Natural disasters, agricultural extension, and productivity: Empirical Evidence from Papua New Guinea

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Abstract

This study aims to look at the impact of two factors that may eradicate each other namely the agricultural extension program which is expected to increase agricultural productivity and natural disasters. Using data from the Papua New Guinea Household Survey on Food Systems in 2018 provided by the International Food Policy Research Institute (IFPRI). This study uses a dual method within the framework of Instrumental variables used in the Stochastic Frontier Analysis (SFA) and the estimation stage of the technical efficiency determinants of farmers. Stage 1, estimation of the effect of the extension program, shows that the extension program is associated with higher agricultural productivity. Meanwhile, stage 2, estimation of the production function, shows that farmers in agricultural production show a pattern of decreasing returns to scale. In stage 3, the estimation of the effect of natural disasters on agricultural technical efficiency shows a negative number, which means that drought and irregular rain are types of natural disasters that significantly affects the technical efficiency of agriculture, technical efficiency shows how farmer resources are used in the production process. Intuitively, the findings show that natural disasters increase the resources used by the farmers in production making less efficient production. The extension program for farmers is expected to minimize the negative impact of natural disasters as a productivity recovery stage and an orientation towards sustainability based on the environment is expected to reduce the potential risk of natural disasters getting worse.

Keywords: Disaster, Agricultural Extension, Productivity

JEL: Q54, Q16, Q12,

I. Introduction

Natural disasters including earthquakes, landslides, floods, fires, droughts, and hailstorms can threaten the livelihoods of smallholder farmers and their access to food at any time and everywhere. Disasters can result in the loss of human and animal life, cultivated crops, preserved seeds, agricultural tools, and materials, their supply systems (farming infrastructures such as irrigation canals, dams, and rural roads), and related indigenous knowledge, interfering not only with the current growing season but also with subsequent ones. The damage caused by this natural disaster has had an impact, especially on people living in rural areas where the lives of some people are still very dependent on natural environmental conditions. The concentration of poverty which is generally in rural areas will be a risk of negative impacts of natural disasters that are quite severe. Farmers who rely on nature for their economic activities need intervention from various parties, both the government, non-governmental organizations, and the private sector to recover from their situation after natural disasters. In a study of the effects of extreme weather and climate incidents on farming, Johnson (2003) found that the events most frequently reported by the 57 countries that replied were drought (91 percent) local severe storms (83 percent), floods (79 percent) frost (74 percent), and high winds (72 percent). on the other hand, a few studies show the positive impact of natural disasters where the impacts recorded are quite specific to certain cases, for example, studies from Ryan (1993), Blong (1992), and Chang (1984) but these studies do not show the calculation of the positive and negative impacts so it cannot be known from these studies how much the impact margin of the natural disaster will be.

Natural disasters make farmers need funds and technical assistance to rearrange agricultural land, damaged crops, and dead livestock, as well as infrastructure and supply their daily needs. Restoring agricultural productivity due to natural disasters requires a long process, especially if agricultural commodities take a long time to be harvested. Natural disasters reduce the technical efficiency of farmers because they force farmers to allocate some of their resources to repair damaged land, crops, equipment, and infrastructure. Therefore, program interventions for farmers are important to be dedicated to, besides increasing productivity, it is also necessary to protect the environment from damage so that it has sustainability in production. Even though natural disasters are global in nature, by means of environmentally friendly farming, it will be possible to reduce the risk of natural disasters occurring at least locally. The role of intervention in dealing with the ravages of climate change which results in weather irregularities and natural disasters that are increasingly occurring is urgently needed on two sides. The first is prevention by increasing the productivity of farmers before a disaster occurs and environmental-oriented policies and the second is reducing the burden of agricultural recovery costs due to natural disasters. Land, seeds, and fertilizers as well as improvements to agricultural infrastructure such as irrigation, roads, and reforestation around agricultural land are important to do so that productivity can recover quickly. Many studies show how the government extension program generates higher productivity in agriculture such as Owens et al (2003), Emmanuel et al (2016), Abbeam et al (2018), Sebaggala and Matovu (2020), and Meta-analysis by Ogundari (2022). Agricultural extension to increase farmer productivity is needed both before and after a natural disaster, of course, the extension program must be oriented towards sustainable farming. In addition, an agriculture extension is a tool for communication, contributing to climate change in both developed and developing nations, as well as with smallholder farmers and large-scale farmers, communication is important (Prokopy et al, 2017)

