Utilizing Province Level Data to Predict Provincial Rice Production Levels By Quarter

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Abstract

Rice is a staple food source for south, east, and southeastern Asian countries, especially for the Philippines where 3-4% of the country's GDP is focused on rice production. However, production of rice in the Philippines is sensitive as the crops require stable climates and vast amounts of labor. Coupled with increasing global climate change issues and changing socioeconomic situations, modeling rice production is a complicated challenge. This paper proposes a benchmark that models the rice production of every province in the Philippines with GDP statistics, El Niño 3.4 sea surface temperature, and harvested area information. This work aims to forecast production with accessible features and removes the need to predict features prior to forecasting production, all while accounting the impacts of climate changes. Our findings show clear observations from the experiments between FCNN and RNN models. We find that Recurrent Neural Networks provide the best forecasting accuracy with a Mean Average Error of $5,699 \pm 116.54$ metric tons. In certain cases, MAE can reach as low as $2,892.74 \pm 52.99$ metric tons.

1 Introduction

Filipinos regard rice as an important foodstuff and consume roughly 119 kg of rice per year per capita [1]. 3-4% of their GDP is placed on rice production alone [2, 3]. The Philippine government is taking steps to secure and bolster their production of rice in order to curb dependencies on other nations [4, 5]. This includes investing resources in forecasting rice production based on historical meteorological and economic events.

One major factor that is used for crop production modeling is the El-Niño sea surface temperature (SST). Studies have shown that changes in the El Niño region causes major weather changes, leading to effects on agricultural output volume. [6]. There are many other factors to account for when modeling the production of crops in any other country. Such features include specific fine-grain weather data [7], satellite imagery [8], and solar imaging [9]. Moreover, climate change plays a critical feature that increases the complexity of the features as crop production is modeled [10, 11].

However, developing countries generally do not have the resources or the capabilities to attain such a wide variety of information. Further, some countries don't have the luxury of utilizing long-term historic information, specific for their regions. This proposes a challenge where efficient rice production forecasting is a necessity to aid developing countries on farming policy making.

Our paper provides contributions towards rice production forecasting for the provinces of the Philippines, and by extension, to other crop types and countries as well. This work also provides a dataset compilation and model training framework to dynamically generate agriculture production datasets based on any time interval (e.g., quarterly, monthly, yearly), administrative level type (e.g., municipalities, provinces, regions, counties, etc.), and data source (e.g., GDP statistics, Funding to agricultural sectors, weather data, etc.). Lastly, we provide an analysis on various modeling and data pre-processing techniques that show differences modeling performances. The impact of this work isn't limited to the Philippines, but to other developing countries where specific data is scarce or expensive, and where climate change can be factored in while working with the aforementioned consideration. Refer to Section 9 for access to the source code and dataset of this work.

2 Related Work

Agricultural yield and production forecasting is a growing research field. Stakeholders, mostly governmental agencies, have motivations to explore various modeling approaches as means to provide better policy and decision making [12, 13]. This concern is mostly rooted from possible events of crop failures or forecasted natural disasters.

Researchers have used various statistics to forecast agricultural production and yields. Vegetation Index [14, 15, 16, 17, 18], regional weather [19, 7, 20, 21, 22], and Earth observation data from satellites [8, 23, 24, 25, 26] are amongst the many features used to forecast agricultural outputs. Models developed from these data sources are effective in providing accurate and reliable forecasting.

However, obtaining these data points is difficult. This is largely due to the prerequisite of heavy investments in qualitative data collection, technology, and operations; expenses that developing countries cannot fit into their budgets. Furthermore, climate change affects the way that these variables are accounted into by increasing the complexity of variables towards the output volumes of crops. For example, El Nino seasons had greater impacts on global climates, causing increased natural disasters and ultimately changing regional economies [27]. Factors like this makes climate change more intertwined to other factors, making modeling crop production a more complicated task.

A key factor for production modeling is usage of the El-Nino sea surface temperatures. Multiple studies have shown that rice production forecasting can be done with this type of meteorological data. In fact, some of these models are in use today to forecast the Philippine's rice production [28, 29, 30]. However, none have incorporated economic factors in their models. This is a key feature to consider when forecasting agricultural output, especially with rice, as a country's economic health drastically affects farm production [4].

3 Proposed methodology

For this work, we propose on doing two items: **1)** making a dataset framework that can intake other data sources and turn into a dataset dynamically, and **2)** testing the performance of fully connected neural networks (FCNNs) and recurrent neural networks (RNNs) on the dataset. For the dataset, this work will combine difference sources of information and create different "context-windows" to provide historic information that can aid models in their inference. For testing it, this work will utilize the stratified splits of the compiled dataset and train the models over it. For information, refer to Section 4.

4 Experimentation Setup and Results Discussion

4.1 Data Source Information

The Philippines is composed of 82 different provinces. To properly model rice production, this work forecasts a province's rice output in **metric tons (mt)** for a given fiscal quarter and set of input data (e.g., GDP statistics, area harvested, and El Niño temperature readings). This work uniquely identify each sample via its province, year, quarter, and crop type. There are only two crop types, rainfed and irrigated rice.

4.1.1 GDP Statistics

The GDP statistics was pulled from the Philippine Statistics Authority's (PSA) open source database [31]. This study shares the values of the nation's GDP across all provinces. In other words, even if two provinces are different, but have the same year and quarter, they will have the same GDP value. The data spans from 1981 to 2024 and breakdowns GDP by different three expenditures: Agriculture, forestry, and fishing (AFF), industry, and services. This work focuses on using GDP statistics on AFF. The total amount of data points in this dataset is 172 at a quarterly resolution for the whole nation. The units reported from this data source is in **million Philippine Pesos (M₱)**.

4.1.2 Rice Statistics

Information regarding the production level and area harvested for rice farms were pulled from the same open source dataset by the PSA [32, 33]. This data breaks down rice production by provinces and by fiscal quarter from 1981 to 2024. The total amount of data points in this dataset is roughly around 25,232 samples with the amount of rice harvested in **metric tons (mt)** and the area harvested in **hectares (ha)** for every unique keyset. The rice harvested is part of the features, while the rice output volume information constitute the label of the dataset.

4.1.3 El Nino Sea Surface Temperature (SST) Data

For El Niño SST statistics, this work focuses on the SST of the El Niño 3.4 region. This information is provided by the NOAA National Centers for Environmental Information [34] and is reported in **degrees centigrade (C$^{\circ}$)**. The NOAA provides data at a higher resolution at a per month basis compared to data provided by the PSA. Because of this, a quarterly aggregration is applied to represent the average SST for the corresponding year and quarter. In other words, Quarter one for any will contain sea surface temperature from the months of January, February, and March. Quarter 2 has the months of April, May, and June, so on and so forth. The data provided by the NOAA has roughly 516 datapoints starting from 1981 to 2024.

