

Covid-19 Disruption in Agricultural Productivity: Lessons from Southwestern Bangladesh

T. Billah¹, S. Das^{1*}, M. B. Ahmed¹, P. Mallick², and A. K. Das³

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ABSTRACT

Purpose: Bangladesh is a low-lying deltaic nation in South Asia, and as such, its agriculture is continually threatened by various natural disasters, including floods, drought and storms. Additionally, from March 2020 to the end of 2021, Bangladesh's agricultural productivity encountered grave challenges of the pandemic COVID-19, just like the rest of the world. Therefore, the research was designed to examine how COVID-19 affected agricultural productivity from the perspective of farmers in southwest Bangladesh.

Research Method: Face-to-face interviews, paired t-tests, Pearson's product-moment correlation, multiple linear regression analyses, principal component analyses and cluster analyses were done.

Findings: Significant variation was recorded in yield, production cost, gross income and net income between Covid-19 and non-Covid times. During COVID-19, farmers' perception of crop production was positively correlated to experience, training and in-field extension service whereas market value positively impacted crop yield. During a pandemic, the respondents had the strongest concerns regarding 1) unavailability and the high price of seed, 2) limited transportation facilities and high fair and 3) unavailability of labor and high wages. Principal component analysis (PCA) identified 9 key variables out of 24 explaining the maximum variance of the study. Cluster analysis (CA) categorized all surveyed crops into three clades with cabbage, sweet gourd, eggplant and potato in clade-I being least affected, resulting in relatively higher economic return than others.

Value: All things considered, the study's findings provide insight to policymakers about how to maintain food security and the food supply chain in the event of a future pandemic or other catastrophic event by guaranteeing a steady supply of farming inputs and transportation facilities.

Keywords: Agricultural productivity, COVID-19 challenges, Farmers' perception, Southwestern Bangladesh

INTRODUCTION

Novel coronavirus or SARS-COV-2-induced COVID-19 inflicted a devastating pandemic across the globe affecting agriculture, health, education, transportation and garments since it was first identified in Wuhan, China in 2019. Due to its far-reaching impact across the globe, the World Health Organization (WHO) proclaimed Covid-19 outburst as a global pandemic on March 11, 2020 (Cucinotta and Vanelli, 2020). COVID-19 negatively impacted agricultural production, especially in low and middle-income countries such as Bangladesh, India, Pakistan, Nepal and Myanmar, resulting in food security issues (Uddin *et al.*, 2020). Because of the easy and rapid

transmission of the virus, people across the globe are immensely anxious about their lives, health and income-generating activities (IGAs) (Fitzpatrick *et al.*, 2020; Jakovljevic *et al.*, 2020).

Agrotechnology Discipline, Khulna University, Khulna-9208, Bangladesh.

Department of English, Jahangirnagar University, Dhaka, Bangladesh.

Department of English, National University, Gazipur, Bangladesh.

*shimul@at.ku.ac.bd

 <https://orcid.org/0000-0003-3745-1828>

Table 1: Major pandemics from the 20th to 21th century (Jarus, 2020; WHO, 2022).

Sl.	Pandemic/ epidemic	Year	Causal agent	Death	Area
1	Plague of Athe	430 B.C.	Unnatural and fetid Breath	100,000	Athe
2	Antonine Plague	165-180 AD	Smallpox	5 million	Roman Empire
3	Plague of Cyprian	250-271 AD	Unknown	5,000/ day	Rome
4	Plague of Justinian	541-542 AD	Unknown	10% of the world's population	Byzantine Empire
5	The Black Death	1346-1353	Bacterium Yersinia Pestis	-	Asia to Europe
6	Cocoliztli epidemic	1545-1548	Salmonella paratyphoid C	15 million	Mexico and Central America
7	American Plagues	16th century	Smallpox	90% of the native population in Western Hemisphere	America
8	Great Plague of London	1665-1666	Bacterium Yersinia Pestis	100,000	London
9	Great Plague of Marseille	1720-1723	Bacterium Yersinia Pestis	100,000	Marseille, France,
10	Russian plague	1770-1772	Bacterium Yersinia Pestis	100,000	Moscow
11	Philadelphia yellow fever epidemic	1793	Yellow fever	5,000	Philadelphia
12	Flu pandemic	1889-1890	Virus	1 million	Europe
13	American polio epidemic	1916	Polio virus	6,000	New York City
14	Spanish Flu pandemic	1918-1920	H1N1 virus	>50 million	South sea to North Pole
15	Asian Flu pandemic	1957-1958	H2N2 virus	>1 Million	China
16	AIDS pandemic and epidemic	1981-present	Human immunodeficiency Virus	35 million	Around the world
17	H1N1 Swine Flu Pandemic	2009-2010	H1N1 virus	>1 million	Worldwide
18	West African Ebola Epidemic	2014-2016	Virus	11,325	Guinea, Liberia and Sierra Leone
19	Zika Virus epidemic	2015-present	Virus	Unreported	South America and Central America
20	Covid -19 Pandemic	2019 – present	Coronavirus	COVID-19	Worldwide

The Organization for Economic Co-operation and Development (OECD) forecasted that global economic growth would be reduced by 2.4% to 2.9% in 2020 and it could further be reduced by 1.5% more if the pandemic is prolonged (OECD, 2020). The COVID-19 pandemic is considered the most serious crisis since World War II (ILO, 2020). The covid-19 pandemic is now associated with other past pandemics that have occurred and significantly destroyed or altered human lives (Table 01).

As COVID-19 induced a global shutdown, every

aspect of life including transportation, economics, agriculture, education, labor, trade, social safety nets, employment and food supply chain. have been seriously affected, and the level of impact on a specific sector was interrelated with the impact intensity of multiple sectors (Liverpool-Tasie *et al.*, 2021; Reardon *et al.*, 2020; Sharma *et al.*, 2020; Cullen, 2020). The epidemic affected the agricultural production of China and it was projected the agricultural growth rate of China would be decreased by 0.4-2.0% (Zhang *et al.*, 2020). Research on the estimation of agricultural production lost in Southeast Asia during

this pandemic period revealed that 3.11% or 17.03 million in retrenchment occurred in the total volume of agricultural production by the year 2020 (Gregorio and Ancog, 2020). According to their survey report, 77 thousand people's farming operations were harmed due to lack of labor forces resulting in reduced gross domestic product (GDP) by 1.4 percent in Southeast Asian regions, equating to USD 3.76 billion. Vegetable production in Shanghai, China decreased due to labor shortages and increased labor costs during COVID-19, and 65.2% of farmers surveyed claimed both these factors were equally responsible for affecting agricultural production (Hai-ying and Chang-wei, 2020). Combining four cereals (pearl millet, rice, maize and sorghum), the total production decreased by 1.47 M to 2.47 M in Senegal and 4.51 M to 7.52 M in Burkina Faso due to Covid-19 (Jha *et al.*, 2021). Also, the global availability of food commodities decreased due to low agricultural production resulting from shrunk agricultural inputs and other facilities during COVID-19 (Elleby *et al.*, 2020; Poudel *et al.*, 2020).

Due to lockdowns imposed by countries, formal and informal markets were closed resulting in a global economic recession (Cardwell and Ghazalian, 2020). These lockdowns created transportation difficulties limiting the distribution of essential goods including food commodities and agricultural necessities of seeds, chemicals, fertilizers, machinery, etc. For instance, the food supply chain in Brazil was seriously disrupted during the COVID-19 pandemic resulting in food shortages for its' people (de Paulo Farias and Fernandes, 2020). Similarly, COVID-19 generated transportation issues, which not only limited farmers' marketing options but also prevented them from receiving an accurate selling price. In addition, whole-sellers or even retailers were apprehensive about buying goods from the farmers as they might face unknown difficulties in marketing their purchased food commodities.

Hence, farmers were not well compensated for their goods, although the price of goods was high in food markets. Mayhem in Canadian markets resulted from insufficient and improper disbursement of goods in addition to price hikes in daily necessities (Cranfield, 2020). Lack of food-marketing facilities in combination with low monetary compensations to growers for agricultural produce were common issues in rural areas of Bangladesh during the pandemic (Zabir *et al.*, 2021). This survey determined the pandemic decreased the unit value of cow milk and meat by approximately 45 and 35%, respectively, in the village areas of Bangladesh. In addition, a significant difference in the unit price of food commodities was observed between villages and cities or even village to

village. Overall, the gross production of three major agricultural sectors (crops, fisheries and livestock) was severely decreased in Bangladesh (Khan *et al.*, 2020).

In Zimbabwe, food-marketing facilities were very insufficient and most of the farmers could not market their products promptly and suffered economic losses (Parwada, 2020). Apart from that, COVID-19 created many unforeseen obstacles impacting the supply chain of agricultural products which threatened agricultural production (Pu and Zhong, 2020). It was difficult to find suitable solutions for maintaining food security during the pandemic as COVID-19 proved very disruptive to agricultural research and farming (Henry, 2020).

By disrupting agricultural production, the COVID-19 pandemic not only threatened food and nutritional security for people in low and middle-income countries but also resulted in days of unemployment for agricultural laborers (Kohnert, 2021). Unemployed laborers created significant financial hardship for households. In parallel with varied parts of the globe, there is a dire need for the agriculture of Bangladesh to unveil how farming activities in southwestern Bangladesh got constrained during the pandemic. Therefore, the study was set to evaluate how the COVID-19 pandemic affected the agricultural productivity in southwest Bangladesh (SWB) as perceived by farmers. Additionally, the study sought to identify the crops that were most severely affected by the pandemic as well as the factors that contributed to the study's highest level of variability.