Papua New Guinea as a country in the Pacific islands is a developing country that is still very dependent on the agricultural sector so changing and extreme natural conditions can disrupt the economy. From 1962 to 1979 growth of the agricultural sector, on average is 3.34 percent with a standard deviation of 1.32 (the lowest period of agricultural growth fluctuation), 1980-2019 grew only 2.78 percent with a 5.32 standard deviation (4 times higher fluctuation) (WDI, World Bank). Moreover, in 2009, the direct economic loss attributed to disaster relative to GDP is more than 50 percent, 68 percent in 2020 (UNDRR). Papua New Guinea employment has still dominated by the agricultural sector in which 56 percent (73.8 percent in 1991), based on ILO estimation, of workers' lives depend on this sector's performance. To increase the productivity of the agricultural sector, Government implements some extension programs such as improved seeds, advice, and training. Recent significant climate change has increased the risk for farmers in maintaining their productivity and this can affect food security in a country, and if there are many agricultural countries facing the same problems, it can have a negative impact on world food security. Zhai and Zhuang (2009) imply that the overall effects of agricultural losses brought on by climate change on the world economy are quite minor. The potential risks of natural disasters will be faced by all countries in the world since the trend of natural disaster outbreaks is increasing. Based on the World Disaster Report 2020, the proportion and the total number of disasters that were brought on by climatic and weather-related hazards have increased the highest. While weather and climate-related disasters accounted for 76% of recorded disasters in the 1960s, they now account for 83% of reported disasters (2010–2019).

This study investigates the effect of natural disaster shocks on farmers' efficiency or productivity, then it estimates whether agricultural extension prior to the disasters attenuates the negative impact. Firstly, we will identify the effect of government support on the production function framework using the Stochastic Frontier Production Function (SPFA) to measure the efficiency of farmer's production in the next step, this study tries to investigate the determinants of the efficiency score of the farmers with a focus on natural disasters including drought or irregular rains, earthquakes, landslides, crops damaged by insects, disease, and animals. By knowing the effect of agricultural extension and natural disasters on agricultural performance, it can be seen the potential damage and the role of the extension program in increasing productivity for recovery from natural disasters and how to communicate environmentally friendly technology through government extensions that can play a good role in increasing productivity and maintaining environmental quality. This study uses household survey data provided by IFPRI (International Food Policy Research Institute) in 2018 and covers important aspects of farming households such as production, consumption, natural disasters, and migration, as well as individual and household characteristics of farmers in Papua New Guinea.

II. Literature Review

The literature review related to this study is linked into two parts, namely the impact of natural disasters on agricultural performance and the role of extension in increasing agricultural production. It has long been well known that the forces of nature can have direct adverse effects if they are not properly anticipated by humans, and this will certainly have more pronounced repercussions for an economic region that is underdeveloped. There is a growing number of studies on how natural disasters harm the agricultural sector. Sivakumar (2005) reviews existing studies on how natural disasters predominantly negatively affect agriculture around the world, but there are also some positive impacts as well. Israeli and Briones (2012) found that there is a significant effect of typhoons, floods and droughts have no significant effect on the agriculture sector at the national level but there is an important role at the provincial level, and typhoon has a negative effect on paddy rice production and food security in the Philippines. Trinh, Feeny, and Posso (2021) show that the effect of natural disasters on crops is heterogenous and highly dependent on the type of crops and regions in Vietnam, and Anh (2016) shows that natural disasters have serious consequences on the agricultural sector on Cambodia, Laos, and Vietnam. Moreover, Weerasekara et al (2021) reveal that drought and flood have a significant negative impact on rice production technical efficiency, with droughts having the most severe impact in Sri Lanka and Boustan et al (2017) confirm the same findings in the USA. On the contrary, Israeli and Briones (2012) also considered that there are the direct and beneficial effects on agriculture are actually rather obvious. Typhoons bring rain, which increases the water supply for agriculture. Because they transport nutrients from the uplands to the lowlands, floods increase soil fertility. Floods also momentarily expand the water habitat available to inland fish and other aquatic creatures. These effects of typhoons and floods are seen as beneficial since, ceteris paribus, they enable an increase in agricultural productivity in the afflicted areas and assist to improve the situation with regard to food security. However, other yet-to-be-identified elements may also play a role.