4.2 Data Source Licensing

Data acquired from the PSA, [31, 32, 33] were obtained under a Creative Commons (CC) BY license. Data acquired from the NOAA [34] were obtained under the same CC-BY license. Per CC-BY, the data is available to the public for use and remix, allowing this work to publish datasets based on these data sources. Refer to Section 9 for directions to the datasets of this work.

4.3 Data Source Values Overtime

The following figures show the mean AFF GDP, El Nino 3.4 SST, area harvested, and rice production over time across all provinces. An additional yield timeline graph is also provided to show the change in yield overtime.

Trends over time show a distinct rise in AFF GDP, area harvested, and rice production volume. This is most likely due to the higher agricultural, forestry, and fishery expenditures that allowed farmers to obtain more land, allowing for more production outcomes. Coupled with advancements in farming technology, the "same" area harvested yields more output volume as shown in Figure 5. Furthermore, The fourth tends to have higher production output compared to other quarters. This is held by the fact that expenditure for agriculture increases as well during the fourth quarter.

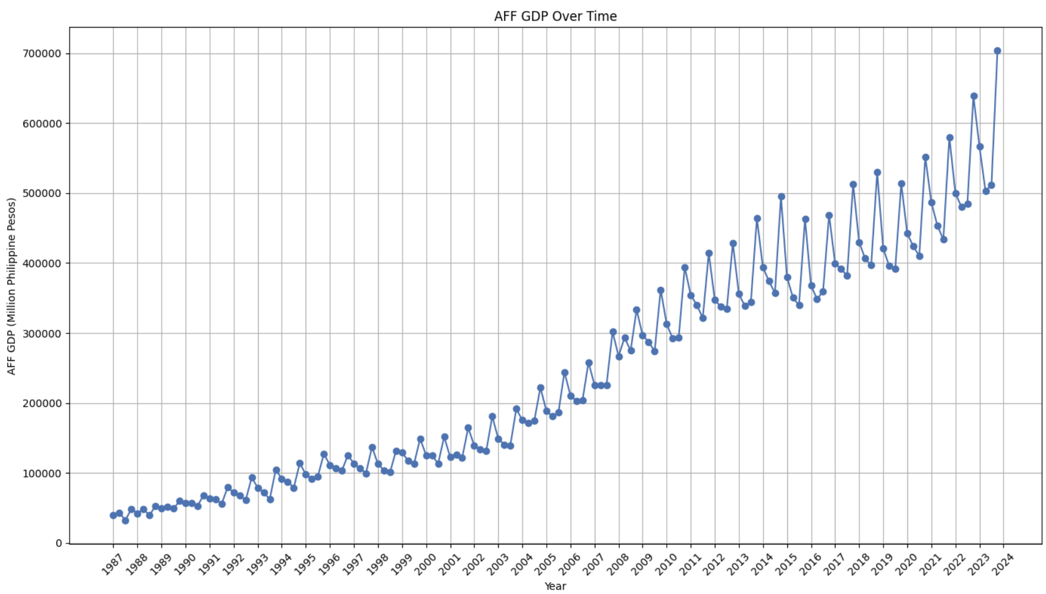

Figure 1: Timeline plot of the AFF GDP from 1988-2024

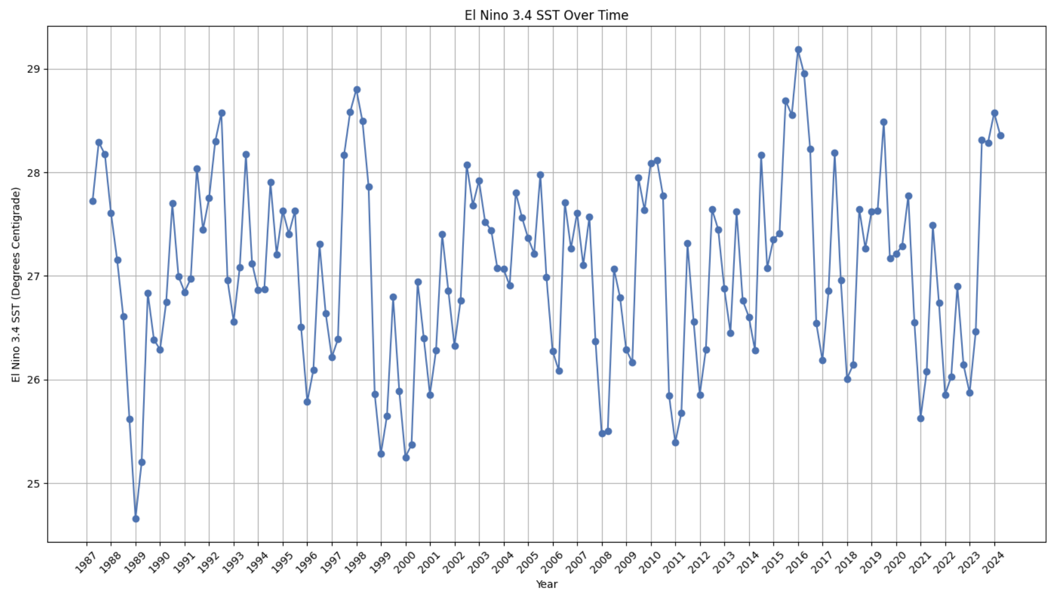

Figure 2: Timeline plot of the El Nino SST from 1988-2024

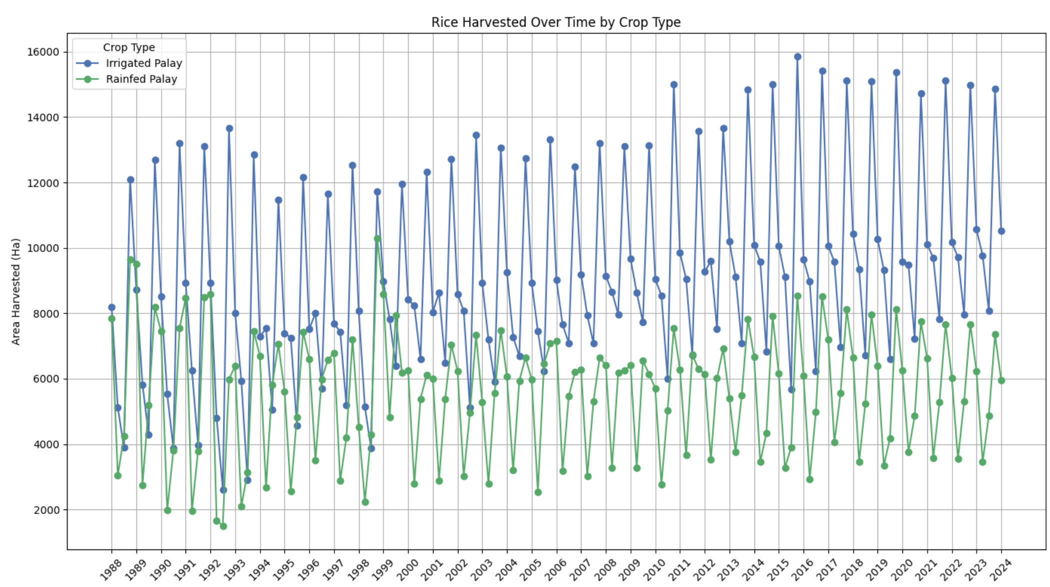

Figure 3: Average timeline plot of the area harvested from 1988-2024 with the different crop types specified in two different lines