MATERIALS AND METHODS

Locale of The Study

The study was undertaken in five districts (Bagerhat, Khulna, Shatkhira, Jashore and Gopalganj) located in the southwestern coastal regions of Bangladesh (Fig. 01). The study areas have a joint area of cultivable land of approximately 651 thousand hectares (BBS, 2018). The rainy season in this region usually spans from June to mid-October (Shahid, 2010). The study areas of the five administrative districts belong to three agro-ecological zones (AEZ) of Bangladesh involving AEZ-11 (High Ganges River Floodplain), AEZ-13 (Ganges Tidal Floodplain) and AEZ-14 (Gopalganj-Khulna Beels) as per given in Table 02 (Rahaman *et al.*, 2019). Agriculture is one of the primary occupations of the people living in these regions.

Research Design and Data Collection

The study was designed to observe the perceptions of farmers regarding the impact of COVID-

Table 2: Details of survey areas in southwestern Bangladesh.

District	Agro Ecological Zone (AEZ)	Upazila	Union (Location)
Bagerhat	Ganges Tidal Floodplain (no. 13)	Rampal	Ujalkur (22.637722 N – 89.629798 E)
			Gourambha (22.659787 N – 89.576259 E)
			Perikhali (22.539034 N – 89.678497 E)
			Bashtoli (22.578759 N – 89.705442 E)
		Fakirhat	Betaga (22.708185 N – 89.625214 E)
			Piljong (22.720101 N – 89.715711 E)
Khulna	Ganges Tidal Floodplain (no. 13)	Rupsha	Lokhpur (22.751061 N – 89.634406 E)
			Fakirhat (22.773722 N – 89.707483 E)
			Noihati (22.796317 N – 89.614331 E)
			Ghatvog (22.796722 N – 89.674878 E)
		Batiaghata	TS Bohiradia (22.812731 N – 89.632801 E)
			Srefoltola (22.814637 N – 89.611374 E)
Shatkhira	Ganges Tidal Floodplain (no. 13)	Tala	Amirpur (22.711274 N – 89.546921 E)
			Batiaghata (22.718442 N – 89.500864 E)
			Vandarkot (22.679137 N – 89.573747 E)
			Jolma (22.668451 N – 89.454108 E)
		ShatkhiraSadar	Nagorghata (22.776189 N – 89.109999 E)
			Kheshra (22.651317 N – 89.235694 E)
Jashore	High Ganges River Floodplain (no. 11)	JashoreSadar	Jalapur (22.713174 N – 89.262633 E)
			Tala (22.731354 N – 89.227576 E)
			Labsha (22.748149 N – 89.060103 E)
			Ghona (22.711033 N – 88.978481 E)
		Abhaynagar	Jhaudanga (22.811350 N – 89.037664 E)
			Alipur (22.681708 N – 89.024416 E)
Gopalganj	Gopalganj-Khulna Beels (no. 14)	GopalganjSadar	Arobpur (23.164723 N – 89.203662 E)
			Ramnagar (23.130558 N – 89.264337 E)
			Nauapara (23.008950 N – 89.387728 E)
			Norendropur (23.115473 N – 89.300082 E)
		Muksudpur	Payra (22.968138 N – 89.392870 E)
			Prembag (23.099528 N – 89.356999 E)

19 on agricultural production using a descriptive and diagnostic research design postulated by Kothari (2004). Descriptive design is a theory-driven approach, primarily concerned with characterizing the subject of the inquiry. It is used in case studies, naturalistic observations, surveys, and so forth. This technique entails the gathering, analysis, and presentation of data. It enables the researcher to explain the problem statement succinctly, allowing others to grasp the importance of this type of research. Diagnostic design is a form of research that focuses on determining the

root cause of a certain condition or phenomenon. It can be beneficial to learn more about the elements contributing to obstacles/challenges our farmers may face. The research design usually comprises three phases – (1) problem inception, (2) problem diagnosis and (3) problem solution. Specific administrative Upazilas and unions were selected for this study whereas the farmers were selected using a random sampling method. On the acreage of grain crops and vegetables cultivated, the study area was divided into the following groups per the crop area index equation

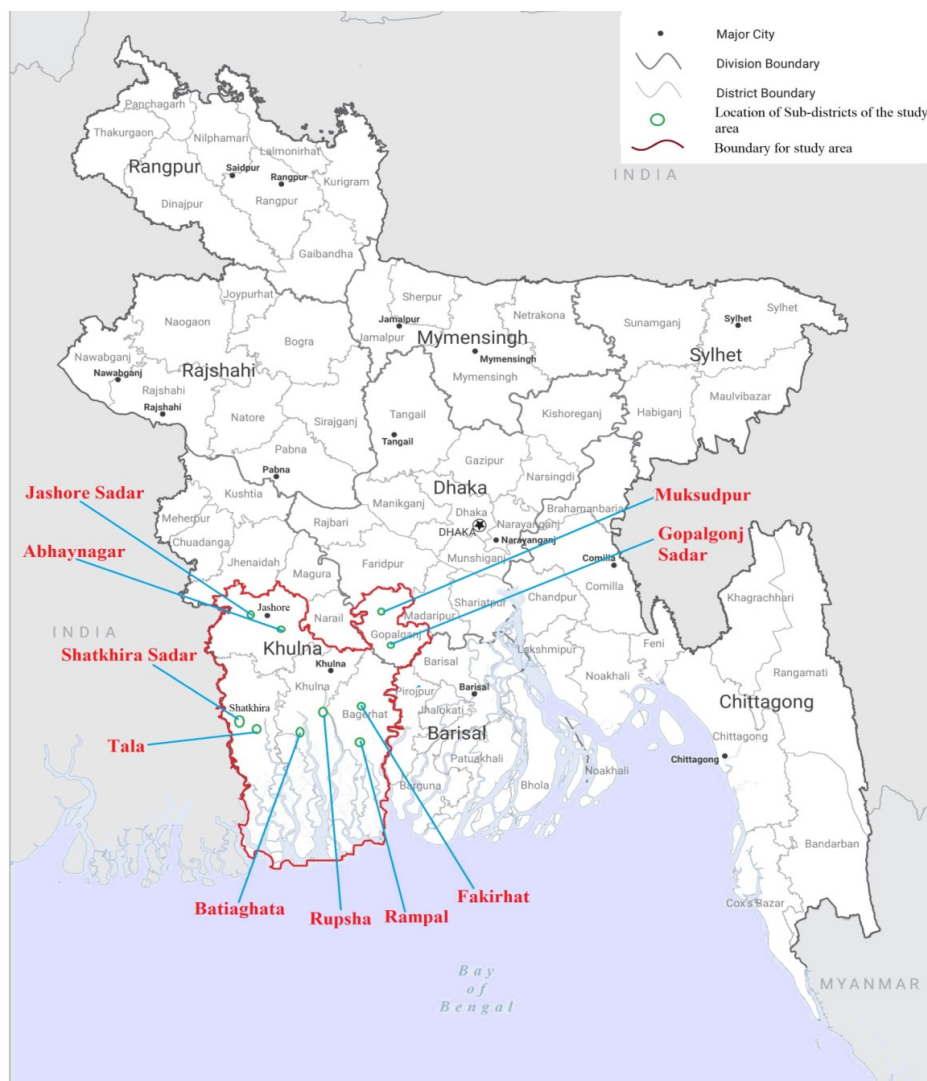


Figure 1: Country map representing different study areas of surveillance in Bangladesh.

(BBS, 2018):

$$CAI = (CA/AC) \times 100 \quad (1)$$

$$VAI = (VA/AC) \times 100 \quad (2)$$

Where, CAI = cereal area index; CA = cereal area; AC = gross cropped area, VAI = vegetable area index, VA = vegetable area

Considering the cereal area index and vegetable area index, the districts under survey were classified as:

Acreage of cereal cultivation:

- i High-intensity area for cereal production (CAI > 60.0) such as Khulna
- ii Medium-intensity areas for cereal production (CAI = 60.0 to 80.0) such as Bagerhat, Shatkira, and Jashore.
- iii Low-intensity area for cereal production (CAI < 60.0) such as Gopalganj.

Acreage of vegetable cultivation:

- i High-intensity area for vegetable production (VAI > 4.0) such as Jashore.
- ii Medium-intensity areas for vegetable production (VAI = 2.0 to 4.0) such as Bagerhat, Shatkira.
- iii Low-intensity areas for vegetable production (VAI < 2.0) such as Khulna, Gopalganj.