The after-effect of natural disasters after they hit agriculture was the economic condition of the farmer's family. Barua and Banerjee (2020) find climate shocks have a detrimental influence on the level of well-being as assessed by total consumption and non-food consumption expenditures. However, the influence of shocks on food consumption is quite minor. Bui et al (2014) show consistent results on how natural catastrophes have been shown to exacerbate spending poverty and inequality in Vietnam. While the patterns vary by country, both reflect environments in which the poorest households suffer the most from shocks, adopting coping methods that are expensive in terms of both immediate and long-term well-being in Ethiopia and Honduras (Carter et al, 2007). Small groups can be more vulnerable than other groups, for example, young, single parents, poor health, and lower social economic status (Johar et al, 2020).

On the other hand, agricultural extension is important in terms of increasing productivity to restore conditions after natural disasters and if the extension program is environmentally oriented, it will not only increase productivity but will also reduce the potential for local natural disasters to occur. Indeed, environmental problems can not only be solved locally but global problems, but the deteriorating local environment and the possibility of local natural disasters can be reduced. Agricultural extension plays the role in these situations, extension services are crucial because they can be used as levers to alter prevalent behavior in the larger agricultural and rural sectors (Cawley et al., 2015). By "the full collection of institutions that help and facilitate persons engaged in agricultural production to solve problems and to gain information, skills, and technology to better their livelihoods," Anderson (2007) defines agricultural extension and advisory services (Waddington et al., 2010). The extension is, in the broadest sense, a method of education with communication at its center. The term extension is defined by Van den Ban and Hawkins (1996) as the intentional dissemination of knowledge to aid in the creation of sound opinions and wise actions. The extension was described by Moris (1991) as the mechanism for information transmission.

FAO (2019) provides cost benefit analysis at farm level in the multi-county study and shows that Disaster Risk Reduction (DRR) has positive impact on both increasing farmer's productivity and farmers' resilience to natural disasters. Moreover, in agriculture, DRR and prevention strategies are particularly helpful in preventing or minimizing loss and damage from low- to medium-intensity, high-to-medium frequency incidents. Farm-level DRR should receive more attention in agriculture sector policies since it is a practical and reasonably inexpensive strategy to prevent and mitigate the kinds of catastrophes that most frequently affect vulnerable smallholders. Benefits included both an increase in agricultural output and the prevention of loss and damage due to hazards. OECD and FAO (2021) argue that government should support targeted training and extension services that help farmers develop their entrepreneurial and risk management skills, and to adapt and transform in response to uncertainty and a changing risk environment

III. Data and Methodology

3.1 Data

This study uses Papua New Guinea Household Survey on Food Systems in 2018 provided by International Food Policy Research Institute (IFPRI). From May to July 2018, the IFPRI conducted a rural home survey in four lowland districts of Papua New Guinea to explore rural families' food systems and how they provide adequate food to fulfill the nutritional needs of their household members. The study was conducted in the provinces (districts) of East Sepik (Maprik), Sandaun / West Sepik (Nuku), and Madang (Middle Ramu), as well as the Autonomous Region of Bougainville (ARoB - Buin and Siwai areas of Southern Bougainville). In all, 1,026 households were polled. The study had two goals: 1) to use the household survey results to guide agricultural production, improved food security, and child nutrition outcomes; and 2) to collect baseline data for freshly developed World Vision initiatives (WV). The survey provides comprehensive information on household characteristics, agricultural production, Household assets, Income apart from own agricultural activities, consumption and expenditures, economic shocks and household well-being as well as food insecurity covering 1026 respondents across the regions.