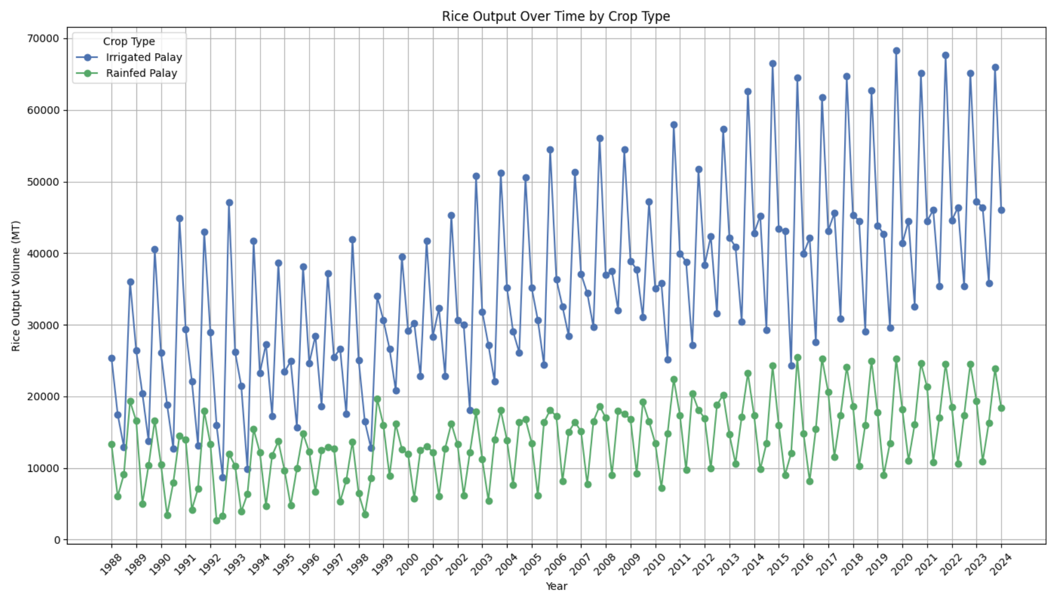

Figure 4: Average timeline plot of the amount of rice produced from 1988-2024 with the different crop types specified in two different lines

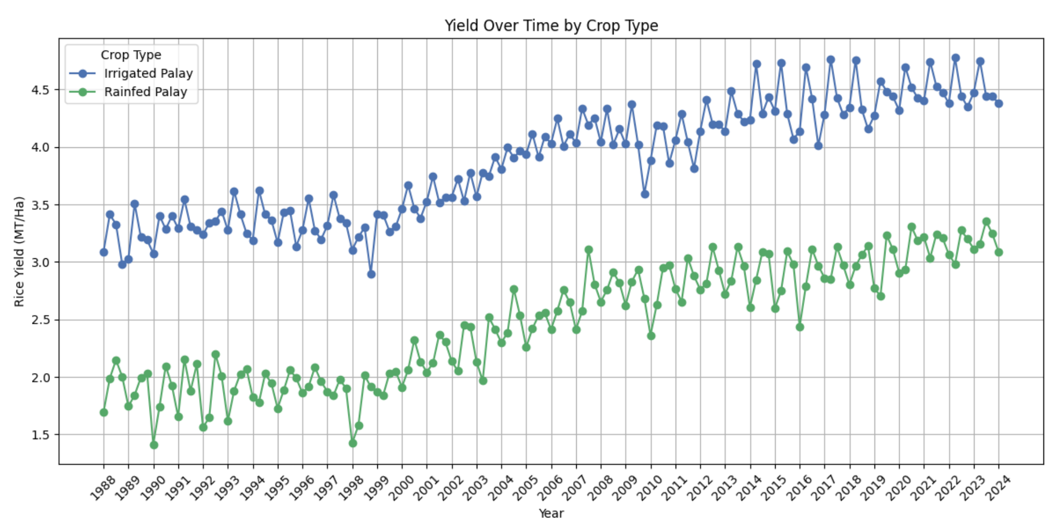

Figure 5: Average timeline plot of the rice yield from 1988-2024 with the different crop types specified in two different lines. This statistic is not used during training or evaluations.

4.4 Province Distribution and Information

Rice statistics provided by the PSA [32, 33] does not contain equal number of samples for all provinces. This is due to some provinces starting rice production surveillance after 1987 or did not track rice statistics in different time periods. Additionally, different crops were tracked at different times as well. Figures 6 and 7 contains a distribution of the provinces, including the start time of the first sample surveyed.

