International Scientific Organization

International Journal of Chemical and Biochemical Sciences
(ISSN 2226-9614)

Journal Home page:www.iscientific.org/Journal.html

Global Warming Effects on Water Supplies and Productivity of Crops

Mala Mathur[1], Tirth Thaker[2], Shakuli Saxena[3]*

[1]*Department of Chemistry, Vivekananda Global University, Jaipur, India.*

[2]*Department of Chemistry, Parul University, PO Limda, Vadodara, Gujarat, India.*

[3]*College of Agriculture Science, Teerthanker Mahaveer University, Moradabad, Uttar Pradesh, India.*

Abstract

The impact evaluation of CC is now a global issue receiving more attention. Water resources and grain production are being seriously impacted by Climate Change (CC). It is essential to develop scientific research in the areas related to CC and raise grain output to assure food security, boost farmer income, and maintain social stability. Established on the original Cobb-Dougla (C-D) production function, this work develops a new economic-climate model that includes climate factors, empirically examines how CC impacts grain yield and emphasizes regional variability. There are also suggested restrictions on agricultural planting structure and agricultural productivity due to water resource limitations. The association between the usage of irrigation water in addition to irrigation is suggested founded on the evaluation of the parallel between Climatic Change as well as grain harvest. Toward a perfect level, human influences like agricultural technological advancement, policy mechanism assurance, and increased farmland water conservation building investment can reduce all types of adverse results of CC on the Chinese agricultural Water supply (WS).

Keywords: Water resources, Cobb-Douglas C-D model, climate change (CC), Grain production, Water supply (WS)

Full length article **Corresponding Author*, e-mail: mathur.mala@vgu.ac.in

1. Introduction

The consequences for water supplies (WS) rank among the most substantial repercussions of global warming for society. Potable water must be available in sufficient quantities for human habitation. The demand for consumptive uses like WS, then non-consumptive services such as navigation, industrial cooling, instream flow benefits of fresh water, and hydroelectric power generation, are frequently outweighed by sustainable surface as well as groundwater sources [1]. In the previous three decades, rice has provided 27%–29% of the nation's total area planted with grains and 32%–54% of its overall crop output. The ability of farmers to grow rice is hampered by concerns about global warming, water scarcity, and other issues [2]. Higher temperatures often negatively influence food yields in most locations by fast-tracking crop yield growth, decreasing the growing season, or amplifying additional factors like warming-driven drought and compound dry-hot events.

Conversely, warming may favor crop output in other regions, such as heat deficits and those with adaptation strategies (such as changing cultivars, planting dates, and irrigation types), t. Therefore, it is difficult to predict potential changes in agricultural output as a result of global warming due to the various ways by which temperature influences crop development [3]. Generally speaking, global warming speeds up crop development, moves maturity forward, and moves flowering time forward. The significance of listing genotype management environment combinations over the long run is highlighted by the fact that these ostensibly small changes brought on by management and climate variability can result in significant variations in profitability. While previous global warming has accelerated flowering times, it is currently unknown how much OFP has altered due to the climate or how OFP interacts with the effects of irrigation [4]. Because direct observation has limitations, Evapotranspiration (ET) is frequently approximated at continental in addition to global scales using model modeling, remote sensing retrieval, and upscaling of direct studies. Machine learning techniques for estimating surface fluxes based on data similar to flux towers, satellite remote sensing, and weather station observations have grown in popularity in recent years due to their accuracy in computing observed surface fluxes [5].