3.2 Empirical Model

I use a stochastic frontier approach (SFA) which is firstly proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1979). Since then, stochastic frontier models have grown in popularity as an econometric subfield. This technique is used in this study to calculate the efficiency or productivity of an economic unit in which the unit of analysis in this study is individual farmers. This technique is relevant for this study to achieve the objectives of this research because apart from being able to estimate efficiency as well as treatment analysis for stage 1 it can be aimed at evaluating extension programs for farmers. So one technique to answer 2 questions at once. However, Karakaplan (2017) and Chen, Hsu, and Wang show the problem of endogeneity using the standard SFA estimation. To come up with the endogeneity problem in applying SFA, this study treats SFA with two-stage least squares (2SLS) using an instrument variable, which is AGEX. Firstly, I estimate the equation:

$$LnQ_{pi} = \alpha_0 + \sum_{j=1}^{9} \alpha_i \, AGEX_i + \mu_i \qquad 1$$

Where LnQ_{pi} is the natural logarithm of crop production for farmer i, two unit of measurement are used, Kilogram and Kina, to check consistency of estimation results, and AGEX is the agricultural extension support received and applied by the farmers, which is the multiplication of dummy variable when household member received the assistance/advice (1 if received and 0 otherwise) and dummy variable of whether the advice or assistance is implemented (1 if applied and 0 otherwise). The estimation of the first stage with equation 1 is carried out with several variable aggregation options where the agricultural extension (agex) program variable is formed in the total sum (totalagex) and also each extension program independently consists of 8 extension variables. which are assumed to be exogenous. Because the exogenous assumption of the AGEX variable may be difficult to fulfill, I also estimated it using the Regression Adjustment (RA) technique which is quite popular for experimental data analysis. Estimation of Equation 1 with direct regression between the agex variables, both the total score and the individual value of each extension program because the random assumption of farmer participation in the extension program can be endogenous.

Although bias exists in most regression estimations, it is minimal for large samples. Adjustment may worsen precision or enhance it; standard errors determined using customary methods may greatly overestimate or greatly underestimate precision (Freedman, 2008), On the other hand, Lin (2013) demonstrates that these issues are either minimal or simple to resolve in sufficiently large samples. When a whole set of treatment-covariate interactions is taken into account, OLS correction cannot harm asymptotic precision. These theories get more exact through asymptotic expansions. Birkhaeuser et al (1991) argues that one of the main problems when measuring the impact of agricultural extension, researchers often consider the extension variable as exogenous by designing it as some type of extension contact. But it's possible that one trait of farmers who are more productive is their eagerness to learn about evolving farming practices or new technologies. Equation 1 is estimated by applying a Regression Adjustment (RA).

In estimating the impact of program interventions, there are many methods used, but in conditions where there are several levels of intervention with more than two choices or binary, the options that can be practically used are regression adjustment (RA) and inverse probability weighting (IPW), and combination between RA and IPW. Because basically, the choice of applying RA and IPW in the assessment of multivalued interventions has consequences both theoretically and empirically. Theoretically, RA has a disadvantage, namely the RA estimation technique produces a combination of factors that have a positive and negative impact on the outcome of a treatment, and therefore RA will be difficult to properly estimate the effect of the treatment, whereas empirically, in the case of this study, the RA technique requires observation, which is sufficient at each level of treatment to produce a standard deviation in the estimation process and the problem in this case study for level 7 treatment has no standard deviation because it only appears once in the variable treatment observation, namely totalagex.

Table 1: Papua New Guinea Agricultural Extension Program

No	Agricultural Extension Program Received	Variable
1	New Crops	Agex 1
2	Improved seeds	Agex 2
3	Fertilizer	Agex 3
4	Advise fertilizer application	Agex 4
5	Advice insect infestations	Agex 5
6	Advise crop diseases	Agex 6
7	Advise treat or prevent livestock disease	Agex 7
8	Advise livestock for an improved breed	Agex 8

There will be nine indicators for AGEX variable. On the second step, I estimate the following equation:

$$\widehat{LnQ_{pi}} = \beta_0 + \beta_1 Ln(Land_i) + \beta_2 LnLabor_i + \frac{1}{2}\beta_3 Ln(Land)_i^2 + \frac{1}{2}\beta_4 (LnLabor)_i^2 + \beta_5 Ln(Land).Ln(Labor) + v_i - \mu_i \quad (2)$$

$\widehat{LnQ_{pi}}$ is the predicted value of crop production from equation 1, Land is the land owned for planting the crops, labor is the number of working farmers and from the equation 2, we measure the technical efficiency score. The i-th farmer's technical efficiency is determined by the ratio of the observed output to the potential output, as determined by the frontier function, given the input vector Xi (input variables) by following equation:

$$Eff_i = \frac{LnQ_i}{exp(X_i\beta)} = \frac{exp(X_i\beta - \mu_i)}{exp(X_i\beta)} = exp(-\mu_i)$$

