956/rwae.v5i4.1200

CITATION

Lu, B., Louis, G.E., 2024. Portfolio Agriculture: A Model for Resilient Regional Agricultural Planning. Research on World Agricultural Economy. 5(4): 128–136. DOI: https://doi.org/10.36956/rwae.v5i4.1200

Keywords: Agriculture Portfolio; Climate Change; Terroir; Climate Risk Management; Agricultural Optimization

1. Introduction

Global food security faces unprecedented challenges as climate change continues to disrupt agricultural systems worldwide. With the global population expected to reach nearly 10 billion by 2050, the pressure on agricultural systems to produce sufficient food in a sustainable manner is immense [1, 2]. Climate change is exacerbating these challenges by altering weather patterns, increasing the frequency of extreme weather events and shifting growing seasons, all of which have profound effects on agricultural productivity [3, 4]. The agricultural sector is particularly vulnerable due to its reliance on climatic factors such as temperature, precipitation, and humidity, which directly influence crop growth and yield [5].

Microclimates, or localized climate conditions near the Earth's surface, play a critical role in agricultural productivity. These microclimates are shaped by a combination of environmental variables including radiation, air and surface temperatures, humidity, wind and carbon dioxide levels [6]. The importance of microclimates is underscored by their influence on key ecological processes such as soil respiration, plant regeneration, wildlife habitat selection, and nutrient cycling [7, 8]. Understanding and managing these microclimatic factors is essential for optimizing crop yields and ensuring the sustainability of agricultural practices in the face of changing global climate conditions [9, 10].

Recent studies have highlighted the need for adaptive strategies in agriculture that take into account the variability and complexity of microclimates [11, 12]. These strategies include the adoption of diversified crop portfolios that are resilient to climatic fluctuations, as well as the development of precise, data-driven approaches to farming that leverage high-resolution climate data [13]. By tailoring agricultural practices to specific microclimatic conditions, farmers can enhance their resilience to climate change, reduce the risk of crop failure, and improve overall productivity [14].

One of the most significant challenges in adapting agricultural systems to climate change is the accurate prediction of how different crops will respond to varying climatic conditions. Traditional crop models often rely on broad, coarse-scale climate data, which can overlook the nuances of local microclimates and lead to less accurate predictions [15, 16]. High-resolution microclimate data, on the other hand, allows for more precise modeling of crop suitability and yield, enabling farmers to make better-informed decisions about which crops to plant and when to plant them [17]. This data-driven approach is particularly important in regions with significant climatic variability, where small changes in temperature or humidity can have a large impact on crop performance [18].

In addition to the challenges posed by climate change, the agricultural sector must also contend with the increasing scarcity of vital resources such as water, arable land and labor [19, 20]. The competition for these resources is intensifying as population growth drives up demand for food, leading to more intensive agricultural practices and greater strain on the environment [21, 22]. Efficient resource management is therefore crucial for maintaining agricultural productivity and sustainability. The application of financial portfolio theory to agriculture offers a promising solution to this problem by optimizing the allocation of resources across different crops, balancing the trade-offs between risk and return [23].

The concept of portfolio agriculture is based on the principles of diversification, which in the financial world involves spreading investments across a range of assets to minimize risk and maximize returns. In agriculture, this approach involves diversifying crop selection and resource allocation to buffer against the uncertainties of climate change and market fluctuations [24]. By adopting a portfolio approach, farmers can increase their resilience to adverse conditions, optimize the use of limited resources, and enhance the sustainability of their farming practices [25].

This study builds on the principles of portfolio agriculture by developing a regional portfolio model that integrates microclimate data with resource allocation strategies. The model is designed to help farmers make informed decisions about crop selection and resource use, taking into account the specific microclimatic conditions of their land. By dividing agricultural land into subunits characterized by distinct microclimates—referred to as terroirs—the model assesses the impact of temperature and humidity on crop yields and optimizes resource distribution accordingly. The goal is to maximize agricultural output while minimizing risk, thereby contributing to more sustainable and resilient farming practices in the face of climate change. Three steps will be taken to achieve these goals. Firstly, we divide regional farmlands by terroir and measure the effect of microclimate on crop yields by inducing the yield coefficient. Secondly, we optimize farming resource allocation among crops and farmlands by using a portfolio model for crop selection in each terroir farm allocation. Finally, a numerical experiment is carried out to verify and validate the model.