The paper [6] focused more on the effects of individual climatic conditions than on the effectiveness of agronomic practices in crop water consumption. Research has been done on the shifting responses of crop water usage efficiency to climatic factors (temperature and precipitation) and agronomic techniques (fertilization and cropping patterns) in semi-arid environments based on long-term field observations and experiment data. The paper [7] harmed Warming temperatures frequently affect crop yields; however, it is uncertain if water availability impacts global products to temperature stress. Using satellite-based information, they present empirical estimates of the worldwide yields of sorghum, millet, soybeans, and grain as a function of surface air temperature and soil moisture in the root zone. The paper [8] intended to conceptually engineer how climate unpredictability harms sustainability across some industries internationally. Everyone should be concerned about the agricultural sector's fragility, mainly because of the threat that unpredictable weather fluctuations pose to adequate output and food supply. The LRB was originally this Model for Soil and Water Assessment (SWAT). Through calibrating City-level corn (Zea mays L.) yields, actual evapotranspiration (ETa) values were calculated using the Surface Energy Balance System (SEBS) model, and the SWAT model employed [9]. Temporal and geographical influence and pattern variables about Crop Water Productivity (CWF) concentrate on statistical and correlation analyses with little attention to attribution research or element significance examination of CWF regional differences [10]. The paper [11] provided geographic average yield change trends for each crop model that, lacking the requirement as further simulations using climate and crop models, allow for a more straightforward explanation of yield alterations under random paths about increases in the CO_2 levels and average world temperature. The research [12] focused on environmental, genetic, and managerial factors to identify the primary sources of variance in Global Warming Potential (GWP) and winter wheat yield in Poland, scaled by yield. Coffee is a particularly vulnerable plant species to ongoing climate change, one of the most popular traded agricultural commodities globally. The physiological responses of the coffee plant to high atmospheric Carbon Dioxide Concentration [CO_2] are summarized below based [13]. The paper [14] randomized trials are conflicting, and variety in rice cropping methods and meteorological circumstances hinder country-scale yield estimations. It is predicted that climate warming will affect rice yields. According to a meta-analysis of field warming, China's many rice cropping methods had quite different yield responses to warming. Climate variables included in an updated version of a Cobb-Dougla (C-D) production function-based economic model conducts an empirical analysis of where climate change affects grain output and highlights regional variations. On agricultural output and planting layout, restrictions on water resources are also suggested [15].

The following sections of the article are organized: The materials and techniques are summarized in Section II; Section III presents the recommended results and discussion in more depth. Section III concludes the study and offers suggestions for more research.

2. Materials and methods

CC significantly affects the impact production of grains. Integrating CC with economic studies to investigate solutions to lessen how CC affects agricultural productivity is crucial. It can be demonstrated that the model accuracy is consistent with the evolution of agricultural production under the effect of CC by incorporating climate variables hooked on the production performance standard of economics. Future grain production can be simulated, tested, and estimated using the air circulation model (GCM) and regional climate model results. The model's development and computation are made more accessible by the ease with which the Cobb-Douglas production function (C-D production function) may be normalized. The following equation (1-6) is how the logarithms of both sides express the relationship:

$$inY = ina + b_1 inx_1 + b_2 inx_2 + b_3 inx_3 \qquad (1)$$

Taking

Then the equation stated above becomes

$$y = a_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 \qquad (2)$$

A linear function model is the one presented above. It can see how altering the input variables affect the outcome by rebuilding it. To ascertain the precise value of each parameter, perform a regression analysis on the three input variables, specifically landX_1, labor X_2, and capital X_3 as well as natural logarithm output (Y).

It is not necessary for the dimensions of the variable quantity to an identical when utilizing the function model to analyze how independent variables affect dependent ones. The economically significant factors for each production factor are related to the simple parameters a,$b_1 b_2$, and b_3. As an illustration, the quantity of labor input can be calculated using the labor force or labor days. Still, the amount of output can be determined using output value or yield.

The function model's elasticity coefficients $b_1 b_2$, and b_3 may provide a reasonable approximation of the actual grain production. However, when used to fit historical data, his precision of the C-D manufacturing model does not always exhibit satisfactory consistency. The primary cause of this is that different items have unique function relationships between their outputs and inputs, and the production process for the research item typically involves a significant amount of multi-structure. Also, the chosen data needs to have the necessary scientific integrity and rigor. With a set of specific coefficients and a determined production function, the practical connection among the production of grains and three input factors, such as labor, money, and technology, can only be weakly represented. Based on this, a new model is developed to enhance the current one. The new model's numerous aspects must be explored to simplify and abstract the roles of various components as much as possible.