The third step, is estimating the determinants of farmer's production efficiency (Eff) the model as follows:

$$Eff_i = \gamma_0 + \sum_{j=1}^{5} \gamma_{ij}\, NATDIS_i + \sum_{k=1}^{6} \delta_{ik} HHcha_{ik} + \theta_6 LAI_i + \theta_7 HCAI_i + \theta_8 Assoc_i + \sum_{l=1}^{3} \rho_{il}\, DP_i + \varepsilon_i \quad 4$$

Where NATDIS is the natural disaster score (drought or irregular rain, floods, earthquake, landslides, damage by insects) experienced by the farmers (total value of dummy variable score of each type of natural disaster, 1 if experience and 0 otherwise). If experiencing 5 types of natural disasters and felt to affect farmer productivity then this variable is worth 5 or the maximum score but if experienced and not significant the impact is felt on the productivity of respondents then it is worth 0.The NATDIS variable ensures that natural disasters experienced by farmers have an impact on agricultural productivity because of the interaction between the experiences of natural disasters experienced by farmers and their perceived impact on farmers' productivity. Model simulations were also carried out to see which natural disaster most affected farmers' efficiency in production, the NATDIS variable was decomposed into NATDIS 1 (Drought and irregular rain), NATDIS 2 (Floods), NATDIS 3 (Earthquake), NATDIS 4 (Landslides), and NATDIS 5 (Crops damaged by insects). Edu is the education level of household head, Age is the age of household head, Child is the number of kids, LAI is the lack of agricultural inputs such as seeds and fertilizer, etc) which is dummy variable, 1 for if farmer has a problem of lack agricultural inputs, and 0 otherwise, HCAI represents for high cost of agricultural inputs experience by the farmers which is also dummy variable, 1 when farmer experienced high cost of agricultural inputs, 0 otherwise, Assoc denotes association and it is1 if farmer joins with any agricultural, industry, and tourism association that connects their agricultural businesses to other farmers, industry or business, and tourism, DP is dummy for provinces.

Table 2: Descriptive Statistics of Variables

Variable	Obs	Mean	Std. dev.	Min	Max
Labor	633	12.63	16.35	1	288
Total Disaster Score	633	2.33	1.16	0	5
Education	633	7.48	2.91	0	14
Total Land	633	38.18	33.53	81	276412
Total Production (Kina)	633	604.72	1236.9	4.9	9863.7
Total Production (Kg)	633	283.79	622.82	3	4414
High Cost Agricu. Input (HCAI)	633	0.15	0.36	0	1
Lack of Agri. Input (LAI)	633	0.17	0.38	0	1
NATDIS 5 (Crop Damaged by insect)	633	0.75	0.43	0	1
NATDIS 4 (Landslide)	633	0.30	0.46	0	1
NATDIS 3 (Earthquake)	633	0.09	0.29	0	1
NATDIS 2 (Floods)	633	0.60	0.49	0	1
NATDIS 1 (Drought and irregular rain)	633	0.58	0.49	0	1
totalagex	633	0	1.22	0	8
ag_assoc (Agricultural Association)	633	0.15	0	0	1
Marstat (Marital Status)	633	0.94	0.24	0	1
sex	633	0.08	0.28	0	1
age	633	41.78	11.26	21	77
Childer (Number of Children)	633	3.36	2.0422	0	11

4. **Results and Discussion**

Stage 1 estimation results, as reported in Table 3 , show that agricultural extension is positively significant to the total output, both the total value and the total weight of the harvest.

As for the IPW technique, the problem faced is the issue of stability and overlapping. Stability issues namely it’s feasible that certain forecasts will be close to zero when we fit our logistics or probit model to get the anticipated probabilities. The weight increases arbitrarily as the likelihood approaches zero because the IPW is the reciprocal of that probability. The IPW may become unstable in those circumstances. We are utilizing weighted means to estimate the Potential Outcome Means (POMs) and Average Treatment Effect (ATE), which is another drawback of the IPW estimator. As a result, unlike the RA estimator, we are unable to forecast treatment effects or probable outcomes at the subject level since we lack the two regression lines needed to do so. The problem with the two estimation techniques, RA and IPW, is also encountered in this study where the resulting RA estimate does not get a standard deviation level 7 treatment because only 1 observation has it, while the IPW approach also faces overlap problems for treatment levels 7 and 8. Therefore, in this study the RA technique is more appropriate to use because less information is lost in decision making. If seen in table 4, the effect of the extension program significantly affects production and if these impacts are accumulated in total, the potential outcome averages 5.3 percent of the total value of production and 4.6 percent of the weight of production.