2. Methodology

In this study, we aim to identify crop choices and portfolio diversification that align with forecasted microclimate variation with the goal of helping local farmers to make tradeoffs between the returns and risks of agricultural production. The methodology encompasses three key components: terroir, resource allocation theory, and the portfolio agriculture planning model. Terroir involves dividing agricultural land into subunits based on environmental factors such as temperature and humidity, which significantly impact crop yields. Resource allocation theory is used to optimize the distribution of limited agricultural resources like water and labor across different crops and subunits. The portfolio agriculture planning model applies financial portfolio optimization principles to agriculture, allowing farmers to balance the tradeoffs between risk and return when selecting crop portfolios and resource allocations.

2.1 Terroir

Terroir, a term rooted in the French tradition of viticulture, broadly encompasses the environmental factors that influence crop growth and quality. Among these factors, temperature and humidity play pivotal roles in determining crop yield. Temperature affects plant metabolism, growth rates, and development cycles, with each crop having an optimal temperature range for maximum productivity. Excessive heat or cold can stress plants, reducing yields or even causing crop failure. Humidity, on the other hand, influences water availability, disease prevalence, and transpiration rates. High humidity can promote fungal diseases, while low humidity can lead to water stress. Together, temperature and humidity create a complex interplay that significantly impacts agricultural output. Understanding and managing these elements of terroir are crucial for optimizing crop yield and ensuring food security in the face of changing climatic conditions.

In this paper, we divide regional agricultural land into farming subunits that each represents a terroir characterized by mean temperature and humidity. We denote all farmlands of a rural household as S and assume that we can divide all farmlands as k distinguished farming subunits with different terroir, such as temperature and humidity, which essentially affect the yield productivity of different crops. For example, 15 distinguished farming subunits have been divided in **Figure 1**. For illustrative purposes of this terroir approach, we assume temperature decreases from north to south by 1°C and humidity increases from west to east by 1% for each farming subunit. Hence, if we denote T and H as temperature and humidity, they can be expressed by the following equation for each farming subunit:

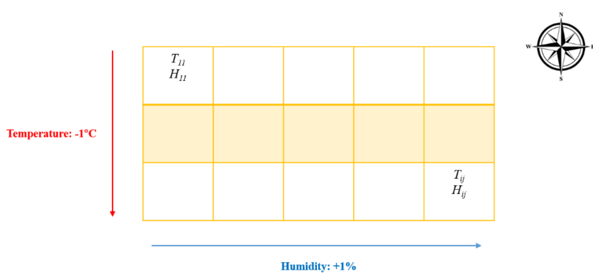

Figure 1. Example of farming subunits.

Temperature Equation:

(1)

Humidity Equation:

(2)

Next, we used a simulated yield coefficient to assess the effect of temperature and humidity on the yield of corn, soybeans and cotton for each farming subunit. These common crops are chosen to illustrate the portfolio model, based on data available in the literature. Actual crop yield data would have to be collected to apply the model in practice. Schlenker and Roberts estimated the impact of climate change on crop yields [26]. **Table 1** shows the data they collected for temperature with the corresponding log yield of corn, soybeans and cotton.

Table 1. Relation between temperature and crop yield.

Temperature (Celsius)	Log Yield (Bushels) Corn	Soybeans	Cotton
0	0.002	0.003	−0.025
5	0.001	0.001	0.01
10	−0.003	−0.005	−0.015
15	−0.002	−0.003	0
20	−0.001	−0.002	−0.003
25	0.01	0.01	−0.006
30	0.0015	0.004	0.02
35	−0.02	−0.02	−0.01
40	−0.04	−0.04	−0.04

In this table, a difference of 0.001 indicates approximately a 1% difference in average yield growth. For example, the yield of corn at a temperature of 25 Celsius is 5% higher than that at 40 Celsius, holding all else the same. We did regression analysis to create polynomial trendline equations below to formulate the relationship between temperature and yield of corn, soybeans and cotton.