The C-D-C model develops the traditional C-D production function model since the issue connects with CC effect studies and economics. The following is the appearance of the latest design, assuming that C is the model parameter denoting the CC factor:

$$Y_i = X_1^{\beta_1} X_2^{\beta_2} X_3^{\beta_3} C^r \mu \qquad (3)$$

This planting area, fertilizer input variables as well as labor force, are denoted by X_1, X_2, and X_3, respectively, and the output resistances of the input mentioned above components are represented by β_1,β_2, andβ_3. The new model distinguishes the classic C-D production functions' b_1, b_2, and b_3 by β_1,β_2 andβ_3, which stand for the various output elasticities of multiple models—the output elasticity corresponding to the parameter C, which measures the influence of CC.In the circumstance of the belongings of CC on crop output, it primarily examines the impact caused by the inclusion of CC factor C.

Since crop manufacture depends on environmental factors, resource inputs, and scientific and technological advancements, climatic and socioeconomic factors impact production variability. The impartial variable quantity of the practical standard, such as the climate and the crop production input variables, are presented as C-D-C. The climate variables choose the standard temperature as well as mean precipitation during the rice growing season, while the crop production input variables specify the planting area or acreage of rice, the number of agricultural workers, the overall function of agricultural machinery, with the introduction of agrarian chemical fertilizer:

This study composes an empirical C-D-C model using the aforementioned explanatory elements in the way shown below:

$$inY_{it} = a_0 + b_1 in(TP_{it}) + b_2 in(RF_{it}) + b_3 in(AC_{it}) + b_4 in(LB_{it}) + b_5 in(FT_{it}) + b_6 In(AM_{it}) + b_7 TE + v_{it} (4)$$

i and t in the model stand for Year t in Area i; $Y_{Kit}$is a measure of rice yield;

According to the equation above, "$W_{it}$is the reason for a water lack throughout the period of time t in the city i and is a clarifying variable; Z_{it}refers to the economic and social characteristics of a village i throughout the period t; $Y_{Kit}$is the average per space crop yield k throughout the time t in an a village i, primarily such as grain and maize; i represents the village; k has the crop's type; and t is the period.Nit stands for the town is natural condition characteristics over the course of time t, primarily such as gradient and soil type; T_{it}denotes the imaginary time factor, represented by 1990 and 2000; $D_{it}$the dummy regional variable $\alpha,\ \beta,\ \delta, \eta, \gamma\ and\ \varphi$ and are the estimable parameters; and,kit stands for the random disturbance term. The economic and social traits of villages i during the time period t are represented by z_{it}in the model.

2.1 Analysis of model outcomes

The National Climate Center provided the statistical data for this study, Using the experimental explanation of how CC affects rice yield described above, and covered 160 sites. This study analyses numerical data from 1968 to 2000 while keeping in mind that the data are only current as of 2000. Regions of North India were subjected to multiple regression analysis using the Eviews Program. The typical regression consequences for each location's influence of CC on rice yield are shown in Table 1.It is evident after Table 1 model's simulation results are generally positive, and that of $AdjR^2$ and R^2 values are greater than 0.88, suggesting these models can explain more than 88% of the data. As a result, the climate variables, coupled with the controls of Rice land (RA), Labor Input, Fertilizer Introduction, Total Capacity of Agricultural Equipment, etc, account for 88% of the variation in rice production among regions.

2.2 Implications for Agricultural Output Due to Water Scarcity

The study shows a negative relationship between crop output and water scarcity. The source separates the model towns obsessed with a shortage of water resources. The crop yields of two different cities can be compared. The results in the villages with abundant water resources are higher than in towns with insufficient water resources. Towns with inadequate water supplies typically yield 5355 kg/hm^2, 9% less than communities with adequate water supplies (Table 1). Corresponding to this, there is a 22% change in wheat berry productionconcerning the two groups.