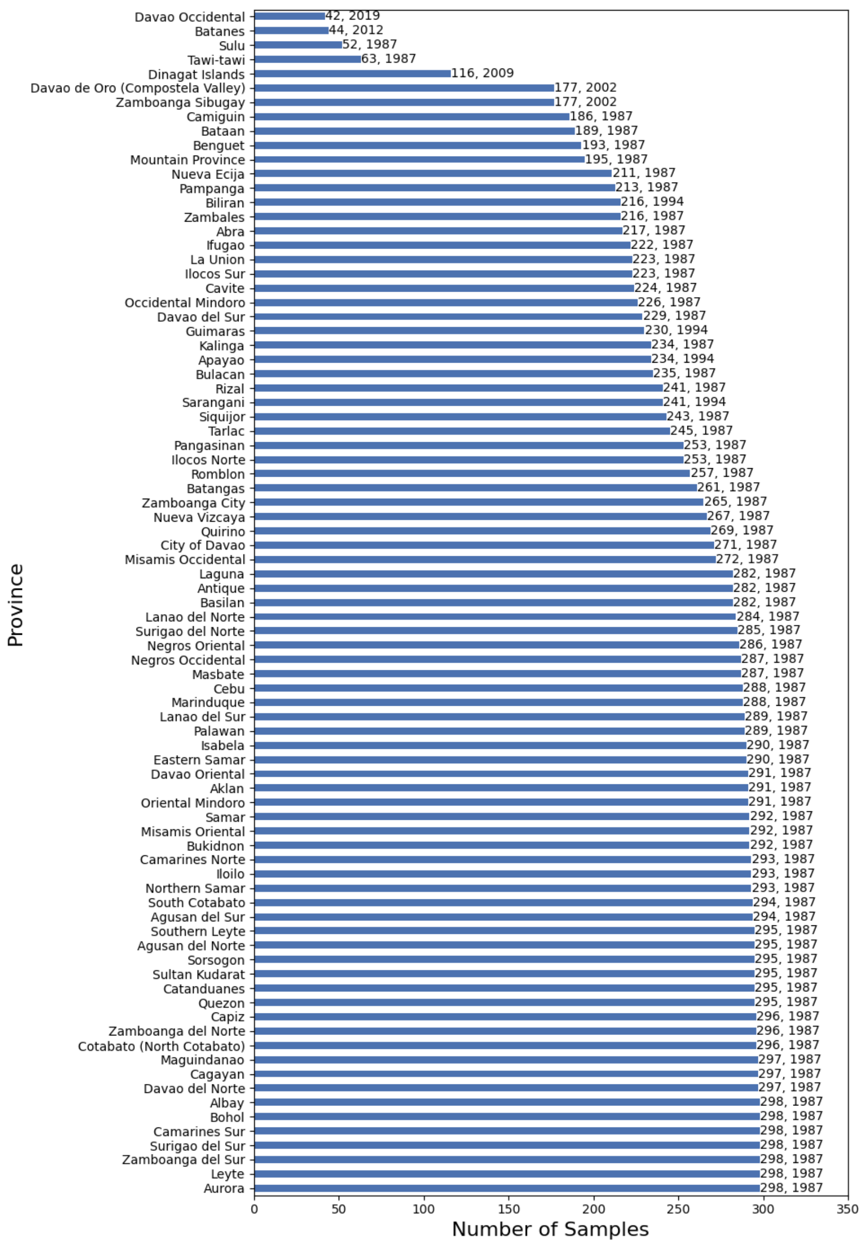

Figure 6: Distribution of samples provided by the PSA. Values to the right of the bars hold two values: amount of samples and the year the province started tracking rice production, respectively.

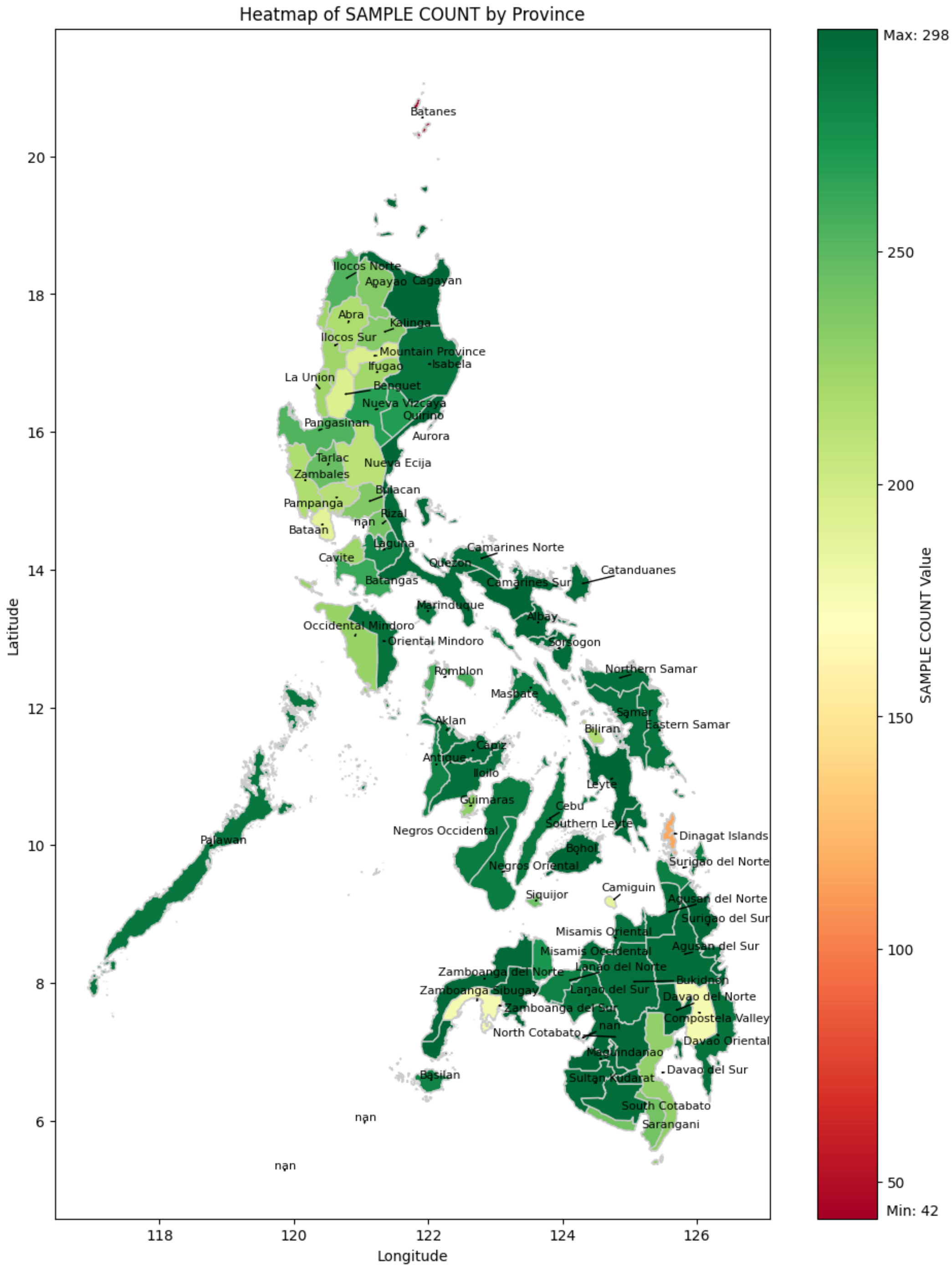

Figure 7: Heatmap distribution of samples in provided by the PSA

In addition, some municipalities are included in the data source and some provinces were excluded. The PSA rice information included the City of Davao and Zamboanga City as a province, despite them being a city. Sulu, Shariff Kabunsuan, Tawi-Tawi, and Metropolitan Manila were the provinces excluded from all data sources related to rice statistics.

4.5 Structure

4.5.1 Context Window (CW)

Various datasets were compiled with varying context windows. For example, if a context window of six quarters is specified, the dataset framework generates features with six previous quarter items. In other words, if the sample requires six previous quarter items, the GDP statistics would be structured as $\{GDP_{Q_n}, GDP_{Q_{n-1}}, GDP_{Q_{n-2}}, \ldots, GDP_{Q_{n-5}}\}$ where Q_n is the target quarter to forecast the rice production and Q_{n-i} is the ith quarter behind the target quarter. To accurately model use cases where the GDP and the aggregated El Niño SST readings are not available during the targeted quarter, we omit the Q_n data from the dataset. This is not the case for Area harvested as this is a required statistic for production estimation and can be easily determined ahead of time via surveys and inquiries from farmers. The datasets can either be represented in one instance for fully connected neural networks or in sequential format (time steps, features) for recurrent neural networks.

4.5.2 Pre-Processing

Samples were removed if they contained any empty or zero values. A label encoding was applied to categorical features to mitigate the number of extra features needed to represent samples. Lastly, a Z-Score normalization was applied to all columns of the dataset.