A total of 225 farmers were selected from forty (40) unions under ten administrative Upazilas (sub-districts) of the five study districts taking 45 farmers from each of the districts following a stratified and multi-stage random sampling method (Etikhan and Bala, 2017). Data were collected using a pretested questionnaire through face-to-face interviews from 22 December 2020 to 9 February 2021. The collected data comprised personal and socioeconomic characteristics of the participating farmers such as age, family size, farming experience, educational qualification, farm size, annual family income, extension contact and training status. In addition, yield, production cost, gross income and net income during Covid-19 and non-Covid times were assessed. Also, survey data were collected on farmers'

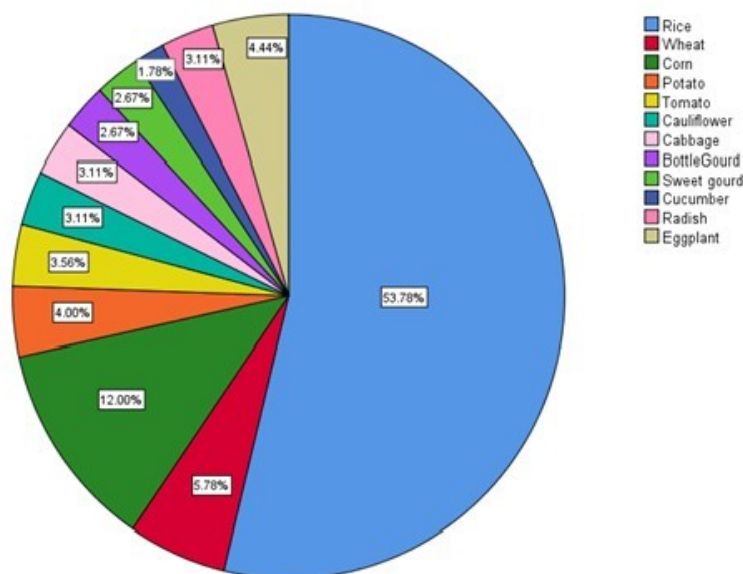


Figure 2: Percentage of the farmers cultivating different crops in southwestern coastal regions of Bangladesh (n=225).

perceptions regarding factors affecting agricultural production during COVID-19. A total of 225 farmers were interviewed in our study cultivating various crops (Fig. 02). Notably, smallholder farmers (<1 ha of arable land) made up the major bulk (49.33%) of the farming community in southwestern Bangladesh.

Specification and Measurement of Variables

The personal and socioeconomic attributes of the farmers such as age, family size, farming experience, educational qualification, farm size, annual family income, extension contact and training experience were considered independent variables for the study, while perceptions of the respondents about the impact of Covid-19 on agricultural production was considered as dependent variables. Actual changes/impacts to agriculture were also assessed by comparing non-Covid and COVID-19 times in terms of yield, production cost, gross income and net income. Among the selected characteristics, age (year), family size (number), farming experience (year), schooling level (passed classes), farm size (hectare), annual income (BDT), extension contact (score), training status (days), yield during Covid-19 and non-Covid times in MT/ha, production cost during Covid-19 and non-Covid times in (BDT/ha), gross income during Covid-19 and non-Covid times in (BDT/ha) and net income during Covid-19 and non-Covid (BDT/ha). Twenty-five statements were incorporated into the questionnaire to determine the farmers' perceptions regarding the impact of COVID-19 on agricultural production. Each of the

respondents was asked to express their perceptions regarding the statements following Likert's type rating scale using the language: strongly agree, agree, undecided, disagree and strongly disagree, which corresponded to number values of 5, 4, 3, 2 and 1, respectively (Likert, 1932). The perceptions score was estimated by summing up all the scores obtained against each of the 25 statements made for the interview. The perception score might vary from 25 to 125, where 25 indicated less clear perceptions and 125 indicated maximum clear perceptions. The perceptions of respondent farmers were categorized according to Roger's recommendations (Rogers, 1983):

- i Less clear perceptions $\leq$ (Mean-SD)
- ii Moderately clear perceptions (Mean-SD to Mean+SD)
- iii Highly clear perceptions $>$ (Mean+SD)

To rank the statements regarding the impact of Covid-19, a Perception Index Score (PIS) was determined by the following formula:

$$PIS = N_{sa} \times 5 + N_{ag} \times 4 + N_{ud} \times 3 + N_{da} \times 2 + N_{sd} \times 1$$

Where PIS = Perception index score of factors affecting agricultural production during COVID-19. N_{sa} = Number of respondents expressing their opinions as strongly agree.

N_{ag} = Number of respondents expressing their opinions as agree.

N_{ud} = Number of respondents expressing their opinions as undecided.

N_{da} = Number of respondents expressing their opinions as disagree.

N_{sd} = Number of respondents expressing their opinions as strongly disagree. The PIS scores could vary from 45-225 for each district and thus 225-1125 for the entire sampling areas of five districts. The PISs were converted to percentages for a clear understanding of the perceptions regarding the statements related to the impact of Covid-19 on agricultural production by using the following formula:

$$FPI = (\text{Observed PIS} / \text{Highest Possible PIS}) \times 100$$

Where, FPI = Farmers' Perception Index

PIS = Perception Index Score

Statistical Analysis

Descriptive statistics such as number, mean, standard deviation, range, percent, rank order etc., were used to interpret data. Pearson's Product Moment correlation and multiple linear regression analyses were performed to find out the nature and strength of relationships among the studied variables as well as to quantify the effect of explanatory variables on the response variable of agricultural production during COVID-19 and non-covid times, respectively. Multivariate PCA (principal component analysis) was also executed to identify key statements influencing farmers' perceptions while CA (cluster analysis) was undertaken to group into distinct clusters of studied crops most or least affected by COVID-19. Also, paired sample t-tests were employed to find out the significant variance of agricultural production in terms of yield of survey crops (MT/ha), production cost, gross agricultural income and net income between COVID-19 and non-COVID periods. In contrast, one-way ANOVA (analysis of variance) were performed to find out a statistical variation of yield, production cost, gross income and net income among districts and crops surveyed. Data were analyzed using the Statistical Package for Social Science (Version 25.0, IBM Corp., Armonk, N.Y., USA) and Origin-Pro (Version 2021, Origin Lab Corporation, Northampton, MA, USA).

Empirical Evaluation

Estimation of COVID-19 effect on agricultural production: In this study, the impact of COVID-19 on agricultural production was appraised by comparing the production status during non-Covid and COVID-19 time. Effect of Covid-19 on agricultural production was identified through the following formula:

$$CAP = (PDC - PNC) / PNC \times 100 \quad (3)$$

Where CAP = Changeover in agricultural production

PNC = Production during non-Covid

PDC= Production during Covid-19

A negative value marked a decrease while a positive value marked an increase in agricultural production.

Quantification of the effect of select factors on farmers' perception and agricultural productivity during COVID-19: Factors that impacted agricultural production due to COVID-19 have been identified through regression analysis. Since agricultural production is a continuous variable, the Tobit model best fits the study, which is as follows:

$$y^* = \beta_0 + x\beta + u, u|x \sim \text{Normal}(0, \sigma^2) \quad (4)$$

$$y = \max(0, y^*) \quad (5)$$

The variable y^* indicates the classical linear model having a homoscedastic distribution with a linear conditional mean. Equation (5) implies the observed variable, y equals y^* when $y^* > 0$, but $y = 0$ when $y^* \leq 0$. The model was formulated into two: one for factors affecting farmers' perception (6.1) and another for factors affecting agricultural productivity (6.2):

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} \quad (6.1)$$

$$Y_j = \beta_0 + \beta_3 X_{3j} + \beta_4 X_{4j} + \beta_5 X_{5j} + \beta_6 X_{6j} + \beta_7 X_{7j} + \beta_8 X_{8j} + \beta_7 X_{9j} + \beta_8 X_{10j} \quad (6.2)$$

Here, Y_i & j = Intensity of factors influencing farmers' perception (Y_i) and agricultural productivity (Y_j), respectively, X_1 = Age (years); X_2 = Experience (years); X_3 = Training status (days); X_4 = In-field extension service (score), X_5 = Production cost during Covid-19 ('000' BDT/ha), X_6 = Market value of agricultural goods during Covid-19 ('000' BDT/MT), X_7 = Seed unavailability and high value (score), X_8 = Pesticide unavailability and high value (score), X_9 = Unavailability and high labor wages (score), X_{10} = Transportation unavailability and high charge (score), β_0 = Intercept; β_1 to β_{10} = Co-efficient to be estimated. To evaluate the relationship between change in agricultural production between Covid-19 and non-Covid time, a polynomial regression model was applied. A theoretical polynomial regression smoothing model was used as follows:

$$y_i = m(x_i) + \delta(x_i)\epsilon_i \quad (7)$$

A set of scatter plot data $(x_1, y_1), \dots, (x_n, y_n)$ from the model is considered to define some unknown variance function (σ^2) and mean (m). Besides symmetric errors, (ϵ_i) is defined with Error $(\epsilon_i) = 0$ and Variance $(\epsilon_i) = 1$. The ultimate target was to evaluate $m(x_0)$

$= E[Y|X = x_0]$, not making any presumption of the functional form of m . A set of scatter plot data $(x_1, y_1), \dots, (x_n, y_n)$ from the model is considered to define some unknown variance function (σ^2) and mean m . Besides symmetric errors, ϵ_i is defined with Error $(\epsilon_i) = 0$ and Variance $(\epsilon_i) = 1$. The ultimate target was to evaluate $m(x_0) = E[Y|X = x_0]$, not making any presumption of the functional form of m .