Corn:

$$\begin{gathered}\mathrm{Y_1 = 2E\text{–}08T^5\text{–}2E\text{–}06T^4 + 7E\text{–}05T^3 - 0.0009T^2} \\ \mathrm{+0.0034T}\end{gathered} \tag{3}$$

Soybeans:

$$\begin{gathered}\mathrm{Y_2 = 2E\text{–}08T^5\text{–}2E\text{–}06T^4 + 8E\text{–}05T^3\text{–}0.001T^2} \\ \mathrm{+0.0038T}\end{gathered} \tag{4}$$

Cotton:

$$\begin{gathered}\mathrm{Y_3 = 2E\text{–}08T^5\text{–}2E\text{–}06T^4 + 8E\text{–}05T^3\text{–}0.0011T^2} \\ \mathrm{+0.0052T}\end{gathered} \tag{5}$$

Furthermore, based on the USDA News Releases from 2021 to 2023 and the relative humidity map for Virginia, **Table 2** was created to show the average relative humidity of Virginia in August and September from 2021 to 2023 with corresponding yield per acre of corn, soybean and cotton.

We did regression analysis to create polynomial trendline equations below to formulate the relationship between the average relative humidity and the yield per arc of corn, soybeans and cotton.

Corn:

$$\begin{gathered}\mathrm{y_1 = -0.0042H^5 + 1.45H^4 - 201.5H^3 +} \\ \mathrm{13977H^2 - 483816H + 7E + 06}\end{gathered} \tag{6}$$

Soybeans:

$$\begin{gathered}\mathrm{y_2 = 0.0125H^5 - 4.5417H^4 + 659.9H^3 -} \\ \mathrm{47929H^2 + 2E + 06H - 3E + 07}\end{gathered} \tag{7}$$

Cotton:

$$\begin{gathered}\mathrm{y_3 = -0.4375H^5 + 157.29H^4 - 22615H^3 +} \\ \mathrm{2E + 06H^2 - 6E + 07H + 8E + 08}\end{gathered} \tag{8}$$

If we regarded 25 Celsius and 70% average relative humidity as a standard terroir combination, then we introduced yield coefficient β to express the effects of terroir on crop yields. To simplify the model, we use a linear function to sum-up the effects of temperature and humidity on crop yields as follows:

Corn:

$$\beta = (\mathrm{Y_1} - 0.01)/0.01 + (\mathrm{y_1} - 162)/162 \tag{9}$$

Soybeans:

$$\beta = (\mathrm{Y_2} - 0.01)/0.01 + (\mathrm{y_2} - 47)/47 \tag{10}$$

Cotton:

$$\beta = (\mathrm{Y_3} + 0.006)/0.01 + (\mathrm{y_3} - 1036)/1036 \tag{11}$$

2.2 Resource Allocation Theory

The portfolio model was originally developed to help investors select asset portfolios that maximize returns or minimize risks in the financial market. The challenge farmers face in selecting the optimal resource allocation among crops can be viewed as a specific application of this investment model. Several studies have utilized the portfolio model to optimize how farmland is allocated among different crops [27, 28]. Lence [29] applied a standard portfolio model, incorporating additional land

Table 2. Relation between Average relative humidity and crop yield.

Year	Month	Average Relative Humidity (%)	Corn (bushels/arc)	Soybean (bushels/arc)	Cotton (pounds/arc)
2021	August	72	158	45	1045
	September	74	157	43	1100
2022	August	71	160	46	1045
	September	70	162	47	1036
2023	August	75	156	41	1131
	September	76	150	40	1000

constraints, to address the issue of land resource allocation. Nalley[30] employed portfolio theory to select wheat varieties, aiming to minimize risk based on historical yield levels. In agricultural production, allocating limited resources is fundamentally similar to how investors manage assets in the financial market. Therefore, optimal resource allocation across different crops is achievable.

2.3 Portfolio Agriculture Planning Model

In this research, the portfolio model was used to optimize the distribution of essential agricultural resources, specifically water and labor. This approach allows stakeholders to balance the trade-offs between return and risk across various investment options, with risk being quantified by the variance in returns[31]. A higher variance indicates greater risk variability and potentially higher investment returns.

We denote all farmlands of a rural household as *S* and assume that we can divide all farmlands as *k* distinguished farmland area with different terroir, such as temperature and humidity, which essentially affect the yield productivity of different crops. We simply measure this effect as a yield coefficient β.