2.3 Setting an econometric model

A variety of factors can impact crop yields per unit area. The econometric model examines the connection between water resources and agricultural economic growth to manage the effects of these factors and thoroughly read the consequence of water shortages thereon. The following econometric model has been created using this method, which was first used in Holtz-research by Eakin.

$$Y_{kit} = \alpha + \beta W_{it} + \delta Z_{it} + \eta N_{it} + \gamma T_{it} + \varphi D_{it} + \varepsilon_{kit} \quad (5)$$

The per unit area crop yield (Y_{kit}) of crop type k for the period t at town i, primarily wheat and corn, is represented by the formula mentioned above, where i signifies a town, k denotes a crop type, and t means a period. The T_{it}dummy time variable, 1990 and 2000, the dummy regional variable, and $\alpha,\ \beta,\ \delta,\ \eta, \gamma\ and\ \varphi$ the estimable parameters are represented by Z_{it}, W_{it}, and t, respectively. Z_{it} indicated the economic characteristics and social of hamlet I for period t, W_{it}, the town's water shortage status during period t, and D_{it}, the dummy regional variable.

Table 1. Results from the model show how location's rice output is impacted by climate change

Independent variables	**North India**			**Northeast India**		
	Coefficient		T value	Coefficient		T value
LOG(TP)	−0.46***		−3.77	0.43***		6.23
LOG(RF)	−0.004		−0.13	0.02		0.95
LOG(AC)	0.91***		37.01	0.99***		20.16
LOG(LB)	0.09***		4.79	0.07***		2.79
LOG(FT)	0.07***		4.12	0.09***		3.45
LOG(AM)	0.09***		5.21	0.04***		2.79
TE	0.08***		14.26	0.80***		42.57
R^2		0.994			0.985	
AdjR^2		0.993			0.949	
F Test value		9337.6***			15,600.3	

Table 2. Estimates of the results for how water supplies affect agriculture output per unit area

Influencing factors	**Rice**	**Wheat**	**Corn**	**Cotton**
Water resource conditions	-0.0012	-0.0005	0.015	-0.005
0=No; 1=Yes			-1.35	-0.65
Per capita population	−0.00004	0.0006	0.002	-0.000 05
(Person/household		-0.98		-0.14
Per capita farmland	−0.021	0.0003	−0.014	0.004
(hm/person)		-0.07		2.04**
Non-agricultural labor force	0.071	0.02	−0.111	0.013
Proportion (0–1)		-0.18		-0.45
Horizontal proportion (0–1)		-1.37		-0.01
Primary school or above	0.045	-0.025	-0.033	0.000 1
Distance from the village committee to the county government	0.0004	0.002	-0.005	0.000 05
	2.55	4.75		-0.45
2004	-0.03	-0.065	0.34	-0.0032
(Time dummy variable)		7.55		-1.33
Loam proportion	-0.765	-0.032	-0.008	0.005
				-1.04
Constant	0.635	0.048	0.084	-0.021
Regional dummy variable	Ignored	Ignored	Ignored	Ignored
Number of observed values	1082	1067	1075	1072
R^2	0.85	0.73	0.66	0.74

Table 3. Agricultural yields as a result of the estimated effects of water resources

Influencing factors	Wheat	Corn
Per capita arable land under water shortage/(kg·hm^{-2})	-275.8	-262.3
(hm2·人−1)	-0.41	5.72
The average population/(people · households−1)	-3.4	2.5
Per capita arable land/(hm2 people−1)		
Proportion of non-agricultural labor force	-10.013.8	-4051.2
Distance from the village committee to the county government (km)	-2.1	2.3
Proportion of primary school level or above the cultural level	-354.2	481.7
Loam proportion (0–1)	-55.2	-877.6
Gradient/degree	-225.3	-1132.2
2005 (Time dummy variable)	1175.6	12.875
Constant	4755.2	5176.3
Regional dummy variable	Ignored	Ignored
Number of Observed Values	681	912
R2	0.15	0.26
Number of villages	342	456

N_{it}stands for the town's natural characteristics during the period t, particularly the soil type, ε_{kit} represents the random disturbance term.

Z_{it}Represents the economic and social characteristics of a village i across the specified time period t in the model. The primary indicators used by the author to describe The number of people in a farmer's household, the amount of arable land or farmland per person, the percentage of the labor force working in other than agriculture employment opportunities, educational attainment, and the stage of market development are all indicators of the economic and social circumstances of peasants.