RESULTS AND DISCUSSION

Personal and Socioeconomic Features of The Respondents

Data displayed in Table 03 denoted, the highest proportion (44.89%) of the respondent farmers were middle-aged. The majority (51.11%) of the respondents belonged to small-sized families. The mean family size (4.54) of the study area was higher than that of the national average. It implied that the farmers of the study area were less aware of planned families. The majority (67.56%) of them had high farming experience followed by medium (24%) and low (8.44%) farming experience. The majority of the respondents (61.78%) had a primary level of education followed by a secondary level of education (25.33%) and a higher secondary level of education (0.89%). About the farm size, about half of the respondents (49.33%) had a small farm, while the smallest proportion of farmers (7.56%) had a large farm. The majority of respondents (52%) had a high annual family income, followed by medium (42.67) and low (5.33%) annual family incomes. The respondents who had medium-sized media contacts (94.22%) were the most numerous, while a few (5.78%) had low-scale media contacts. The highest proportion of farmers (38.22%) received a medium level of agricultural training, while the lowest percentage (5.33%) received a high level of training.

Respondents' Perception About Factors Impacting Agricultural Production During Covid-19

The perception scores of all farmers surveyed ranged from 77 to 99 with a mean $\pm$ SD of 86.12 $\pm$ 4.36. Overall, the majority of respondents (70.22%) had moderately clear perceptions regarding the impact of COVID-19 on agricultural production (Table 04). A similar picture was observed in the districts evaluated encompassing Bagerhat (66.67%), Khulna (77.78%), Shatkhira (68.89%) Jashore (71.11%) and Gopalganj (60%). The findings of the analysis of variance (ANOVA) of farmers' perceptions among the five districts also depicted that mean perception values did not differ significantly from each other (Table 04).

Rank Order of Survey Statements on COVID-19 Affecting Agriculture

According to the Farmers' Perception Index (PI) score, the survey statements were organized in rank order by districts as well as by the whole sample, as shown in Table 05. The overall result depicted the respondent farmers had highly clear perceptions of the unavailability and high price of seed, low transportation facilities high fair and unavailability of labor, and high wages during COVID-19. The farmers expressed their weak perceptions of the reluctance of middlemen to purchase crop produce, government incentive availability unavailability of the sprayer and high fare, and so on during COVID-19. The respondents of the selected five districts showed nearly similar types of perceptions pertinent to statements.

Yield, Production Cost, Gross Income and Net Income During Covid-19 and Non-Covid Years

The overall yield was 6.2 $\pm$ 0.21 MT/ha during non-Covid, while it significantly (t-statistics = -3.69; p-value = 0) decreased to 6.05 $\pm$ 0.20 MT/ha during Covid-19 times (Table 06). In addition, there were significant differences in yield/ha in Khulna and Jashore while no significant differences were observed in Bagerhat, Shatkhira and Gopalganj during Covid-19 and non-Covid years. Significant differences were also observed in overall production cost during COVID-19 (119.40 $\pm$ 2.64) and non-COVID years (102.09 $\pm$ 2.23) (t-statistics = 16.71; p-value = 0). A similar scenario was also recorded in all the districts for production costs during COVID-19 and non-Covid. Notably, due to price hikes of agricultural produce, overall gross income increased from 273.35 $\pm$ 4.35 '000' BDT/ha during non-Covid to 313.35 $\pm$ 5.67 '000' BDT/ha during COVID-19 and was significant statistically (t-statistics = 8.96; p-value = 0). Similar results were also documented in the case of the districts studied. Overall net income significantly increased during Covid-19 (191.79 $\pm$ 3.41) relative to non-Covid times (167.01 $\pm$ 2.86) (t-statistics = 13.64; p-value = 0.77), significant differences were also observed in net income of all the districts separately between Covid-19 and non-Covid years. Analysis of variance (ANOVA) found yield/ha, production cost, gross income and net income of the respondents varied significantly at $p = 0.01$ among the five correspondent districts during COVID-19 and non-COVID.

Fig. 03 shows the status of yield/ha, production cost, gross income, and net income of the respondent farmers during COVID-19 and non-COVID according to crops, respectively. Results of descriptive analysis

Table 3: Distribution of the respondents on selected socio-economic characteristics.

Characteristics	Categories	Score	Respondent (N=225)		Range		Mean±SE
			Number	Percent (%)	Min.	Max.	
Age (Years)	Young	35	27	12	23	60	47.22±0.61
	Middle	36-50	101	44.89			
	Old	>50	97	43.11			
	Total		225	100			
Family size (Number)	Small	4	115	51.11	2	7	4.54±0.07
	Medium	5-6	102	45.33			
	Large	>6	8	3.56			
	Total		225	100			
Farming experience (Year)	Low	10	19	8.44	7	40	24.96±0.53
	Medium	11-20	54	24			
	High	>20	152	67.56			
	Total		225	100			
Schooling level (passed class)	Illiterate	0	27	12	0	12	4.57±0.20
	Primary	1-5	139	61.78			
	Secondary	6-10	57	25.33			
	Higher secondary	11-12	2	0.89			
	Above HSC	>12	0	0			
	Total		225	100			
Farm size (ha)	Landless	(<0.02)	0	0	0.28	15	1.44±0.09
	Marginal	(0.02-0.20)	0	0			
	Small	(0.21-1.00)	111	49.33			
	Medium	(1.01-3.00)	97	43.11			
	Large	(>3.00)	17	7.56			
	Total		225	100			
Annual family income ('000' BDT)	Low income	150	12	5.33	125	1056.39	381.79±16.44
	Medium income	151-300	96	42.67			
	High income	>300	117	52			
	Total		225	100			
Extension contact (score)	No contact	0	0	0	11	19	15.78±0.14
	Low contact	11	13	5.78			
	Medium contact	12-22	212	94.22			
	High contact	>22	0	0			
	Total		225	100			
Training status (Number)	No training	0	56	24.89	0	5	2.06±0.11
	Low-level training	1-2	71	31.56			
	Medium level training	3-4	86	38.22			
	High-level training	>4	12	5.33			
	Total		225	100			

found cucumber had the highest yield (11.72±0.97 MT/ha) and wheat had the lowest yield (3.92±0.13 MT/ha) during non-Covid while potato had the highest yield (11.37±0.47 MT/ha) and wheat had the lowest yield (4.04±0.12 MT/ha) during Covid-19. Maximum production cost was required for producing eggplant (145.95±3.34 '000' BDT/ha) and minimum production cost was required for producing corn (26.08±1.10 '000' BDT/ha) during non-Covid while maximum and minimum production costs were recorded for potato (174.48±8.71 '000' BDT/ha) and corn (31.67±0.98

'000' BDT/ha), respectively during Covid-19. The highest and the lowest gross incomes were found for cucumber (281.75±22.46 MT/ha) and wheat (60.59±2.06 '000' BDT/ha), respectively during non-Covid while cabbage (312.26±12.59 '000' BDT/ha) and wheat (71.70±2.19 '000' BDT/ha) were found to have the highest and the lowest gross income respectively during Covid-19. The results also depicted that bottle gourd (172.73±9.21 '000' BDT/ha) and wheat (38.76±1.44 '000' BDT/ha) had the highest and the lowest net income, respectively during non-

Table 4: Distribution of respondents according to their perceptions on factors impacting agricultural production during COVID-19.

Districts	Categories	Score	Respondent		Range	f- statistic (p-value)	Mean±SD
			(N=45)				
			Number	Percent (%)			
Bagerhat	Weak perceptions (Mean-SD)	82	7	15.56	79-97		86.38±3.93
	Moderate perceptions (Mean-SD to Mean+SD)	83-90	30	66.67			
	Strong perceptions> (Mean+SD)	>90	8	17.78			
Total			45	100			
Khulna	Weak perceptions (Mean-SD)	81	5	11.11	77-96		86.44±4.20
	Moderate perceptions (Mean-SD to Mean+SD)	82-90	35	77.78			
	Strong perceptions> (Mean+SD)	>90	5	11.11			
Total			45	100			
Shatkhira	Weak perceptions (Mean-SD)	82	7	15.56	79-99	1.06	86.56±4.25
	Moderate perceptions (Mean-SD to Mean+SD)	83-90	31	68.89		(0.38)	
	Strong perceptions> (Mean+SD)	>90	7	15.56			
Total			45	100			
Jashore	Weak perceptions (Mean-SD)	81	8	17.78	78-95		86.4±4.58
	Moderate perceptions (Mean-SD to Mean+SD)	82-91	32	71.11			
	Strong perceptions> (Mean+SD)	>91	5	11.11			
Total			45	100			
Gopalgonj	Weak perceptions (Mean-SD)	80	9	20	78-96		84.96±4.76
	Moderate perceptions (Mean-SD to Mean+SD)	81-89	27	60			
	Strong perceptions> (Mean+SD)	>89	9				
Total			45	100			
	Categories	Score	Respondent		Range		Mean±SD
			(N=225)				
			Number	Percent (%)			
Overall	Weak perceptions (Mean-SD)	81	35	15.56	77-99		86.12±4.36
	Moderate perceptions (Mean-SD to Mean+SD)	82-90	158	70.22			
	Strong perceptions> (Mean+SD)	>90	32	14.22			
Total			225	100			

Covid, on the contrary cabbage (161.08±8.89 '000' BDT/ha) and wheat (34.45±1.53 '000' BDT/ha) had

the highest and the lowest net income respectively during Covid-19. Analysis of variance (ANOVA) of yield/ha, production cost, gross income and net income of the respondent farmers depicted that all of these variables differed significantly at $p = 0.01$ during both Covid-19 and non-Covid periods.