Assuming that a rural household grows *n* kinds of crops in *k* farmlands, the net return rate from farming can be calculated as:

$$R=\sum_{s=1}^{s=k}\sum_{m=1}^{m=2}\sum_{i=1}^{i=n}x_{msi}r_{mi}\cdot\alpha_s\cdot(1+\beta_{si}) \tag{12}$$

where:

$$\sum_{s=1}^{s=k}\sum_{i=1}^{i=n}x_{si}=1 \tag{13}$$

Where: *R* is the total net return rate of farming resources invested in all farmlands for this household or farming subunit. All returns in this study are net returns. x_{msi} is the proportion of the agricultural resource *m* (water or labor) invested in crop *i* in farmland *s*. r_{mi} is the net return per unit resource *m* of crop *i*. α_s is the proportion of the total area of farmland *s*. β_{si} is the yield coefficient for crop *i* in farmland *s*, which is affected by terroir. *m = 1, 2. s = 1, 2 ,..., k. i = 1, 2 ,..., n.*

Then the investment risk is:

$$V=\sum_{i=1}^{i=n}\sum_{j=1}^{j=n}x_ix_j\sigma_{ij} \tag{14}$$

Where *V* is the investment risk measured by variance without unit. x_i is the proportion of an agricultural resource invested in crop *i*. x_j is the proportion of an agricultural resource invested in crop *j*. σ_{ij} is the covariance of net return per unit resource between crop *i* and *j*. *i, j = 1, 2 ,..., n.*

The covariance of net return per unit resource between two crops is:

$$\sigma_{ij}=E\left\{[r_i-E(r_i)][r_j-E(r_j)\right\} \tag{15}$$

Where: r_i is the net return per unit resource of crop *i*; r_j is the net return per unit resource of crop *j*.

To maximize the net return rate of farming under a certain risk level, the objective equation is expressed as follows:

$$Max\ R=\sum_{s=1}^{s=k}\sum_{m=1}^{m=2}\sum_{i=1}^{i=n}x_{msi}r_{mi}\cdot\alpha_s\cdot(1+\beta_{si}) \tag{16}$$

$$s.t.\ V=\sum_{i=1}^{i=n}\sum_{j=1}^{j=n}x_ix_j\sigma_{ij}\leq\gamma \tag{17}$$

$$\sum_{s=1}^{s=k}\sum_{i=1}^{i=n}x_{si}=1 \tag{18}$$

$$\sum_{s=1}^{s=k}\alpha_s=1 \tag{19}$$

Where: γ is the actual average risk of farming.

3. Results and Discussions

In this section, we perform a numerical experiment to demonstrate the application of the portfolio agriculture planning model. We divide the farmland of a rural farming region into 20 distinct farming subunits with different terroir. **Tables 3–5** show the information of area proportion, temperature and humidity for each farming subunits.

Table 3. Area proportion of farming subunits.

	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}
α	0.05	0.03	0.04	0.06	0.04
	S_{21}	S_{22}	S_{23}	S_{24}	S_{25}
α	0.02	0.06	0.04	0.03	0.05
	S_{31}	S_{32}	S_{33}	S_{34}	S_{35}
α	0.03	0.04	0.08	0.03	0.02
	S_{41}	S_{42}	S_{43}	S_{44}	S_{45}
α	0.05	0.07	0.06	0.12	0.08

Temperatures (Celsius) decrease from north to south. We assume the temperature for farming subunits S_{11} is 25 Degree Celsius; then the temperature for other farming subunits can be derivative from the temperature equation as shown in **Table 4**:

Table 4. Temperature for farming subunits.

	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}
T	25	25	25	25	25
	S_{21}	S_{22}	S_{23}	S_{24}	S_{25}
T	24	24	24	24	24
	S_{31}	S_{32}	S_{33}	S_{34}	S_{35}
T	23	23	23	23	23
	S_{41}	S_{42}	S_{43}	S_{44}	S_{45}
T	22	22	22	22	22

Average Relative Humidity (%) increase from west to east. We assume the average relative humidity for farming subunit S_{11} is 70%; then the average relative humidity for other farming subunits can be derived from the humidity equation as shown in **Table 5**:

Furthermore, the assumed net return of agriculture resources, water and labor, for the three crops corn, soybean and cotton are shown in the **Table 6.**

Table 5. Average relative humidity for farming subunits.