2.4 Water resource limitations' effects on the structure of agricultural plantings

Water resource limitations also impact the planting structure of the crops. Farmers will explicitly increase the area set aside for rice if the WS is sufficient, and no scarcity of space will be used to plant due to their focus on growing more water-intensive crops than on rice. Without a water shortage, RA financial records for 24% of the total planting area for all crops. However, RA only makes up 8% of the total crop acreage in water-scarce towns, which is 5% less than in cities without water constraints (Table 2).

If WS is insufficient, in addition to rice, the percentage of cotton acres will also somewhat fall. Because corn requires less irrigation water to grow, it is produced at a higher rate, as evidenced by the fact that the proportion of corn acres in water-scarce towns is significantly higher (3% higher) than that of rice and cotton. According to descriptive statistical research, 36% of acres are constantly planted in wheat, regardless of a water shortage, indicating that growing grain may be fine.

2.5 Setting model

According to relevant economic theory, the following kind of econometric model is created for the situation of water scarcity influencing agriculture plant organization:

$$C_{kit} = \alpha + \beta W_{it} + \delta Z_{it} + \eta N_{it} + \gamma T_{it} + \varphi D_{it} + \varepsilon_{kit} \qquad (2)$$
(6)

The $letters\ i\ k, and\ t$ in the formula above represent different types of towns, crops, and periods, respectively. The primary crops characterized by C_{kit} , which stands for the crop planting structure, are wheat, corn, rice, and cotton.It details the proportion of cropland inside the hamlet planted during the period t. Most authors are interested in the extent of a water shortage W_{it} in the hamlet i throughout each period t as an explanatory variable. The random disturbance term is ε_{kit}, and the estimable parameters are $\alpha,\ \beta,\ \delta,\ \eta, \gamma, and\ \varphi$. The model and all of the controls are very similar.

2.6 The dimension estimation's findings

Table 3 displays the findings of the dimension estimation for the effect of water scarcity on crop structure. When R2 is higher than 0.65, the regression results demonstrate that the model more closely approximates the data. The estimation findings show that several controls are of statistical significance, and the signs of the coefficients are consistent with predictions. For instance, the loam ratio strongly and favorably influences the model for the proportion of wheat acreage, demonstrating that the more significant the bigger percentage of wheat land, the greater the loam proportion. The model's corn acreage proportion is severely impacted by the amount of arable land per person. showing that the greater the corn acreage percentage, the lower the per capita arable land. Each RA aggregates model shows a strong and positive correlation between educational attainment and paddy RA. The paddy RA proportion rises as the education level increases. The results of the statistical description demonstrate a variety of impacts of a shortage of water on the proportion of land used for various crops. The percentage of rice land in the RA proportion is negatively impacted by the lack of water supplies.

3. Results and Discussions

3.1 Correlation analysis of grain output, water resources, and climate change

Both human activity and climatic Change influence every grain production per unit area. According to the examination findings of the Palm Drought severity scale (PDSI) and the Percentage of hectare wheat Production (PHGO), PHGO and PDSI showed a significant linear correlation between 1960 and 2000. To quantify and investigate every effect of climatic modified rice output area per unit and follow the characteristics of global warming shown in Figure 1. When PHGO and PDSI are regressed linearly, created based on this association (equation 7) as follows:

$$PHGO = -1095.4\ PDSI + 1669 \quad (7)$$

The dependent variable, PHGO, is represented by the independent variable, PDSI, a climatic component with a coefficient of 0.7611 in the linear regression equation. As a result, climate variables were responsible primarily for rice production between 1960 and 2000. In contrast, human factors like technical advancement, political systems, agricultural production inputs, etc., had a much less impact. That accords with the reality of technological advancement in terms of some pesticides and fertilizers widely, every irrigation about farms, and the significant rice crop variations rural contract responsibility system implementation, which led every continued rise into agricultural production and pays household members according to their performance.