According to Poudel *et al.* (2020), COVID-19 had an impact on all stages of production, from farm to consumer. The impact of Covid-19 on the food production system and supply chain has been estimated to be significant. World food consumption, on the other hand, remained mostly unaffected during COVID-19 due to the inelastic demand for agricultural commodities (Elleby *et al.*, 2020). According to Harris *et al.* (2020), the majority of vegetable growers in India have seen negative effects on their output, sales, expenditure and earnings. The overall variances in production of the four cereals (pearl millet, rice, maize and sorghum) at the national level in Senegal were reduced by 1.47 metric tons to 2.43 metric tons and by 4.45 metric tons to 7.52 metric tons in Burkina Faso depending on six different hypothetical scenarios (Jha *et al.*, 2021).

In India, as a result of lower agricultural production and lower marketing facilities, agricultural product availability declined by 10% for vegetables, fruits and edible oils, with no influence on their costs (Mahajan and Tomar, 2020). According to Alvi *et al.* (2021), the inaccessibility of agricultural information during the lockdown in India and Nepal had a detrimental impact on agricultural productivity for nearly half of the farmers.

Covid-19 has enhanced the sale price of farmers' food commodities, according to the current study. Mandal *et al.* (2021) reported that 75 percent of their respondents faced a price hike while buying fish in Dhaka during the COVID-19 lockdown. According to Altieri and Nicholls (2020), limitations on travel and trade and the lockdown of entire cities reduced the influx of imported goods resulting in severe consequences for the poor in accessing food, as the cost of essential commodities increased. Food and supply shortages resulting from the pandemic, according to Obayelu *et al.* (2021), had a detrimental impact on agriculture, food and nutritional intake in Nigeria.

During the 2020 farming season, southwestern Bangladesh encountered a shortage of hired workers during the COVID-19 pandemic that constrained the farming operations to maintain the food supply chain. Chiwona-karlton *et al.* (2021) emphasized that African nations, like the rest of the globe, are suffering from

Covid-19 harmful influences on health, agriculture, economy and society. The pandemic, according to Bhavani and Gopinath (2020), is disturbing the food supply chain and impacting lives and livelihoods. Varshney *et al.* (2020) revealed prices of non-perishable (wheat) and perishable (tomato and onion) commodities surged for the first time in April of 2020, while Covid casualties were high, then immediately recovered while Covid was near being controlled in India.

They claimed once movement restrictions eased in May 2020, delivery of agricultural commodities expanded. Agricultural commerce, according to Barichello (2020), would be less affected because the demands for agricultural products would not be reduced as these commodities are fundamental requirements for human beings. The Covid-19 lockdown had a severe negative impact on the marketing of horticulture commodities in Zimbabwe, according to Parwada (2020) Covid-19 outbreak lockdown and its impacts on marketing of horticultural produces in Zimbabwe, demonstrating that the restricted movement of sellers and buyers during Covid-19 lockdown limited their market access resulting in substantial (>35%) sales leftovers.

Higher prices of seed, fertilizers, pesticides, labor, transportation and poor marketing facilities, among other things, were shown to have a significant impact on reduced agricultural productivity in southwestern Bangladesh during COVID-19. Evident that the Covid-19 pandemic continued to spread around the world fueling fears of risks to global food security due to challenged agricultural operations from 2019 to 2021. The pandemic created labor shortages and disrupted transportation, processing, retailing and distribution of food products, resulting in a halt in the food supply system.

This study showed the decrease in agricultural production of commodities and the increase in production costs associated with COVID-19 and how this impacted the financial security of low-income farmers in Bangladesh. The COVID-19 epidemic, as per Lioutas and Charatsari (2021), impacted not just food production and distribution, but also food security. Similarly, Bogweh *et al.* (2021) claimed that government restrictions during COVID-19 hampered the availability and proper pricing of agricultural supplies and labor, as well as the distribution and consumption as reported in Africa's eastern and southern regions.

The Covid-19 pandemic had a lower impact on traditional subsistence agriculture than on commercial (Adhikari *et al.*, 2021). Despite the fact traditional

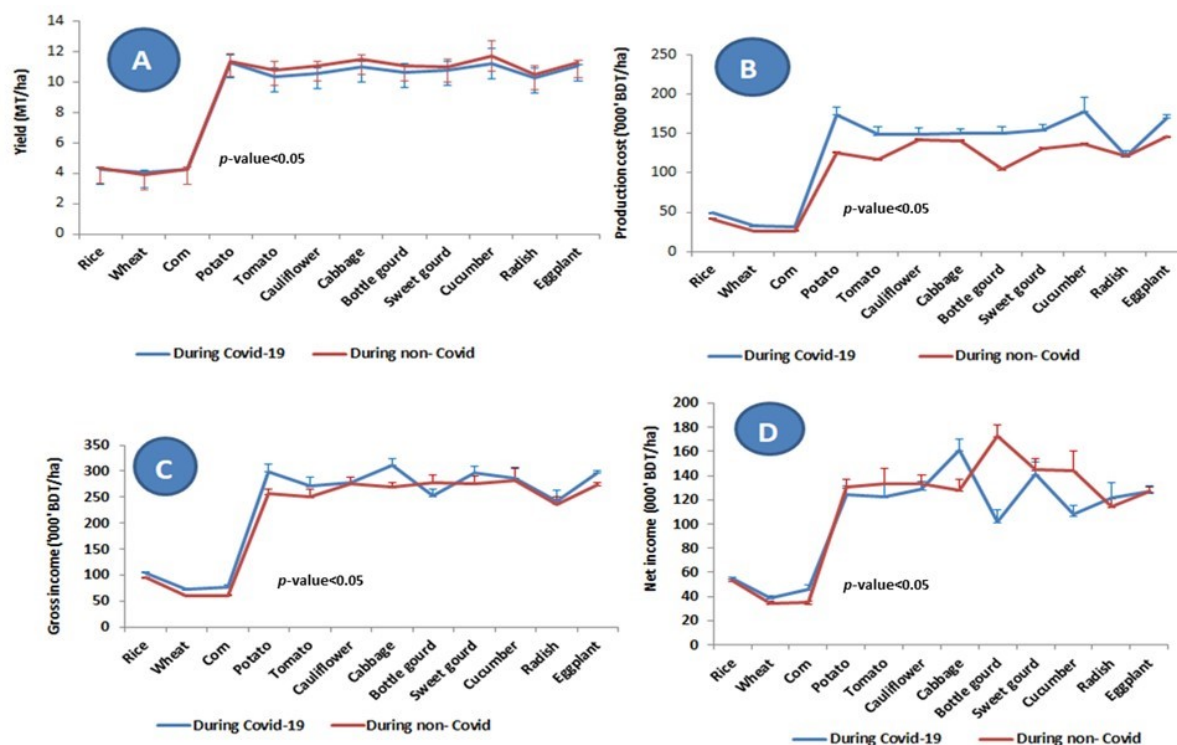


Figure 3: Line graphs indicating the status of the yield of different crops of the respondents (A), the production cost for different crops of the respondents (B), gross income of the respondents from different crops (C) and net income of the respondents (D) during Covid-19 and non-Covid times (with standard error).

subsistence agriculture was associated with poor production, it appeared to be relatively resilient to COVID-19 and capable of contributing to the key pillars of food security in terms of cost and stability. Commercial agriculture, on the other hand, is vulnerable to the pandemic because it relies on long-term supply chains that might be severely disrupted by an outbreak.

According to Boughton *et al.* (2021), grain yields in Myanmar during COVID-19 were lower than average due to reduced rainfall and insufficient irrigation water, making the COVID-19 pandemic crisis more challenging. As per their research, farmers are having greater difficulty selling their products during COVID time than they do during the non-Covid time. Ruan *et al.* (2021) highlighted the increased price of food commodities in the fourth week of the lockdown and then progressively decreased to normal levels by week eleven in China.

Relationship Between Selected Attributes and Perceptions of The Respondents Regarding The Effects of Various Factors on Agricultural Production During COVID-19

The findings related to the relationship of the selected characteristics of the respondent farmers with their

perceptions were calculated using a Pearson's Product Moment correlation. Data shown in Table 07 depicts that among 8 selected characteristics of the farmers, age (years), experience (years), training (days) and in-field extension service (score) showed a significant positive relationship with their perceptions, indicating perceptions on effects of various factors on agricultural production during Covid-19 increases with the increment of respondents' age, experience, training and extension contacts.

Multiple Linear Regressions Quantifying The Degree of Factors' Impact on Respondents' Perceptions

The results of linear regression found the level of significance of respondents' age (years), experience (years), training (days) and in-field extension service (score) on perceptions of the respondents (Table 08). Among the significant coefficients, experience had a greater impact than the other components on farmers' perceptions. The high R^2 value (0.967) denoted data of multiple variables used in this linear regression were well fitted to the line and explained 96.7% of total study variability. The result also indicated that unit increase of age, experience, training and extension contacts of the respondents increased respondents' perceptions by 0.112, 0.624, 0.173, and 0.117 units, respectively.

Table 5: Relative position (rank order) of the statements pertinent to farmers' perceptions on various factors influencing agricultural production during COVID-19.