Table 3: Estimation Results of The Effects of Totalagex on Total production

Variable: lntotalprod		
ATE totalagex	Kina	Kg
(1 vs 0)	-0.1147	-0.0941
	(-0.1597)	(0.1754)
(2 vs 0)	0.6725***	0.6524***
	(0.2138)	(0.2253)
(3 vs 0)	-0.0709	0.0570
	(0.4360)	(0.4481)
(4 vs 0)	1.9827***	2.1041***
	(0.1559)	(0.2333)
(5 vs 0)	0.3462	0.2658
	(0.6218)	(0.6738)
(6 vs 0)	0.6251***	1.3562***
	(0.0807)	(0.0783)
(7 vs 0)	-0.0085	0.2687
(8 vs 0)	2.2103***	2.4392***
	(0.1260)	(0.1385)
POmean	5.3840	4.4639
totalagex	(0.0583)	(0.0621)
Obs	633	633

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The prediction results from the estimated value of the effect of the extension program on total production in both Kina and Kg currency units are used as a total production variable in the production function analysis stage, namely efficiency analysis in the Stochastic Frontier Analysis scheme. The standard model used in this technique applies the form of a translogarithmic model considering that the estimation results show a quadratic shape and the interaction variables between input variables are statistically significant because this model form is more feasible than the standard Cobb-Douglas model.

The estimation stage of the production function is used to see the level of efficiency or productivity of farmers where the unit of production used is the same as the analysis in the previous stage, namely Kina and Kg. Table 4 provides a summary of the production model estimates. At this stage, the translog function is used by entering quadratic variables for input and input interaction variables. Tipi et al (2021) argue that one of the bases that can be used to see which model is most suitable for the Stochastic Frontier model is the Wald test where if the results are significant in the estimation of the translog model then the translog model can be selected in the model. Table 5 shows that the Wald test values for both models in Kina and in Kg are statistically significant so that the translog model is chosen to estimate efficiency.

Table 4: Production Function Estimation Results (Stochastic Frontier Model)

	Lntotalprod	
Variables	Kina	Kg
Ln (labor)	0.1646***	0.2088***
	(0.0586)	(0.0662)
$(\text{Lnlabor})^2$	-0.0295**	-0.0323**
	(0.0137)	(0.0144)
Ln (Land)	0.1504***	0.1402***
	(0.0181)	(0.0194)
$(\text{LnLand})^2$	-0.0098***	-0.0092***
	(0.0016)	(0.0017)
LnLabor.LnLand	0.0709***	0.1084***
	(0.0180)	(0.0211)
lnsig2v	-4.8618***	-3.7781***
	(0.3843)	(0.1975)
lnsig2u	0.2268***	-0.1672***
	(0.0608)	(0.0656)
sigma_v	0.0879	0.1512
	(0.0169)	(0.0149)
sigma_u	1.1200	0.9197
	(0.0340)	(0.0301)
sigma2	1.2623	0.8688
	(0.0756)	(0.0546)
lambda	1.2734	6.0826
	(0.0412)	(0.0365)
Obs	633	633
LR test Sigma u	5.3	3.8
Wald Test (Chi)	825	702

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The estimation results of the production function of labor input and land area show a quadratic pattern with the coefficient values of the two quadratic variables being statistically significant (Inlabor2 and lntotaland2). In addition, from the estimation results it is also known that the total coefficient of the estimation of the two models is 0.4 for Kina and 0.62 for Kg. This means that farmers' production shows decreasing returns to scale.

Table 5: Summary Statistics of Technical Efficiency Scores

Variable	Obs	Mean	Std. dev.	Min	Max
Efficiency 1 (Kina)	633	0.6205	0.1948	0.0126	0.9682
efteffect 2 (Kg)	633	0.6208	0.1902	0.0290	0.9565

The results of the calculation of the technical efficiency values are shown in table 5. The efficiency score shows how farmers use the resources they have. The closer to 1 the more efficient the agricultural production process and conversely the closer to 0 meaning that less efficient the production process. The efficiency values range from 0.01 to 0.96 for the production value in Kina and 0.02 to 0.95 in Kg. if you look at the average value of the two is almost the same, namely 0.62. The Efficiency score of most of the observations is at a value of 0.62 for both models. This is very clearly seen in Figure 1.