The actual value of PHGO has consistently exceeded expectations since 1984, with the most significant mistake being a 1708 kg/hm^2 maximum in 1993. Every thorough analysis demonstrates that a fraction of the effect of climate change on rice output steadily reduced between 1984 and 2000, indicating the ability to increase rice production in response to climate change steadily. Such was primarily because of technological and other human advancements, significant growth in agricultural output input, and policy systems. The maximum increase under the effect of the aforementioned human variables, rice yield per unit area, occurred in 1993 at $1706 kg/hm^2$, and the average addition of 1170 $kg/hm2$ between 1984 and 2000. In the same year, the average increase was a 42.94% yield of paddy rice per area, and the highest percentage was 70.49%, showing that the yield advantage was significant. Climate change has caused a more than 1000 kg/hm^2 drop in the grain produced per unit area, as shown in this data. Every result demonstrated that human variables like innovation in the technology employed, assurance of the rule procedures, and increased input into agricultural production might mitigate the detrimental effects of global warming on rice output.

3.2 Evaluation of the connection between water availability and grain yield

As part of a study to determine how the Palmer Distress severity rating and the yield of grains per unit area relate to one another (F.P. (PDSI), it was found such from 1960 to 2000, GIQ and PDSI had a strong linear relationship, as shown in Figure 2. This finding examines how water resource limitations affect planting structure and agricultural production per unit area and considers every characteristic of global warming. An equation for linear regression linking GIQ and PDSI is generated in light of this association (equation 8) as follows:

$$FP = PDSI - 943.6 + 7405 \quad (8)$$

Grain production per area is every dependent variable, while PDSI, a meteorological factor, is the independent variable (F.P.). The coefficient of the equation for linear regression is 0.7064. Consequently, likely, the impact of climatic factors on agricultural water use from 1960 to 2000 stood dominant. At this time, human causes had minimal impact. This was commensurate with the natural growth in agricultural irrigation. In addition, each predicted F.P. from 1960 to 2000 was calculated using the linear regression equation.

The data demonstrate that after 1990, F.P.'s exact value was much lower than its expected appraisal, indicating such predicted grain yield by a climatic unit of area parameters continued much higher than the actual worth. The greatest failure was recorded and attained 2444 m3/hm2 in 2000. From the thorough analysis, it can be seen one percentage influence of climatic grain yield per unit area has changed progressively decreased between 1990 and 2000. This shows that agriculture's capacity to adjust to global warming dramatically improved, primarily because of human factors like water conservation technologies advancement, policy instrument assurance, and a rise in irrigation water conservation initiatives that is considerable. The highest value in 2000 was 43.13%, indicating a significant advantage. Every yearly average value of human forces has conserved agricultural water of about 139.4 billion m^3, and 27.22% of that water is saved on average. Additionally, every average rise in grain yield per square inch brought on more than 100 billion m3 by climate change. The outcomes also demonstrated that human variables, the water-conserving farming equipment, a governmental instrument that ensures, and an increase in the funding of water conservation initiatives could offset climate change's detrimental consequences on agricultural water supply.