Sl.	Statements Pertinent to Perceptions	Perceptions Index (%)											
		Bagerhat (N=45)		Khulna (N=45)		Shatkhirra (N=45)		Jashore (N=45)		Gopalganj (N=45)		Overall (N=225)	
		FPI	Rank	FPI	Rank	FPI	Rank	FPI	Rank	FPI	Rank	FPI	Rank
1	Unavailability and high price of seed	88.00	1 st	87.11	1 st	93.33	1 st	90.67	1 st	79.56	4 th	84.27	1 st
2	Low transportation facilities and high fare	82.22	3 rd	80.44	3 rd	80.44	3 rd	85.78	3 rd	86.22	1 st	83.02	2 nd
3	Unavailability of labor and high-wage	68.00	14 th	75.11	10 th	91.11	2 nd	91.11	2 nd	79.56	3 rd	80.98	3 rd
4	Farmers' unwillingness in agricultural production	80.00	5 th	80.00	4 th	80.00	4 th	80.00	5 th	79.11	5 th	79.82	4 th
5	Unavailability and high price of miticide	73.78	8 th	77.33	6 th	77.33	6 th	78.22	6 th	77.78	6 th	76.89	5 th
6	Unavailability of harvester and high-fare	84.00	2 nd	80.89	2 nd	80.00	5 th	70.67	4 th	66.67	16 th	76.44	6 th
7	Unavailability and high price of fertilizer	79.56	6 th	72.89	11 th	73.33	10 th	73.33	10 th	80.00	2 nd	75.82	7 th
8	Unavailability of thresher and high-fare	81.78	4 th	79.56	5 th	76.00	7 th	72.89	7 th	67.11	15 th	75.47	8 th
9	Unavailability and high price of pesticide	76.00	7 th	75.11	9 th	71.11	11 th	72.00	11 th	74.67	8 th	73.78	9 th
10	Inadequate marketing facilities	71.56	12 th	76.44	7 th	73.78	9 th	72.89	9 th	72.00	9 th	73.33	10 th
11	Unavailability and high price of herbicide	66.67	15 th	75.56	8 th	75.56	8 th	76.00	8 th	68.44	12 th	72.44	11 th
12	The high price of fuel for maintaining machinery	72.00	10 th	69.78	12 th	69.33	13 th	73.78	13 th	76.89	7 th	72.36	12 th
13	Unavailability of power tiller and high fare	60.00	20 th	68.00	14 th	70.67	12 th	76.89	12 th	71.11	11 th	69.33	13 th
14	Reluctance of the whole seller to purchase produces	62.67	17 th	65.33	16 th	69.33	14 th	72.00	14 th	71.56	10 th	68.18	14 th
15	Unavailability and high price of fungicide	66.67	16 th	66.22	15 th	67.11	15 th	68.44	15 th	68.44	13 th	67.38	15 th
16	Unavailability of water pump and high fare	62.67	18 th	69.78	13 th	62.22	18 th	71.11	18 th	66.22	17 th	66.40	16 th
17	Low in-field extension service by Go, NGO, and PO	72.89	9 th	64.44	17 th	64.44	16 th	56.89	16 th	67.56	14 th	65.24	17 th
18	Wide use of mobile-based extension service	68.44	13 th	62.22	18 th	56.89	22 nd	62.67	22 nd	65.78	18 th	63.20	18 th
19	Unavailability and high price of bactericide	60.00	21 st	60.00	20 th	60.00	19 th	60.00	19 th	60.00	20 th	60.00	19 th
20	Reluctance of retailers to purchase crop produces	59.56	22 nd	61.33	19 th	59.56	20 th	59.11	20 th	58.67	22 nd	59.64	20 th
21	Growers' scary attitude toward commercial cultivation	61.78	19 th	55.11	24 th	55.11	23 rd	64.44	23 rd	60.00	21 st	59.29	21 st

22	Reluctance of consumers to purchase crop produces	55.56 23rd	57.78 22nd	64.00 17th	56.44 17th	57.33 23rd	58.22 22nd
23	Unavailability of the sprayer and high fare	72.00 11th	59.11 21st	50.22 25th	41.78 25th	48.00 25th	54.22 23rd
24	Govt. incentive availability	48.00 25th	57.78 23rd	57.78 21st	44.44 21st	60.89 19th	53.78 24th
25	Reluctance of middlemen to purchase crops produces	53.78 24th	51.56 25th	52.44 24th	56.44 24th	52.89 24th	53.42 25th

Table 6: Comparison of Agricultural Metrics During and After Covid-19

Comparison	Yield (MT/ha)		Production cost ('000' BDT/ha)		Gross income ('000' BDT/ha)		Net income ('000' BDT/ha)		
	During Covid-19	Non-Covid	During Covid-19	Non-Covid	During Covid-19	Non-Covid	During Covid-19	Non-Covid	
Bagerhat (N=45)	Mean (±SE)	4.91±0.33	4.98±0.32	131.98±4.37	134.55±5.00	343.29±9.61	384.46±7.17	209.83±6.02	270.87±8.10
Khulna (N=45)	Mean (±SE)	5.72±0.25	5.95±0.37	128.96±4.78	125.61±4.21	315.73±11.33	343.29±8.71	193.91±7.8	217.68±6.9
Shatkthira (N=45)	Mean (±SE)	6.54±0.32	6.33±0.40	120.65±4.37	113.47±5.65	313.45±13.13	300.35±10.1	191.79±8.5	186.88±7.2
Jashore (N=45)	Mean (±SE)	6.64±0.28	6.45±0.45	122.98±5.48	117.13±6.32	315.73±11.32	376.42±10.5	167.04±8.9	159.78±8.3
Gopalgonj (N=45)	Mean (±SE)	5.98±0.20	5.72±0.41	115.65±4.0	109.87±4.9	313.55±12.92	376.54±15.2	197.94±5.7	166.22±6.1
Overall (N=225)	Mean (±SE)	6.05±0.25	5.95±0.30	125.48±4.15	120.35±4.85	313.45±14.52	373.55±13.5	167.04±7.7	158.22±8.9
f-statistic	13.02**	13.64**	10.21**	9.94**	12.53**	11.04**	10.65**	9.55**	
p-value	0.00	0.00	0.01	0.03	0.00	0.01	0.02	0.05	

Table 7: Coefficient of correlation (r) between farmers' perception (response variable) and the selected characteristics (explanatory variables).

Characteristics (Independent variable)	Dependent variable	Correlation coefficient	p-value
Age (years)		0.826**	0.000
Experience (years)		0.974**	0.000
Schooling level (passed class)	Perceptions of the respondents	0.06	0.371
Family size (number)		0.024	0.724
Farm size (ha)		0.07	0.293
Annual family income ('000' BDT)		0.051	0.448
Training status (days)		0.932**	0.000
In-field extension service (score)		0.897**	0.000

**0.01 level of significance

Table 8: Linear regression of factors impacting respondents' perceptions.

Characteristics (Independent variable)	Dependent variable	R square	Coefficient (β)	p-value
Age (years)			0.112**	0.000
Experience (years)	Perceptions of the respondents	0.967	0.624**	0.000
Training status (days)			0.173**	0.000
In-field extension service (score)			0.117**	0.000

**0.01 level of significance

Table 9: Linear regression of factors impacting agricultural production during COVID-19.

Characteristics (Independent variable)	Symbol of variables	Dependent variable	R square	Coefficients (β)	p-value
Constant	0			-1.520	0.124
Training status (days)	X3			0.310**	0.003
In-field extension service (score)	X4	Agricultural production during COVID-19 (MT/ha)	0.942	0.390**	0.003
Production cost during Covid- 19 ('000' BDT/ha)	x10			0.586**	0.002
Market value during Covid- 19 ('000' BDT/MT)	x11			0.552**	0.001
Seed unavailability and high value (score)	x12			-0.172**	0.005
Pesticide unavailability and high value (score)	x14			-0.165**	0.006
Unavailability and high labor wages (score)	x15			-0.268**	0.003
Transportation unavailability and high charge (score)	x17			-0.185**	0.005

**0.01 level of significance

Correlation Matrix among Studied Characteristics Impacting Agricultural Productivity during Covid-19

A correlation matrix determined the strength of relationships among the factors associated with agricultural production during Covid-19 (Fig. 04) in which the top four ($r > 0.80$) positive significant associations were: yield during Covid-19 (MT/ha) and production cost during Covid-19 ('000' BDT/ha) ($r = 0.973$, $p < 0.001$); yield during Covid-19 (MT/ha) and 'market value of agricultural goods during Covid-19 ('000' BDT/MT) ($r = 0.921$, $p < 0.001$); production cost during Covid-19 ('000' BDT/ha) and market value of agricultural goods during Covid-19 ('000' BDT/MT) ($r = 0.906$, $p < 0.001$); and age (years) and experience (years) ($r = 0.833$, $p < 0.001$).

On the other hand, the top three ($r < -0.45$) negative significant associations were found between fertilizer unavailability and high value (score) and farmers' unwillingness in agricultural production during Covid-19 (score) ($r = -0.589$, $p < 0.001$); electronic extension service (score) and in-field extension service (score) ($r = -0.547$, $p < 0.001$) and electronic extension service (score) and transportation unavailability and high charge (score) ($r = -0.467$, $p < 0.001$). The highest positive significant correlation was found between yield during Covid-19 (MT/ha) and production cost during Covid-19 ('000' BDT/ha), while the highest negative correlation was found between fertilizer unavailability and high value (score) and farmers' unwillingness in agricultural production during Covid-19 (score).