	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}
H	70	71	72	73	74
	S_{21}	S_{22}	S_{23}	S_{24}	S_{25}
H	70	71	72	73	74
	S_{31}	S_{32}	S_{33}	S_{34}	S_{35}
H	70	71	72	73	74
	S_{41}	S_{42}	S_{43}	S_{44}	S_{45}
H	70	71	72	73	74

Table 6. Net return of agriculture resources for corn, soybean and cotton.

	Water (USD per m^3)	**Labor (USD per day)**
Corn	0.3	66.7
Soybean	0.6	143.3
Cotton	0.19	19.3

These net return data are chosen to illustrate the portfolio model, and actual net return data would have to be collected to apply the model in practice. It should be calculated by the following equation:

$$\begin{gathered}\text{Net return} = \text{price} \times \text{yield} - \text{production cost} \\ (\text{the cost of labor, machinery, seeds, water,} \\ \text{fertilizer, pesticide, and so on}).\end{gathered} \tag{20}$$

We assume that the original farming strategy for the rural farms can be described in **Table 7**, which means that the farmer distributes water and labor equally to each farming subunit, and terroir has not been considered at this stage.

Based on the growing strategy described above, the total net return rate of resources of farming invested in all farmlands for this region is $4.32, and the actual average risk of farming γ is 1.24.

Next, we input the initial data of area proportion, temperatures, average relative humidity, and net return of agriculture resources into the Portfolio Agriculture Planning Model. The aim is to optimize the farming resource allocation across crops and farming subunits and maximize the yield and associated financial return rate from farming across the agricultural region. The optimal farming strategy is shown in **Table 8.**

Table 7. Original farming strategy.

Farming Subunit	Crop	Water	Labor
S_{11}	Corn	0.050	0.050
S_{12}	Corn	0.050	0.050
S_{13}	Soybean	0.050	0.050
S_{14}	Soybean	0.050	0.050
S_{15}	Cotton	0.050	0.050
S_{21}	Corn	0.050	0.050
S_{22}	Corn	0.050	0.050
S_{23}	Soybean	0.050	0.050
S_{24}	Soybean	0.050	0.050
S_{25}	Cotton	0.050	0.050
S_{31}	Corn	0.050	0.050
S_{32}	Corn	0.050	0.050
S_{33}	Soybean	0.050	0.050
S_{34}	Soybean	0.050	0.050
S_{35}	Cotton	0.050	0.050
S_{41}	Corn	0.050	0.050
S_{42}	Corn	0.050	0.050
S_{43}	Soybean	0.050	0.050
S_{44}	Soybean	0.050	0.050
S_{45}	Cotton	0.050	0.050

Table 8. Optimal farming strategy.

Farming Subunit	Crop	Water	Labor
S_{11}	Corn	0.024	0.065
S_{12}	Corn	0.062	0.011
S_{13}	Cotton	0.037	0.063
S_{14}	Soybean	0.049	0.047
S_{15}	Cotton	0.084	0.027
S_{21}	Soybean	0.013	0.086
S_{22}	Corn	0.025	0.067
S_{23}	Soybean	0.064	0.021
S_{24}	Corn	0.071	0.033
S_{25}	Cotton	0.092	0.029
S_{31}	Soybean	0.05	0.066
S_{32}	Corn	0.036	0.071
S_{33}	Soybean	0.028	0.043
S_{34}	Corn	0.049	0.058
S_{35}	Cotton	0.057	0.069
S_{41}	Cotton	0.083	0.027
S_{42}	Corn	0.044	0.039
S_{43}	Soybean	0.039	0.047
S_{44}	Soybean	0.042	0.096
S_{45}	Cotton	0.051	0.035

Based on this strategy, farmers have a clear guidance on growing selected crops in each farming subunits and the optimal agriculture resources (water, labor) input. Considering terroir as essential factors for crop agriculture and applying the Portfolio Agriculture Planning Model (PAPM) to optimize the resource allocation, the total net return rate is increased from 4.32 to 5.81, and the actual average risk of farming, γ, is decreased from 1.24 to 0.89. Consequently, we can conclude that PAPM can help regional farmers to select crop portfolios and make resource allocations based on terroir to maximize overall profit.