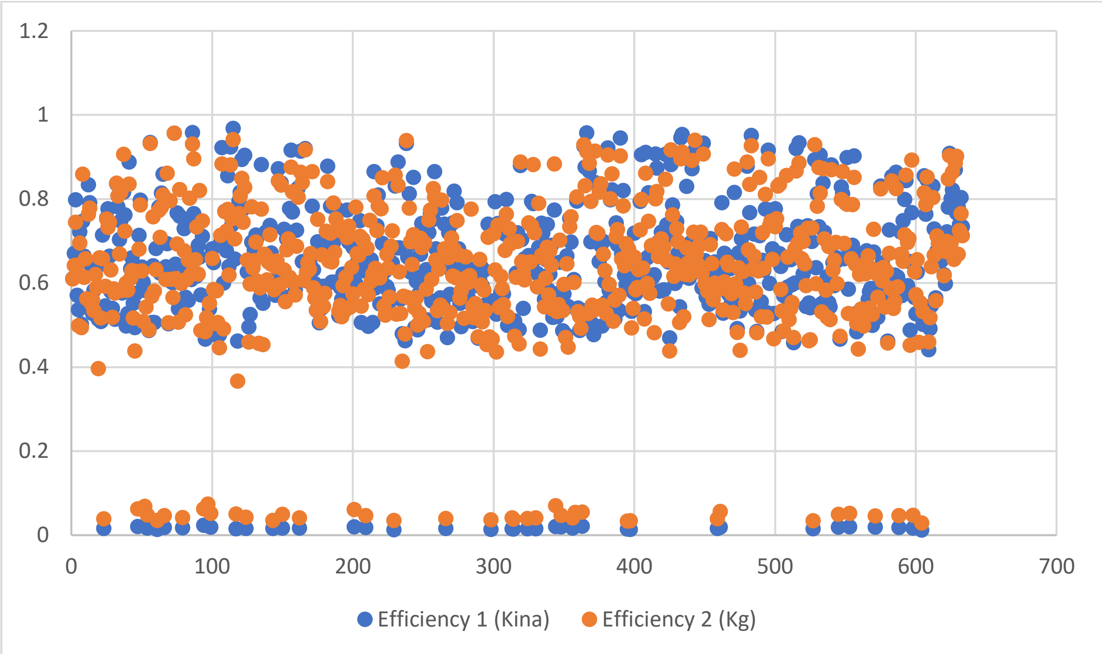

Figure 1: Distribution of Technical Efficiency Score

After getting the efficiency score in the previous stage, the next estimation stage is aimed at seeing how the influence of several types of natural disasters (NATDIS) has on the technical efficiency score. The estimation results are summarized in table 6. Based on the results of robust regression estimation, the variable NATDIS 1 or drought and irregular rain. the level of efficiency that is affected by the level of drought or rainfall is supported by previous studies including Gallardo et al (2019), Ray et al (2018), and Manning et al (2021) which show that drought has an impact on reducing agricultural productivity. Climate change that results in changes in rainfall or drought in PNG can have serious long-term impacts considering the trend of worsening world environmental conditions. The World Bank (2021) reported that meteorological (often connected with a deficit in precipitation) and hydrological (typically associated with a deficit in surface and subsurface water flow, sometimes originating in the area's wider river basins) droughts are the two main types that may affect PNG. According to a standardized precipitation evaporation index (SPEI) of less than 2, PNG currently faces an annual median likelihood of severe meteorological drought of roughly 4%. Previous instances of drought in PNG have resulted in major disasters, with a prominent drought in 1997 causing a widespread famine.

Food production will be impacted by climate change through both direct and indirect effects on crop growth cycles. Modifications to precipitation, temperatures, and carbon dioxide availability are examples of direct effects. The advent of invasive species, changes in pest and disease profiles, soil erosion, the transformation of soil organic matter, and a loss in arable areas as a result of coastal lands becoming submerged are examples of indirect consequences. According to the UNDP's 2018 assessment, 70% of PNG households are still reliant on subsistence farming. These areas are particularly at risk from climate-related dangers. Due to a severe drought brought on by ENSO in 1997, which affected over a million people (about 20% of the population), the country's food insecurity was brought to light.