4.5.3 Dataset Stratification

Datasets are split into three versions, training, validation, and testing in a 60-20-20 ratio, respectively. This data is split by their year and quarter. In other words, the training split represents data from 1987 to roughly 2010 with 9,552-11,049 samples. The validation split represents data from around 2011 to 2018 with 3,593-3,921 samples. And the testing split represents values from roughly 2019 to 2024 with 3,799-4,631 samples. In total, there are 16,994 to 19,601 samples with one to six context windows, respectively.

4.6 Example of a Sample in the Datasets

To help conceptualize the context window idea, this section illustrates a sample from a dataset with a context window of four (CW-4). $\mathrm{Q_n}$ denotes the current reference quarter and any subtraction to n indicates the $\mathrm{i^{th}}$ quarter before $\mathrm{Q_n}$. Table 1 is an example of a sample from the Abra province on 1988 Q1 for irrigated rice. The context window of four quarters contextualizes the history of the AFF GDP, El Niño 3.4 SST, and the area harvested by four previous quarter. This means that AFF GDP $\mathrm{Q_{n-1}}$ represents the AFF GDP of the Philippines on 1987 Q4, AFF GDP $\mathrm{Q_{n-2}}$ is the AFF GDP on 1987 Q3, and so forth. For the El Niño 3.4 SST and the AFF GDP data, these features do not contain values for $\mathrm{Q_n}$. This is so that the model is not reliant on predicted features prior to making a forecast as these values are not known prior to the completion of $\mathrm{Q_n}$. However, Area harvested does have a value for $\mathrm{Q_n}$ as it is readily easy to survey the area of rice that is expected to be harvested. The label is represented as a single value to the features in the sample.

Table 2 is another example of the same sample shown above, but structured for RNNs. The number of time steps correlates to the context window, plus one. The difference between this example versus the previous, other than the structure, is the representation of the $\mathrm{Q_n}$ values for AFF GDP and El Niño 3.4 SST. These values are simply represented to 0 as they are not determined during the training and evaluation process. The label for this sample is still represented similar to the previous structure.

Table 1: Depicts the structure of a sample in a CW-4 dataset. This sample structure is used in FCNN models. Rice prediction is boldened as it is a label for the whole sample.

Key Name	Value
Province	Abra
Year	1988
Quarter	1
Crop	Irrigated Rice
AFF GDP $\mathrm{Q}_{\mathrm{n}-1}$	₱48,597.8 million
AFF GDP $\mathrm{Q}_{\mathrm{n}-2}$	₱32,527.7 million
AFF GDP $\mathrm{Q}_{\mathrm{n}-3}$	₱42,938.7 million
AFF GDP $\mathrm{Q}_{\mathrm{n}-4}$	₱39,782.8 million
El Niño 3.4 SST $\mathrm{Q}_{\mathrm{n}-1}$	27.61 C°
El Niño 3.4 SST $\mathrm{Q}_{\mathrm{n}-2}$	28.17 C°
El Niño 3.4 SST $\mathrm{Q}_{\mathrm{n}-3}$	28.29 C°
El Niño 3.4 SST $\mathrm{Q}_{\mathrm{n}-4}$	27.73 C°
Area Harvested Q_{n}	820 ha
Area Harvested $\mathrm{Q}_{\mathrm{n}-1}$	5030 ha
Area Harvested $\mathrm{Q}_{\mathrm{n}-2}$	140 ha
Area Harvested $\mathrm{Q}_{\mathrm{n}-3}$	3210 ha
Area Harvested $\mathrm{Q}_{\mathrm{n}-4}$	240 ha
Rice Production	1379 mt

Table 2: Depicts the structure of a sample in a CW-4 dataset. This sample structure is used in RNNs models. Features are only shown.

Key Name	Value (Q_{n})	Value ($\mathrm{Q}_{\mathrm{n}-1}$)	Value ($\mathrm{Q}_{\mathrm{n}-2}$)	Value ($\mathrm{Q}_{\mathrm{n}-3}$)	Value ($\mathrm{Q}_{\mathrm{n}-4}$)
Province	Abra	Abra	Abra	Abra	Abra
Year	1988	1987	1987	1987	1987
Quarter	1	4	3	2	1
Crop	Irrigated Rice	Irrigated Rice	Irrigated Rice	Irrigated Rice	Irrigated Rice
AFF GDP	₱0	₱39,782.8 M	₱32,527.7 M	₱42,938.7 M	₱39,782.8 M
El Niño 3.4 SST	0 C°	27.61 C°	28.17 C°	28.29 C°	27.73 C°
Area Harvested	820 ha	5030 ha	140 ha	3210 ha	240 ha

4.7 Stratification Discrepancies Based on Context Windows

Stratification of the dataset can incur different time frames for the training, validation, and testing splits. This is because of the definition of the context window and the pre-processing steps prior to stratification. For instance, a context window of six quarters, would start the temporal lower bound around 1988 at Quarter 3. On the other hand, a context window of one quarter would start the temporal lower bound around 1987 Quarter 1. These differences in lower bound brings varying changes to the time frames of the stratified splits. Table 3 illustrates this notion and summarizes the stratification results.

Table 3: Depicts the number of items and the time frame of each split and the entire dataset.

	Train		Valid		Test		Total	
	Count	Time Period	Count	Time Period	Count	Time Period	Count	Time Period
CW-1	11,049	1987-2008	3,921	2009-2015	4,631	2016-2024	19,601	1987-2024
CW-2	10,278	1987-2008	3,765	2009-2015	4,468	2016-2024	18,511	1987-2024
CW-3	9,789	1987-2008	3,688	2009-2015	4,382	2016-2024	17,859	1987-2024
CW-4	10,054	1988-2009	3,640	2010-2016	3,848	2017-2024	17,542	1988-2024
CW-5	9,797	1988-2009	3,616	2010-2016	3,823	2017-2024	17,236	1988-2024
CW-6	9,552	1988-2009	3,593	2010-2016	3,799	2017-2024	16,944	1988-2024

At a context window of four quarters (CW-4), the number of samples in the training set increases to 10,054 samples even though CW-1 to CW-3 decreases overtime. This is because of the full year of information being cut out, allowing for more data to be passed into the training set. In other words, because the time frame changed to 1988-2009, data samples from provinces that started collecting rice production data later in the entire 1987-2024 time frame are passed into the train split, explaining the sudden bump in training samples as the context window increases in length. Section 4.4 explained this notion.

4.8 Model Training

As stated earlier, this work will train over two different model types: FCNNs and RNNs. To accurately test these modeling techniques, this work will first test a set of hyperparameters on the training and validation splits. The hyperparameter configuration with the best Mean Absolute Error (MAE) will be selected for further training where roughly 25 different models intialized on different weights will be trained on the same hyperparameter configuration, training split, and validation split. The objective function for training is the Root Mean Squared Error and the learning algorithm is the AdamW optimizer. Training runs will be conducted over 1000 epochs.

5 Comparison

5.1 General Overview

Utilizing the training and validation splits from various datasets, we train two types of models: FCNNs and RNNs. These models are trained with a Mean Squared Error loss and an AdamW optimizer [35]. Models are first tested on different hyperparameters (e.g., learning rate, hidden sizes, and dropout rate). The hyperparameter configuration with the lowest Mean Average Error (MAE) is then selected to be run 20 times on the same configuration. All 20 of the best models (lowest MAE) respective to their run are then inferenced and evaluated with the testing split.