4. Conclusions

This study underscores the potential and efficacy of the Portfolio Agriculture Planning Model in optimizing resource allocation across various crops and farming subunits by incorporating unique terroir characteristics. By integrating microclimate factors such as temperature and humidity, the model has demonstrated a significant enhancement in the total net return rate, increasing from \$4.32 to \$5.81, while simultaneously reducing the actual average farming risk from 1.24 to 0.89. These improvements highlight the model's ability to provide regional farmers with a robust framework for selecting crop portfolios and allocating resources to maximize overall profitability and sustainability.

The application of the Portfolio Agriculture Planning Model offers a strategic advantage in efficiently managing agricultural resources, addressing critical challenges such as limited farmland, water scarcity, and labor shortages. By tailoring crop choices and resource inputs to specific microclimates, farmers can achieve higher yields and improved economic outcomes, contributing to more resilient and sustainable agricultural practices. The model's ability to optimize resource allocation based on terroir ensures that agricultural practices are both economically viable and environmentally sustainable, supporting the broader goals of food security and climate adaptation.

Moreover, this research provides valuable insights for policymakers and agricultural planners aiming to enhance food security and optimize agricultural productivity amidst climatic variability and resource constraints. The model's flexibility allows for the incorporation of additional variables, such as soil characteristics and economic factors, to further refine agricultural planning strategies. This adaptability ensures that the Portfolio Agriculture Planning Model can be tailored to address broader regional and global agricultural challenges, making it a versatile tool for diverse agricultural contexts.

Future research should focus on expanding the model to incorporate real-time data and more granular variables to further improve its predictive accuracy and applicability. Additionally, field trials and practical implementations of the model can provide empirical validation and offer opportunities to refine the model based on real-world feedback. By continuing to develop and refine the Portfolio Agriculture Planning Model, we can support the agricultural sector in adapting to climate change, optimizing resource use, and ultimately securing a sustainable and resilient food supply for the future.

Author Contributions

Garrick E. Louis conceived of the presented idea. Boyang Lu developed the theory and performed the computations. Garrick E. Louis verified the analytical methods and supervised the findings of this work. All authors discussed the results and contributed to the final manuscript.

Funding

This research was funded by NSF EAGER Grant #2025372.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon request.

Acknowledgments

We thank National Science Foundation for the funding support of our research. We would also like to show our gratitude to Jeffrey Justice and ESERG research group members, who provided comments for writing this paper.

Conflict of Interest

The authors disclosed no conflict of interest.

References

[1] Godfray, H.C.J., Beddington, J.R., Crute, I.R., et al., 2010. Food security: The challenge of feeding 9 billion people. Science. 327(5967), 812–818.

[2] Tilman, D., Balzer, C., Hill, J., et al., 2011. Global food demand and the sustainable intensification of agriculture. Proceedings of the National Academy of Sciences. 108(50), 20260–20264.

[3] Intergovernmental Panel on Climate Change (IPCC), 2014. Climate change 2014: Impacts, adaptation and vulnerability (Part A: Global and sectoral aspects). Cambridge University Press: Cambridge.

[4] Wheeler, T., Von Braun, J., 2013. Climate change impacts on global food security. Science. 341(6145), 508–513.

[5] Schlenker, W., Roberts, M.J. 2009. Nonlinear temperature effects indicate severe damages to US crop yields under climate change. Proceedings of the National Academy of sciences. 106(37), 15594–15598.

[6] Behera, S.K., Mishra, A.K., Sahu, N., et al., 2012. The study of microclimate in response to different plant community association in tropical moist deciduous forest from northern India. Biodiversity and Conservation. 21, 1159–1176.

[7] Bramer, I., Anderson, B.J., Bennie, J., et al., 2018. Advances in monitoring and modelling climate at ecologically relevant scales. In Bohan D.A., Dumbrell A. (eds). Advances in Ecological Research. Academic Press: New York. pp. 101–161. .

[8] Rao, V.U.M., Rao, B.B., 2016. Coping strategies for extreme weather in dryland agriculture. Mausam. 67(1), 5–14.

[9] Challinor, A.J., Watson, J., Lobell, D.B., et al., 2014. A meta-analysis of crop yield under climate change and adaptation. Nature Climate Change. 4(4), 287–291.