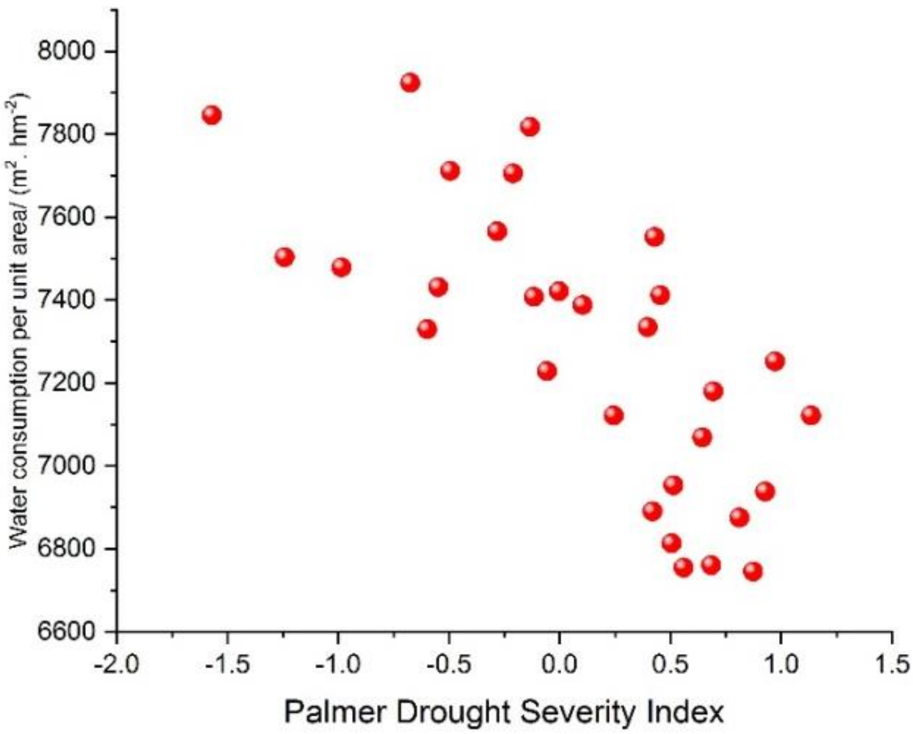

Figure 1. The relationship between Palmer DroughtSeverity Index and grain yield per unit area

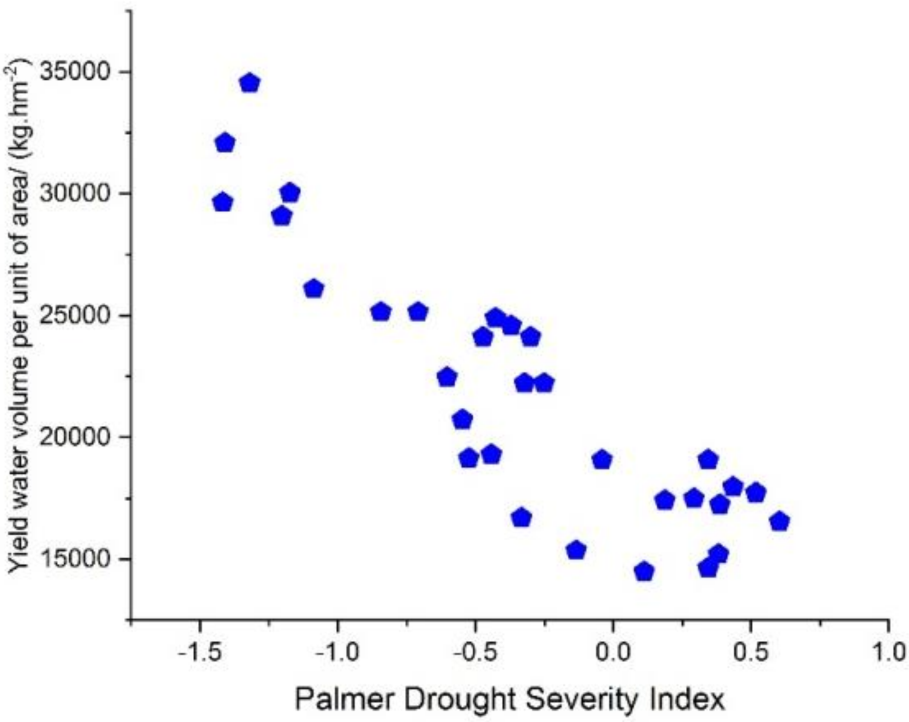

Figure 2. Examining the relationship between Palmer Drought Severity Index and grain yield per unit area

4. Conclusions

The utilization of India's production of grains and agricultural water is now significantly impacted by the effects of climate change. Palmer Drought Severity Index (PDSI) was used to paper India's climate change features from 1960 to 2000. This tool revealed that the tendency of drought in India generally tempered preceding the 1990s and became increasingly assistant. Climate change has caused an average increase in irrigation water consumption, although grain yield per unit area in India has declined by more than 1000 kg/hm2 and has exceeded 100 billion m3. The production of rice is significantly impacted by climate change. Outside of Northeast India, rice suffered substantially due to the temperature increase output during those times, and significant regional variations in that impact existed. The natural environment varies depending on geography and conditions affecting agriculture manufacturing; it represents every variation in how well each region has adapted to climate change. The connection between agricultural economic expansion and water resources varies significantly across various geographical areas. Economic development in agriculture and water resources has a short-term two-cause link in every eastern region, but the two elements have a long-term one-way causal relationship.