Table 4: MAE performances (in mt) with varying context windows with 95% confidence intervals. Best performance is bolded.

	RNN	FCNN
CW-1	$8,989.96 \pm 132.01$	$14,469.63 \pm 99.33$
CW-2	$7,929.42 \pm 120.07$	$17,824.06 \pm 108.85$
CW-3	$9,488.00 \pm 136.13$	$17,286.86 \pm 113.63$
CW-4	$\mathbf{5,699.33 \pm 116.54}$	$11,427.26 \pm 99.85$
CW-5	$5,820.41 \pm 116.87$	$10,158.88 \pm 100.93$
CW-6	$6,223.36 \pm 122.20$	$10,564.35 \pm 91.13$

Table 4 illustrates the performance of models trained on varying context windows across all provinces and croptypes. The best performance from this experimentation is with the RNN trained on a dataset with a context window of 4. Performance across all RNN inferences result in better performance than the best configuration and dataset variation for FCNN. This is due to the RNN's ability to handle sequential data easily. In regards to the optimal context window length, a length of 4 or 5 is best to minimize MAE performances.

Table 5 displays performances of the two models across the two types of rice. With a context window length of 2, RNNs achieves better performance on rainfed rice compared its overall performance on a context window of 4 items. As for irrigated rice, the best model for this aspect would be RNNs trained over a context window 4. However, FCNNs fail to provide

Table 5: MAE performances (in mt) based on rainfed and irrigated rice. Best performance is bolded for the respective crop type.

	RNN Rainfed Rice	RNN Irrigated Rice	FCNN Rainfed Rice	FCNN Irrigated Rice
CW-1	$3,515.42 \pm 63.78$	$13,254.13 \pm 223.09$	$9,168.90 \pm 85.49$	$18,613.95 \pm 154.80$
CW-2	$\mathbf{2,892.74 \pm 52.99}$	$11,558.08 \pm 197.20$	$11,221.67 \pm 99.56$	$22,580.73 \pm 161.03$
CW-3	$3,748.11 \pm 70.74$	$13,440.67 \pm 218.25$	$10,921.47 \pm 107.48$	$21,663.52 \pm 166.91$
CW-4	$3,247.70 \pm 73.45$	$\mathbf{7,390.81 \pm 188.76}$	$7,392.49 \pm 90.97$	$14,211.02 \pm 150.85$
CW-5	$3,185.85 \pm 68.80$	$7,613.07 \pm 188.96$	$6,385.04 \pm 78.54$	$12,726.75 \pm 155.86$
CW-6	$3,036.23 \pm 68.49$	$8,363.07 \pm 196.57$	$7,512.54 \pm 82.86$	$12,613.21 \pm 138.64$

any better performance gains even when performances are observed in the two types of rice crops.

5.2 Overall Model Performances

This section includes Root Mean Squared Error (RMSE), R^2, and R^2 Adjusted evaluations on all context windows (CW-1 to CW-6) and on all models of this study (FCNNs and RNNs). Table 6 contains the performances on all crop types, while Tables 7 and 8 shows these evaluations based on each rice crop type.

Table 6: Overall performances of FCNN & RNN models across all context windows (CW-1 to CW-6). Best Performances are bolded for the respective model type.

	RMSE (in mt) ↓		R^2 ↑		R^2 Adjusted ↑	
	RNN	FCNN	RNN	FCNN	RNN	FCNN
CW-1	22,379.43	21,147.88	0.89	0.90	0.89	0.90
CW-2	19,955.13	24,358.29	0.91	0.87	0.91	0.87
CW-3	22,644.84	24,357.18	0.89	0.87	0.89	0.87
CW-4	17,452.32	17,616.59	0.93	0.93	0.93	0.93
CW-5	17,484.75	16,598.92	0.93	0.94	0.93	0.94
CW-6	18,277.97	**16,608.93**	0.93	**0.94**	0.93	**0.94**

Table 7: Overall performances of FCNN & RNN models across all context windows (CW-1 to CW-6) on **rainfed rice**. Best Performances are bolded for the respective model type.

	RMSE (in mt) ↓		R^2 ↑		R^2 Adjusted ↑	
	RNN	FCNN	RNN	FCNN	RNN	FCNN
CW-1	7,442.42	12,703.60	0.95	0.86	0.95	0.86
CW-2	**5,976.72**	14,915.85	**0.96**	0.73	**0.96**	0.73
CW-3	7,784.63	15,058.15	0.93	0.73	0.93	0.73
CW-4	7,394.30	10,750.03	0.94	0.87	0.94	0.87
CW-5	6,949.87	9,111.38	0.95	0.91	0.95	0.91
CW-6	6,818.22	10,534.80	0.95	0.88	0.95	0.88

Table 8: Overall performances of FCNN & RNN models across all context windows (CW-1 to CW-6) on **irrigated rice**. Best Performances are bolded for the respective model type.

	RMSE (in mt) ↓		R^2 ↑		R^2 Adjusted ↑	
	RNN	FCNN	RNN	FCNN	RNN	FCNN
CW-1	29,139.47	25,898.31	0.87	0.90	0.87	0.90
CW-2	25,677.99	22,580.73	0.90	0.87	0.90	0.87
CW-3	28,708.54	29,080.46	0.88	0.87	0.88	0.87
CW-4	21,840.46	21,088.67	0.93	0.93	0.93	0.93
CW-5	21,928.80	20,162.17	0.93	**0.94**	0.93	**0.94**
CW-6	22,960.06	**19,660.78**	0.92	**0.94**	0.92	**0.94**

5.3 Best Performance Overview

This section goes over the performance of the model and CW type combination that achieve the lowest MAE performance, RNNs trained on the CW-4 dataset. As stated above, the performances listed here are observed by inferencing the models on the testing split.

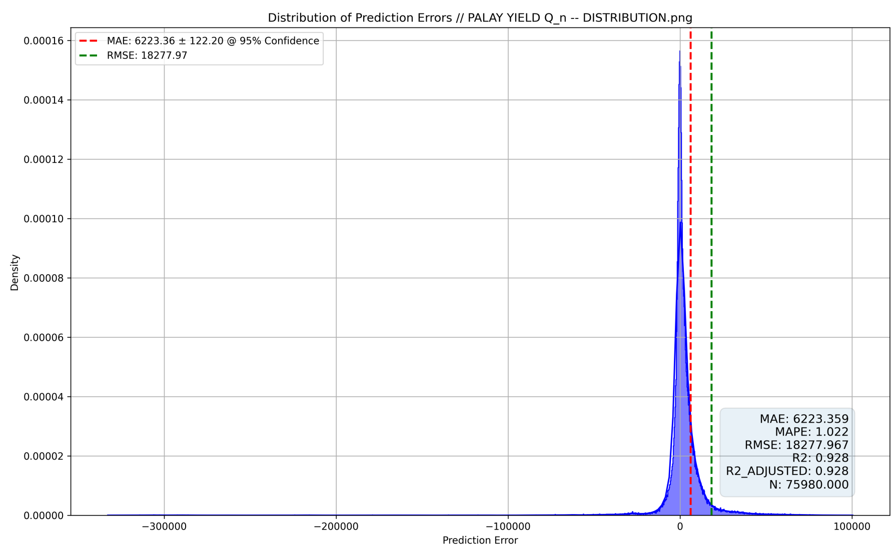

Figure 8: Distribution plot model errors with additional performance details. Read dashed line indicates model's MAE performance and green dashed line indicates RMSE model performance.