According to PNG's Second National Communication to the UNFCCC, 63% of the calories consumed in rural areas come from the production of sweet potatoes, making this country's people highly reliant on this crop. In light of this, it is noteworthy that a review of several research found that the effects of climate change may cause a 10% drop in sweet potato yields in PNG by 2050.

Table 6: Determinants of Technical Efficiency

	Efficiency	
Variable	Kina	Kg
Marital Status	0.6414***	0.6011***
	(0.0091)	(0.0102)
Sex	0.0078	0.0135
	(0.0079)	(0.0089)
Agricultural Association	-0.0021	0.0012
	(0.0051)	(0.0058)
children	0.0003	-0.0009
	(0.0011)	(0.0012)
Age	0.0075***	0.0079***
	(0.0011)	(0.0013)
Age2	0.0000	-0.0000
	(0.0001)	(0.0000)
Prov		
East Sepik Province	0.0522***	0.0521***
	(0.0055)	(0.0063)
Madang Province	0.1323***	0.1434***
	(0.0058)	(0.0066)
Sepik (Sandaun) Province	0.2027***	0.2195***
	(0.0062)	(0.0070)
LAI (Lack of	-0.0004	-0.0008
	(0.0052)	(0.0059)
HCAI (High Cost of Agri. Input)	-0.0066	-0.0097
	(0.0054)	(0.0061)
NATDIS 1 (Drought and irregular rain)	-0.0144***	-0.0098***
	(0.0038)	(0.0044)
NATDIS 2 (Floods)	0.0047	0.0048
	(0.0045)	(0.0051)
NATDIS 3 (Earthquake)	0.0087	0.0059
	(0.0063)	(0.0071)
NATDIS 4 (Landslides)	0.0028	0.0013
	(0.0046)	(0.0052)
NATDIS 5 (Crop damaged by insect)	0.0090	0.0095
	(0.0043)	(0.0049)
educ	-0.0008	0.0168
	(0.0006)	(0.0007)
_cons	-0.3936	-0.4746
	(0.0268)	(0.0302)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Natural conditions that show an increasingly uncertain trend and this is supported by many studies and empirical data, mean that the potential impact that will occur is also more difficult to predict but what is certain is a negative effect for people whose lives depend on natural conditions such as farmers. Based on the World Development Indicators from The World Bank, it shows that more than half of the total workers, in 2019, work in the agricultural sector (56.15 Percent). Of course, this is quite risky for the welfare of society, especially farmers. Environmental-based policy interventions need to be carried out intensively to reduce risks or for the recovery of workers in the agricultural sector. Agricultural extension programs must be provided appropriately according to the needs of farmers not only for the short term but for the sustainability of the agricultural sector.

5. Conclusion

This study aims to see how extension programs for farmers have an impact on agricultural production and see how natural disasters have a negative impact on farmer productivity. These two factors which have opposing effects are analyzed to see how natural disasters which a global natural phenomena have a negative impact on the welfare of farmers. On the other hand, efforts need to be made to reduce the effect of reducing the productivity of these farmers with an extension program. The current program needs to be accompanied by the application of a sustainable development framework which is an attempt to improve human relations with nature.

The extension program for farmers has proven to be effective in increasing the productivity of farmers and this is certainly good for increasing the welfare of farmers. The implementation of this extension program must be carried out innovatively and implemented on a broad scale in order to increase farmer productivity in uncertain natural conditions. Furthermore, extension programs are also important to be directed to programs that support productivity and sustainability. On the other hand, natural conditions that have a negative impact on farmers need special attention to be overcome. Most of the workforce in PNG is still alive and dependent on the agricultural sector so that efforts of extension program to protect the negative impacts of natural disasters must be carried out in a comprehensive and sustainability-oriented manner. Based on the results of a literature review, the results of studies in other countries show that extension programs such as Disaster Risk Reduction not only increase agricultural productivity but also increase the capacity of farmers to natural disasters, starting from small to medium local scales. Therefore it is necessary to plan an extension program that is environmentally oriented to prevent natural disasters and increase the welfare of farmers.

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