[10] Grass, I., Loos, J., Baensch, S., et al., 2019. Land-sharing/-sparing connectivity landscapes for ecosystem services and biodiversity conservation. People and Nature. 1(2), 262–272.

[11] Marko, O., Brdar, S., Panić, M., et al., 2017. Portfolio optimization for seed selection in diverse weather

scenarios. PlOS ONE. 12(9), e0184198.
[12] Holzkämper, A., 2017. Adapting agricultural production systems to climate change—what's the use of models? Agriculture. 7(10), 86.
[13] Early, R., Sax, D.F., 2011. Analysis of climate paths reveals potential limitations on species range shifts. Ecology Letters. 14(11), 1125–1133.
[14] Burke, M., Lobell, D., 2010. Food security and adaptation to climate change: What do we know? In: Lobell, D., Burke, M. (eds). Climate Change and Food Security: Adapting Agriculture to a Warmer World. Springer: Berlin. pp. 133–153. https://web.stanford.edu/~mburke/papers/Chap8_adaptation.pdf
[15] Khanal, A.R., Mishra, A.K., 2017. Enhancing food security: Food crop portfolio choice in response to climatic risk in India. Global Food Security. 12, 22–30.
[16] Alkimim, A., Sparovek, G., Clarke, K.C., 2015. Converting Brazil's pastures to cropland: An alternative way to meet sugarcane demand and to spare forestlands. Applied Geography. 62, 75–84.
[17] Challinor, A.J., Müller, C., Asseng, S., et al., 2018. Improving the use of crop models for risk assessment and climate change adaptation. Agricultural Systems. 159, 296–306.
[18] Lu, B., Louis G. (editors), 2021. Addressing schedule risks in the process of a multi-period production-inventory system. Proceedings of the International Annual Conference of the American Society for Engineering Management; 2021 Nov 27–30. p. 1–9.
[19] Liu, H., Soares-Filho, B.S., Leite-Filho, A.T., et al., 2023. How to balance land demand conflicts to guarantee sustainable land development. iScience. 26(5), 106641.
[20] Chen, W., 2021. China's arable land wasting problem. China Agricultural Economic Review. 13(3), 521–527.
[21] Harmel, R.D., Chaubey, I., Ale, S., et al., 2020. Perspectives on global water security. Transactions of the ASABE. 63(1), 69–80.
[22] Meng, X., Wu, L., 2021. Prediction of per capita water consumption for 31 regions in China. Environmental Science and Pollution Research. 28, 29253–29264.
[23] Ale, S., Harmel, R.D., Nejadhashemi, A.P., et al., 2020. Global water security: Current research and priorities for action. Transactions of the ASABE. 63(1), 49–55.
[24] Rădulescu, M., Rădulescu, C.Z., Zbăganu, G., 2014. A portfolio theory approach to crop planning under environmental constraints. Annals of Operations Research. 219, 243–264.
[25] Palash, M.S., Bauer, S., 2017. Diversification of farmland use in Bangladesh: Land allocation impacts on farm profitability. Open Agriculture. 2(1), 175–188.
[26] Schlenker, W., Roberts, M.J., 2008. Estimating the impact of climate change on crop yields: The importance of nonlinear temperature effects. National Bureau of Economic Research. Working Paper no. 13799. 12 February.
[27] Lowenberg-DeBoer, J., López-Pereira, M.A., 1990. Risk assessment for herbaceous biomass crops: the case of perennial grasses. Biomass. 23(4), 263–274.
[28] Rădulescu, M., Rădulescu, C.Z., Zbăganu, G., 2014. A portfolio theory approach to crop planning under environmental constraints. Annals of Operations Research. 219, 243–264.
[29] Lence, S.H., Hart, C., 1997. Index models and land allocation reconsidered. Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie. 45(3), 267–284.
[30] Nalley, L.L., Barkley, A.P., 2010. Using portfolio theory to enhance wheat yield stability in low-income nations: An application in the Yaqui Valley of northwestern Mexico. Journal of Agricultural and Resource Economics. 35(2), 334–347.
[31] Markowitz, H.M., 2010. Portfolio theory: As I still see it. Annual Review of Financial Economics. 2(1), 1–23.