This survey also determined the COVID-19 pandemic inflicted labor shortages with an increase in labor wages. There was minimal labor due to the lockdown and worker movement restrictions and it became worse during harvesting the winter crops such as rice, wheat and other horticultural produce. Even if farmers were capable of hiring laborers, social distancing measures reduced their performance (Amjath-Babu *et al.*, 2020). They also found food production systems in South Asia, especially countries that maximally relied on external resources and labor, had been severely affected due to the COVID-19 crisis. Hai-ying and Chang-wei (2020) surveyed vegetable production in Shanghai, China during Covid-19 and reported the pandemic had impacted nearly all levels of vegetable production and the delivery chain with an extra adverse effect on its marketing, analogous to our results.

Siche (2020) stated that COVID-19 interrupted agriculture by interfering with food delivery chains and eventually food security, especially for the susceptible

population. The farmers of southwestern Bangladesh were constantly confronting challenges in accessing agricultural inputs due to their unavailability and higher prices. Similar instances were documented in India by Goswami *et al.* (2021) who determined that farming ingredients such as mustard oil cake and di-ammonium phosphate (DAP) fertilizer prices climbed by nearly 70% and 20%, respectively while no notable hurdles were noticed in the availability of farm machinery. A total of 41% of farmers in Haryana, India had to pay extra wages to harvest the crops during lockdown, while 25% of farmers paid more labor fees and 23% spent extra on machinery owing to reduced availability (Ceballos *et al.*, 2020). Pan *et al.* (2020) discovered COVID-19 significantly impacted China's agricultural productivity due to difficulties in the timely availability of crop production substances such as seeds, fertilizers, pesticides and other agricultural inputs during the pandemic.

In addition, non-stop COVID-19 control measures impacted productivity by forbidding businesses associated with seed, fertilizer, pesticides, crop production and marketing from resuming work by shutting down roadways, this research also supports these conclusions. The government also urged their citizens to stay in their residences unless inevitably necessary. Covid-19-related health concerns were key elements associated with the unavailability of the farming labor force. Apart from that, the controlled movement of vehicles constrained agriculture due to uneven transportation of agricultural inputs and goods. Mansingh *et al.* (2020) also found that restricted motion of humans and vehicles intervened in the harvest of Rabi season crops in India.

Multiple Linear Regressions Quantifying The Degree of Factors' Impact on Agricultural Production during Covid-19

The results of multiple linear regression depicted the factors having positive significant coefficients were production cost during Covid-19 ('000' BDT/ha), market value during Covid-19 ('000' BDT/MT), training status (days) and in-field extension service (score), while unavailability and high labor wages (score), transportation unavailability and high charge(score), seed unavailability and high value (score) and pesticide unavailability and high value (score) had significantly negative coefficients on agricultural production during Covid-19 (MT/ha) among the 23 factors evaluated (Table 09).

Multiple linear regression found production cost during Covid-19 ('000' BDT/ha) had the greatest positive

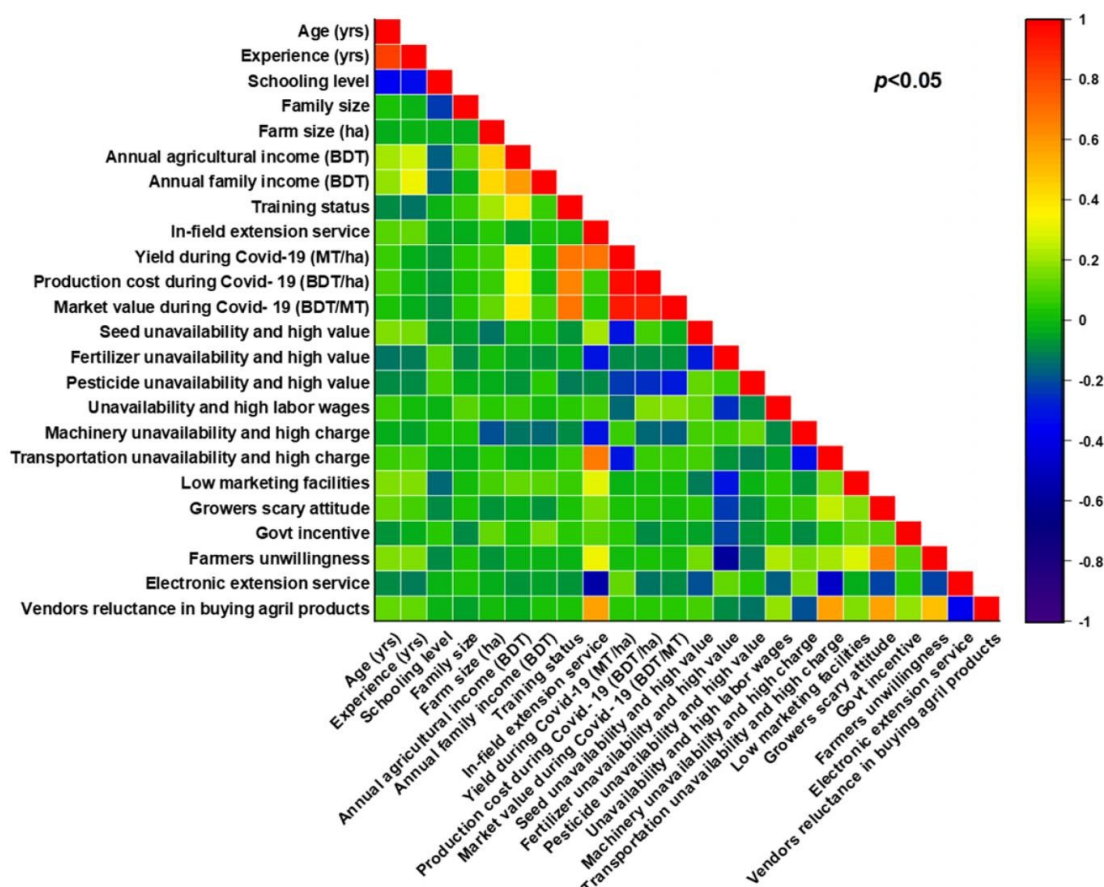


Figure 4: Pairwise correlation among the factors associated with agricultural production during COVID-19.

impact, with a value of 0.61, while unavailability and high labor wages (score) had the greatest negative impact, with a value of -0.26 on agricultural production during Covid-19 (MT/ha). The result also indicated that a unit increase in production cost helped agricultural production (MT/ha) climb by 0.61 units during COVID-19 implying that the farmers who expended more money on production got greater yields during Covid-19. By contrast, the unit rise of unavailability and high labor wages (score) declined agricultural production (MT/ha) by 0.26 units during COVID-19. The high R^2 value (0.961) denoted data of multiple variables used in this linear regression were well fitted to the line and explained 96.1% of total study variability.

Principal Component Analysis (PCA)

Principal component (PC) analysis for the factors associated with agricultural production during COVID-19 showed the first principal component (PC1) and second principal component (PC2) accounted for 27.7% and 17.2% of the total variation, respectively (Table 10). Of the 24 variables studied, 9 variables both from PC1 and PC2 exerted greater influence on agricultural production during Covid-19.

Variables' of yield (MT/ha), the market value of agricultural goods ('000' BDT/MT) and production cost ('000' BDT/ha) during COVID-19 had high positive loadings with values greater than 0.300 for each, while electronic extension service (score) had high negative loadings in PC1 with values less than -0.200. For PC2, the highest positive loadings were contributed by farmers' unwillingness (score), vendors' reluctance to buy agricultural products (score), and in-field extension service (score) having impact values greater than -0.300 for each.

Family size (number) pesticide unavailability and high value (score) inflicted the weakest positive impact on agricultural production during COVID-19, respectively, which were less than 0.035. Conversely, schooling level (passed classes) machinery unavailability and high charge (score) had the weakest negative loadings on variability explanations which were both less than -0.115. The relationship between factors associated with agricultural production during COVID-19 was presented by the principal component biplots (Fig. 05) wherein closely correlated factors were represented by unidirectional line vectors with smaller angles in between factors. Training status (days), yield during Covid-19 (MT/ha), production cost during Covid-19 ('000' BDT/MT), and market value of