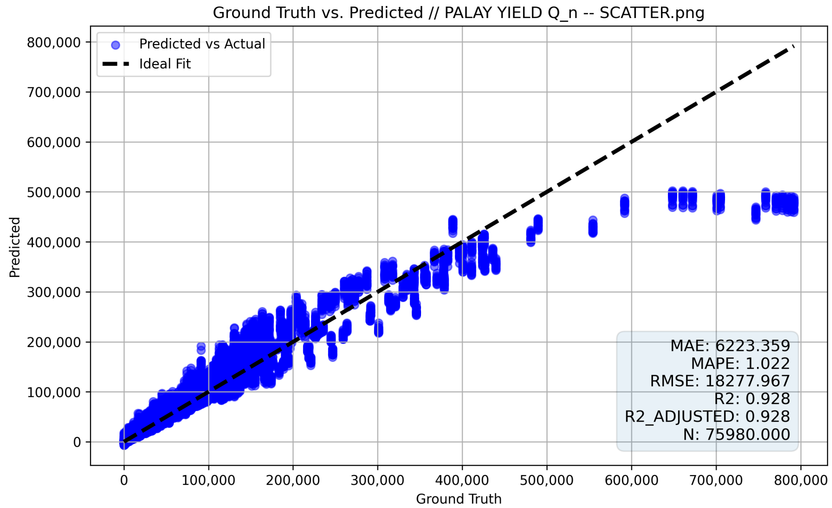

Figure 9: Scatter plot of each model's prediction. The black dashed line is the ideal fit of the model on such datapoints.

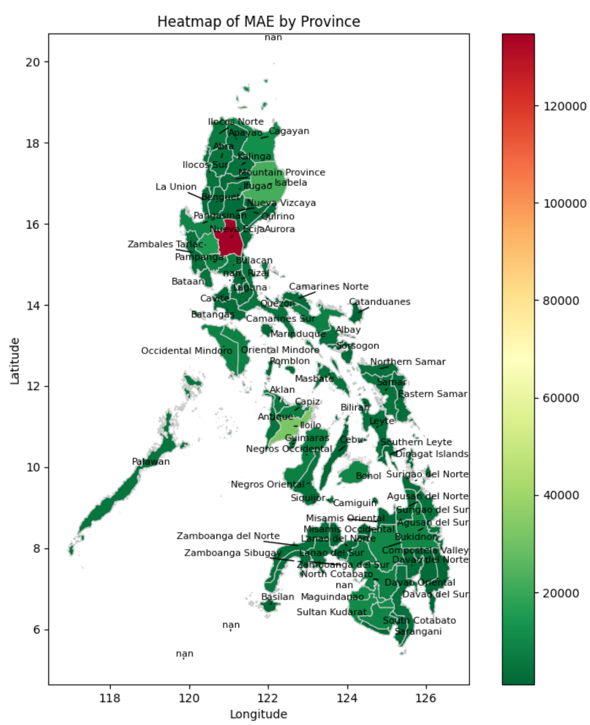

Figure 10: MAE of the models by each province in the Philippines.

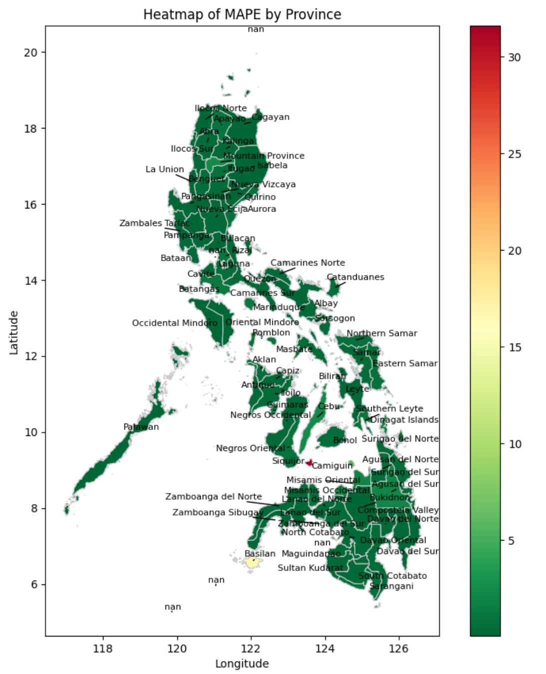

Figure 11: MAPE of the models by each province in the Philippines.

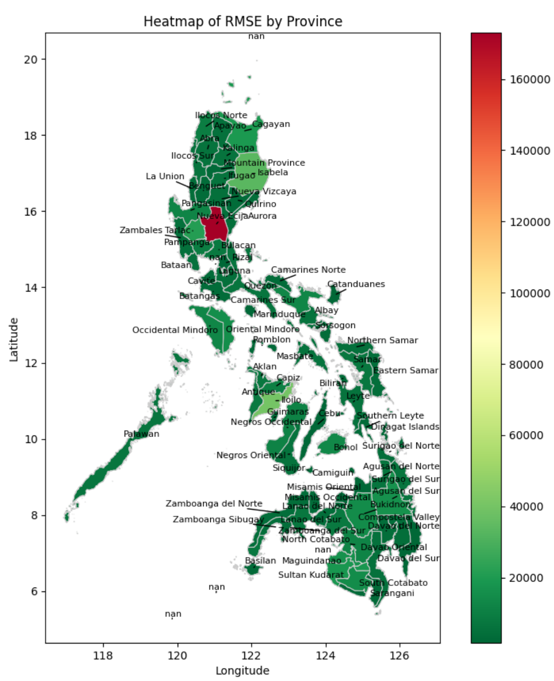

Figure 12: RMSE of the models by each province in the Philippines.

