Modeling the Historical Temperature in the Province of Laguna Using Ornstein-Uhlenbeck Process

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Abstract. The behavior of temperature is one of the major factors in the study of climate change which has already invited a lot of researchers and policymakers. Studies in this area help in deciding the best adaptation and mitigation strategy. However, there are little studies on the progression of climate change in a local setting, such as in a municipal or provincial level. This study explored to model, using regression, the daily temperature in the province of Laguna, Philippines. The daily maximum and minimum temperature from 1960 to 2018 were modeled using the Ornstein-Uhlenbeck (OU) process with additive seasonality. The model showed that the province saw an increase of 1.16°C (resp. 0.55°C) in the mean daily minimum (resp. maximum) temperature from 1960 to 2018. It was also found that the minimum temperature showed a consistent increase than the maximum temperature, which poses threats to agricultural activities. Consistent with other international predictions, there was a 0.02°C annual increase in 1960 to a 0.05°C annual increase in 2010. The proposed model can be used by policymakers in designing and creating adaptive measures that would be more effective to the province of Laguna.

2020 Mathematics Subject Classifications: 60G10, 60G15
Key Words and Phrases: Temperature, Laguna, Ornstein-Uhlenbeck process

1. Introduction

The Philippines caught international recognition as being vulnerable to climate change [17]. In recent years, the country experienced extreme weather conditions such as super typhoons. In 2013, Super Typhoon Yolanda, internationally known as Typhoon Haiyan, was recorded as one of the strongest typhoons that made landfall and claimed thousands of lives. Aside from loss of human lives, these natural disasters and severe weather conditions had greatly impacted economies. In 2019, as El Niño continue to bring the country dry conditions and high temperature of around 35°C to 40°C, there was a reported loss equivalent to around 7.96 billion pesos [6]. These extreme events had led to reduced economic and agricultural productivity.

In the advent of the 21st century, there had been debates and speculations that climate change could be one of the leading causes of calamities. According to NASAs online article [7], The Causes of Climate Change, climate change could be due to both natural causes and anthropogenic activities, and researches had claimed that it had intensified over the last few years. According to the Intergovernmental Panel on Climate Change (IPCC) in its Fourth Assessment Report (AR4), the world experienced warming during the last 50 years due to observed increased emission from human activities [5]. In the country, PAGASA leads in modeling and predicting future climate scenarios. In 2011, in its report Climate Change in the Philippines, the agency had mentioned that there was a 0.648°C per year increase in mean temperature since the 1950s, and that while there were no indications of increase in average number of tropical cyclones entering the Philippine Area of Responsibility (PAR), there was a slight increase in the number of tropical cyclones with maximum sustained winds of greater than 150 kph [9]. These studies were done using available observed data, and predictions were modeled using downscale modeling. The United States Agency for International Development (USAID) in 2017 also projected that the Philippines will experience 1.8°C to 2.2°C increase in temperature by 2050, drier dry season and wetter wet season, 0.48 to 0.6 m sea level rise by 2100, and increased incidence of extreme weather events [17]. The same agency also mentioned that the country had an increase of 1°C in average annual temperature since the 1970s with a rate of 0.3°C per decade increase [16].

Industries That Are Vulnerable to Increase in Temperature

Weather had, and continues to have, great effect on several important industries. In the agricultural setting, weather is needed in planning when and what to plant in a certain season. Rice planting is highly dependent on rainfall and temperature. For instance, rice fields must be flooded by 5 to 10 cm during the planting season [10], and must receive at least 1,000 mm of rainfall during the whole planting season [20]. Furthermore, rice also grows in an environment with 20°C to 31°C [20] and any variation from these temperatures can result in crop sterility.

In the economic setting, severe weather conditions had resulted in suspension of classes and work due to hazards such as flooding and collapsing of structures. Poultry industry had also been affected by high temperature. Poultry has been found to be sensitive to temperature. A day-old chick has a body temperature of 39°C which increases to 41.1°C when the chick is about 5 days old [3]. Extreme temperature for a long period of time may cause chick mortality or affect performance.

Other than those previously mentioned, the level of dissolved oxygen is crucial in the habitability of aquatic environments. It is vital for almost all forms of aquatic life ranging from phytoplankton, bacteria to bony fishes. There are three factors that affect oxygen solubility, namely temperature, salinity, and atmospheric pressure. It has been known that oxygen solubility decreases as temperature increases [19].