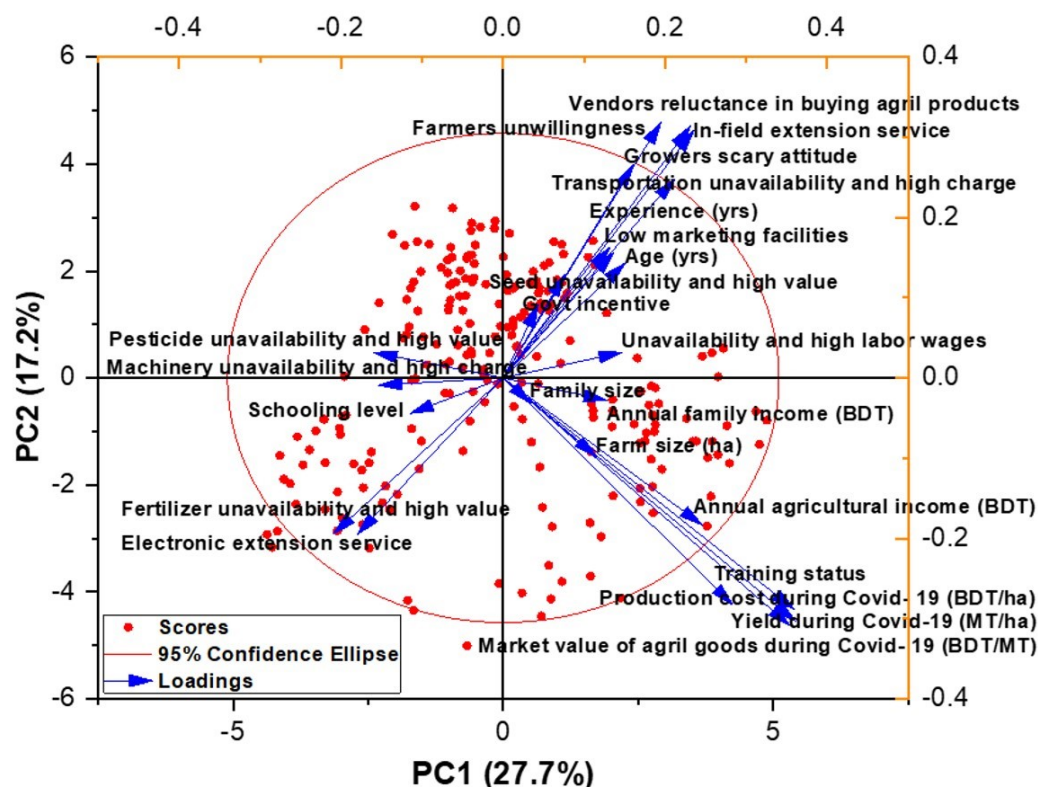


Figure 5: Principal component bi-plots displaying the variability observed among the studied variables and identifying key variables impacting agricultural production during COVID-19.

agricultural goods during Covid-19 ('000' BDT/MT) showed a close association which explained higher variance out of all the variables of the study.

PCA is a widely used statistical tool to extract key variables from a variety of traits analyzed in a given experiment and the variables contributing the maximum amount of total experimental variation are counted as key components. In our study, training status, annual agricultural income, in-field extension service, crop yield and production cost during COVID-19 were the key variables with a higher level of variability explained. Apart from that, the dendrogram in this study grouped 12 crops into 3 clades based on yield (MT/ha), production cost ('000' BDT/ha), gross income ('000' BDT/ha) and net income ('000' BDT/ha) during Covid-19. Correspondingly, Meena *et al.* (2017) clustered their 23 crops into three groups based on their acreage, production and productivity in India for two time intervals (1980-1995 and 1996-2014).

Cluster Analysis

In the present experiment, the dendrogram rooted on Euclidean distance metrics clustered twelve crops into three main clades wherein cereal crops belonged

to the same node, although the rice was positioned in a separate branch, based on gross income ('000' BDT/ha), net income ('000' BDT/ha), yield (MT/ha) and production cost ('000' BDT/ha). In contrast, vegetables were grouped into two broad nodes which were further subdivided into two additional branches for each node (Fig. 06). Although vegetables of potato, eggplant, sweet gourd and cabbage shared the same node, cabbage sat on a distinct branch. Likewise, despite sharing a similar node, five other vegetables radish, cucumber, bottle gourd, tomato and cauliflower were further clustered into two separate clades: one with tomato and cauliflower and another with bottle gourd, cucumber and radish. Based on net income, cabbage (153.61 '000' BDT/ha), sweet gourd (136.89'000' BDT/ha), eggplant (124.56 '000' BDT/ha) and potato (124.04 '000' BDT/ha) were superior to other crops, as a result, they shared the same branch whereas rice (52.86'000' BDT/ha), corn (42.40'000' BDT/ha) and wheat (38.81'000' BDT/ha) sat on a separate node of the circular dendrogram due to relatively lower economic return. Overall, the present study aimed to perceive the effects of COVID-19 on agricultural production encompassing cereal and vegetables. The social distancing and lockdown measures severely affected agricultural farming activities all through Bangladesh. Most of

Table 10: Identification of key factors associated with agricultural production during COVID-19 and their contributions to explaining the variance of the study.

Variables studied	PC1	PC2
Age (years)	0.151	0.143
Experience (years)	0.132	0.163
Schooling level (passed class)	-0.115	-0.044
Family size (number)	0.034	-0.031
Farm size (ha)	0.115	-0.098
Annual agricultural income ('000' BDT)	0.246	-0.183
Annual family income ('000' BDT)	0.128	-0.028
Low marketing facilities (score)	0.136	0.157
In-field extension service (days)	0.235	0.309
Yield during Covid-19 (MT/ha)	0.361	-0.303
Production cost during Covid- 19 ('000' BDT/ha)	0.359	-0.288
Market value of agricultural goods during COVID-19 ('000' BDT/MT)	0.354	-0.309
Seed unavailability and high value (score)	0.076	0.129
Fertilizer unavailability and high value (score)	-0.180	-0.195
Pesticide unavailability and high value (score)	-0.159	0.031
Unavailability and high labor wages (score)	0.146	0.032
Machinery unavailability and high charge (score)	-0.154	-0.009
Transportation unavailability and high charge (score)	0.212	0.249
Training status (days)	0.263	-0.258
Growers scary attitude (score)	0.161	0.266
Govt. incentive (score)	0.043	0.091
Farmers' unwillingness (score)	0.195	0.319
Electronic extension service (score)	-0.210	-0.194
Vendors' reluctance to buy agricultural products (score)	0.231	0.314
Eigenvalue	8.25	3.41
Variance (%)	27.7	17.2

the crops' productivity was found to be lower during COVID-19 than non-Covid period. the findings of this study deciphered how COVID-19 warranted the farming activities and thereby the productivity of major cereal and horticultural crops widely grown

in Bangladesh, ultimately disrupting the food supply chain in 2020.

The study pointed out that horticultural products were less affected than cereals due to their wider span

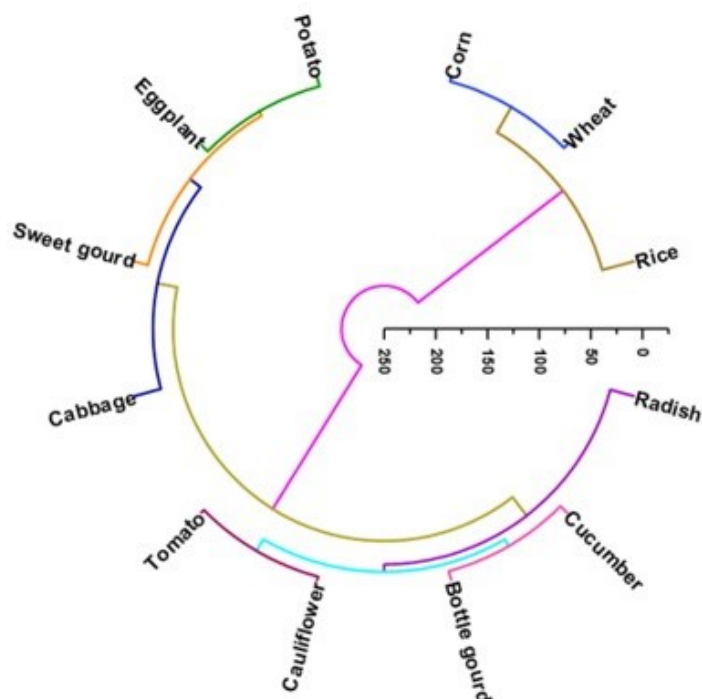


Figure 6: Circular dendrogram clustering 12 agricultural crops into 3 distinct groups based on yield (MT/ha) and economic return during the COVID-19 pandemic.

of harvesting and higher pricing. Insufficiency of transportation facilities, labor force and agricultural inputs posed a gross agricultural productivity temporary threat with a long-term negative effect on the vulnerable marginal farming community. Overall, the survey brought some crucial factors into light that the policymakers of Bangladesh should address well ahead of combating any future pandemic to maintain the constant food supply.

CONCLUSION

COVID-19 had a stringent impact on every stage of crop production, from planting to harvesting to marketing in SWB (southwestern Bangladesh). The combined yield, production cost, and gross income of each of the 12 crops surveyed in SWB were severely affected by COVID-19 because of the unavailability and high price of seed, limited transportation facilities and high fair, and unavailability of labor and high wages, as perceived by the respondent farmers. Market value of agricultural produce, and in-field extension service were all positively related to crop productivity during Covid-19. On the other hand, unavailability and high labor wages, transportation crisis and high fare, seed unavailability and high value, and pesticide unavailability and high value were all negatively related to crop productivity during COVID-19. Notably, cereal crops were more affected than vegetables by the pandemic regarding yield and gross income. The findings of this research will provide

insight into how to better maintain regular daily living in the event of a future pandemic, assuring that no one (producers or consumers) will have difficulty in receiving agricultural inputs or obtaining a daily food supply. It is recommended that widespread participation of GOs and NGOs (government and non-government organizations) in agriculture during any future pandemic or endemic situation could enhance agricultural productivity by making agricultural inputs available to farmers at the customary price and ensuring that marketing facilities are in place.

Disclaimer

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