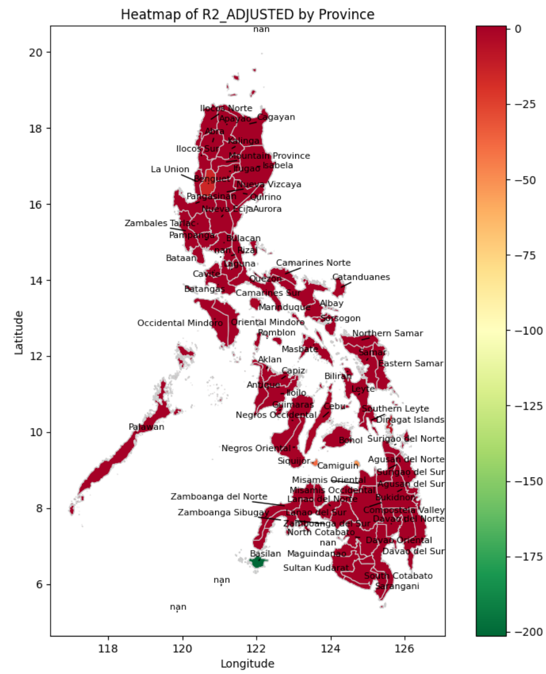

Figure 13: R^2 of the models by each province in the Philippines.

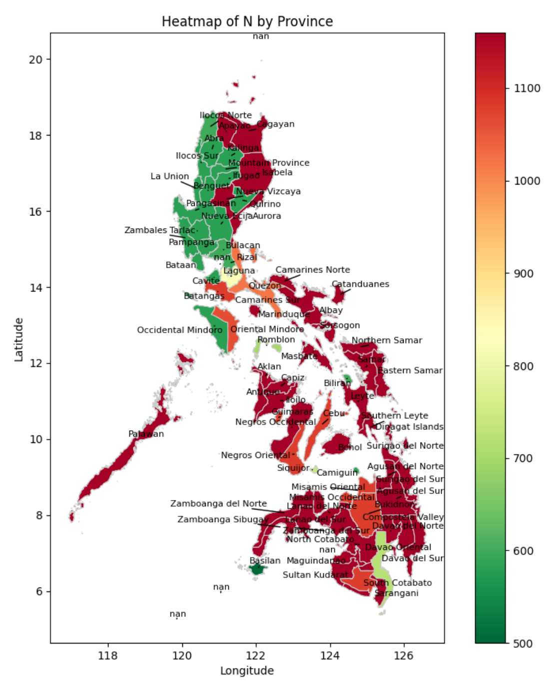

Figure 14: Number of samples conducted for each province in the Philippines.

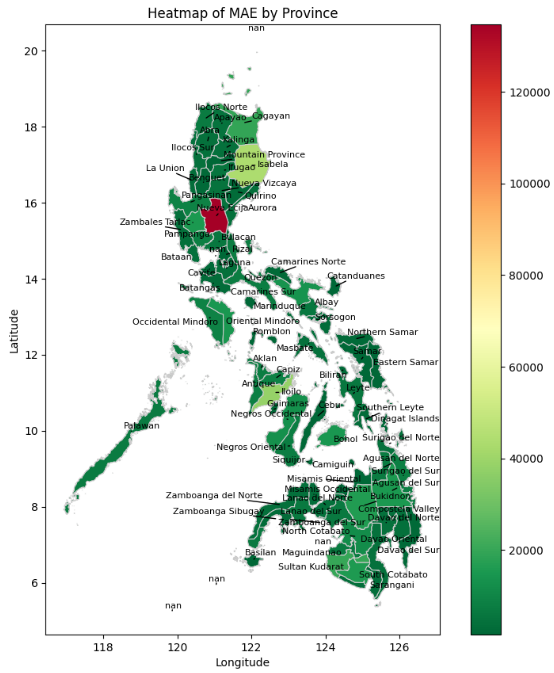

Figure 15: MAE of the models by each province in the Philippines on irrigated rice.

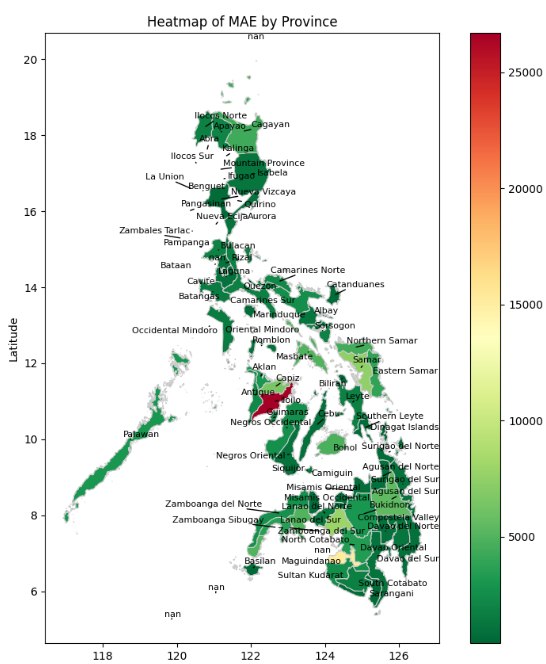

Figure 16: MAE of the models by each province in the Philippines on rainfed rice.

5.4 Comparison to Other Works

With the RNNs trained on CW-4, the performance that they offer compared to prior works is substantially different. In fact, most works achieve far greater performances compared to our methodology with some work achieve 100x times better performances. The reason for this is because of the data availability used to make such predictions in our work. In most works, they utilize fine-grained data that can provide a better picture for making evaluations. In our work, we utilized the least number of factors to make such a decision. Because of this, we suffer greater prediction performance. This is well indicated in Figure 11 where the performances in certain regions exceed 25%. However, this does not dissuade others on searching other methods that minimizes the number of data used to make such agricultural evaluations.

6 Conclusion

This work aims to show the idea of efficient and low complexity modeling for agricultural production. By utilizing statistics that are readily available and provide lower feature complexity, models can perform well on forecasting the upcoming quarter's rice output for any region and crop type. This plays well with the issues of rapid climate change as our work does not rely on specific and difficult-to-attain data to conduct a forecast. Such changes in the global climate can drastically affect the values of climate-dependent values, increasing the complexity of the modeling needed to provide estimations. In addition to this, our work has shown levels of performance without the need to predict features for the target values. This means that there is no need to forecast the target quarter's El-Niño 3.4 SST nor it's GDP, allowing for practical use for provincial governments on policy making and communication for farmers.

However, further work needs to be done such as ablations to the features to observe and analyze the importance of certain features. Approaches like state-space and transformer models have yet to be explored in depth and they obtain the potential to provide better performances. Furthermore, studies in different countries can provide a better insight into what the minimum set of features are required to achieve accurate and data-efficient forecasting.

Another area of focus is Earth Observation Data. In comparison to other research work focusing on the regression of rice statistics in an area, this work is far less effective than those works. This is because the aggregate statistics from the survey data loose too much information and don't account for many other complexities when it comes to rice production estimation. The utilizing of geospatial data on the rice fields in the Philippines can provide better performance altogether. Combined with newer time-series modeling techniques as discussed previously and the condition of tabular data on the satellite imagery, it has the potential to model effectively. This aspect of modeling has not been fully explored and provides plenty of potential for areas with low statistical resources to survey crop production.

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8 Author Contributions

All efforts made in this work (i.e., source code, data collecting, paper and proposal writing, and research) was all conducted by Benjamin Herrera. No other personnel was involved in the creation of this work.

9 Data Availability and Source Code

The source code and the dataset used in this work can be found at the paper's GitHub repository.

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