References

[1] D.P Lettenmaier, A.W Wood, R.N Palmer, E.F Wood, and E.Z Stakhiv, (1999). Water resources implications of global warming: A US regional perspective. Climatic Change, 43(3):pp.537-579.

[2] F. Tao, Y. Hayashi, Z. Zhang, T. Sakamoto, and M. Yokozawa, (2008). Global warming, rice production, and water use in China: developing a probabilistic assessment. Agricultural and forest meteorology, 148(1): pp.94-110.

[3] Wang, Feiyu, Chesheng Zhan, and Lei Zou (2023). Risk of Crop Yield Reduction in China under 1.5° C and 2° C Global Warming from CMIP6 Models. Foods 12, no. 2: 413.

[4] A. Muleke, M.T Harrison, P. De Voil, I. Hunt, K. Liu, M. Yanotti, and R. Eisner, (2022). Earlier crop flowering caused by global warming is alleviated by irrigation. Environmental Research Letters, 17(4): p.044032.

[5] R. Wang, L. Li, P. Gentine, Y. Zhang, J. Chen, X. Chen, L. Chen, L. Ning, L. Yuan, L. and G. Lü, (2022). Recent increase in the observation-derived land evapotranspiration due to global warming. Environmental Research Letters, 17(2): p.024020.

[6] A. Bhattacharya, (2019). Global climate change and its impact on agriculture. Changing Climate and Resource Use Efficiency in Plants; Academic Press: Cambridge, MA, USA, pp.1-50.

[7] J. Proctor, A. Rigden, D. Chan, and P. Huybers, (2022). More accurate specification of water supply shows its importance for global crop production. Nature Food, 3(9): pp.753-763.

[8] K. Abbass, M.Z. Qasim, H. Song, M. Murshed, H. Mahmood and I. Younis, (2022). A review of the global climate change impacts, adaptation, and sustainable mitigation measures. Environmental Science and Pollution Research, 29(28): pp.42539-42559.

[9] Y. Zhang, H. Liu, J. Qi, P. Feng, X. Zhang, D. Li Liu, G.W. Marek, R. Srinivasan and Y. Chen, (2023). Assessing impacts of global climate change on water and food security in the black soil region of Northeast China using an improved SWAT-CO2 model. Science of The Total Environment, 857: p.159482.

[10] Q. Wang, K. Huang, H. Liu, and Y. Yu, (2023). Factors affecting crop production water footprint: A review and meta-analysis. Sustainable Production and Consumption.

[11] S. Ostberg, J. Schewe, K. Childers and K. Frieler, (2018). Changes in crop yields and their variability at different levels of global warming. Earth System Dynamics, 9(2): pp.479-496.

[12] E. Wójcik-Gront, Variables influencing yield-scaled Global Warming Potential and yield of winter wheat production. Field Crops Research. (2018) Oct 1;227:19-29.

[13] F.M. DaMatta, E. Rahn, P. Läderach, R. Ghini, and J.C. Ramalho, (2019). Why could the coffee crop endure climate change and global warming to a greater extent than previously estimated? Climatic Change, 152: pp.167-178.

[14] C. Chen, van K.J. Groenigen, H. Yang, B.A. Hungate, B. Yang, Y. Tian, J. Chen, W. Dong, S. Huang, A. Deng and Y. Jiang, (2020). Global warming and shifts in cropping systems together reduce China's rice production—Global Food Security, 24: p.100359.

[15] S. Lu, X. Bai, W. Li and N. Wang, (2019). Impacts of climate change on water resources and grain production. Technological Forecasting and Social Change, 143: pp.76-84.