The Ornstein-Uhlenbeck Process in Temperature Modeling

Standard textbooks in stochastic calculus, define the Ornstein-Uhlenbeck (OU) Process X_t as a solution to the stochastic differential equation given by

$$dX_t = \alpha \left(\beta - X_t \right) dt + \sigma dW_t; \qquad (1)$$

where α is the mean reversion coefficient, β is the drift of the process, σ is the volatility, and W_t is the standard Weiner process.

The OU process has been used in several studies on modelling temperature, each with different applications in mind. Alaton [1] used the OU process in temperature modelling to be able to price weather derivatives. They described temperature movement using seasonality, randomness, and mean reversion as the main components. Mean reversion indicates that temperature cannot keep on increasing day after day for a long period of time and it will eventually revert to the seasonal mean. They modeled the temperature using the stochastic differential equation

$$dT_t = dT_t^m + \alpha \left(T_t^m - T_t \right) dt + \sigma_t dW_t; \qquad (2)$$

where α is the speed of mean-reversion, σ_t is the volatility at time t, T_t is the temperature at time t, and T_t^m is the mean temperature and is given by the deterministic model

$$T_t^m = A + Bt + C \sin \left(\omega t + \phi \right); \qquad (3)$$

where A, B, C, ϕ are regression parameters and $\omega = \frac{2\pi}{365}$.

In the same year, Brody et. al. [2] used the OU process to model temperature where the driving noise process W_t is represented by a fractional Brownian motion (fBM) from which the model was called a fractional OU process. The use of fBM followed from observations that temperature exhibit a long-range temporal correlation or long-range dependence. This means that an existence of an anomaly in the past will tend to persist and influence the future behavior of the temperature. In 2015, Wang et. al. [18] published their study using the same model as Alaton et. al. to price weather derivatives. In 2018, Zhu et. al. [21] published a study modeling water temperature from air temperature using standard models and using machine-learning algorithms. For standard models, they specifically used the stochastic model

$$T_w \left(t \right) = a + b \sin \left[\frac{2\pi}{365} \left(t + t_0 \right) \right] + \beta_1 T_a \left(t \right) + \beta_2 T_a \left(t - 1 \right) + \beta_3 T_a \left(t - 2 \right); \qquad (4)$$

where T_w is the water temperature, T_a is the air temperature, and $a, b, t_0, \beta_1, \beta_2, \beta_3$ are regression parameters.

Selection of Study Area and Objectives of the Study

About 30 km from Manila lies the province of Laguna. According to the Philippine Statistics Authority (PSA), Laguna covers six cities and 24 municipalities. In the 2015

census, the province had a population of 3,035,081. The province had 38,445 farms covering 62,555 ha of arable land as of 2002, and palay was the most common crop planted. Palay remained to be the top crop in 2017, while poultry was the top livestock reared in the area. There were also several light industry and science parks in the province, most of which are in the cities of Calamba, Biñan and Cabuyao. Laguna borders Laguna Lake which is home to many aquatic industries with tilapia (*Oreochromis niloticus*) and bangus (*Chanos chanos*) as some of its main products. To gain some perspective of the yield of the industries mentioned, the PSA indicated that Laguna produced 129,538 metric tons of palay in 2017 and 17,502.9 metric tons of chicken products in 2019. Meanwhile, Guerrero [4] reported that Laguna de Bay produced 156, 831 metric tons of fish products in 2015. Thus, weather conditions for the coming planting or rearing season would be very helpful for farmers in deciding when and what variety to plant to achieve optimal harvest, in building poultry houses that would protect poultry or other livestock, and would also be helpful for businesses to set-up work schedules so as to reduce economic loss.

While PAGASAs and USAIDs results were viable, modeling climate change on-site could also be done. These models could be more usable for the local government in designing their adaptation and mitigation strategies to counter the effects of climate change. This study aims to model the temperature in the province of Laguna using stochastic models. Employing regression and Ornstein-Uhlenbeck Process, this paper studied the behavior of historical temperature data in the hope of giving estimate of the increase in temperature for the coming years, provided that changes in the environment that affects temperature are negligible.

2. Methodology

The location of this study was the province of Laguna due to availability of data. Laguna experiences Type 1 climate, where it is relatively dry from November to April and wet for the rest of the year. Figure 1 show the map of Laguna and the location of the weather station.

Collection and Generation of Data

Historical daily minimum and maximum temperature were collected from 1 Jan 1960 to 31 Dec 2018 from the UPLB National Agrometeorological Station. Data was cleaned, i.e. data showing a reading of $0°C$ or $-99°C$ were replaced by interpolated data between the two adjacent days. All in all, there were 17 data points which showed a reading of either $0°C$ or $-99°C$.

Modeling of Temperature

Let T_t be the daily temperature. This was broken into two components and was expressed as
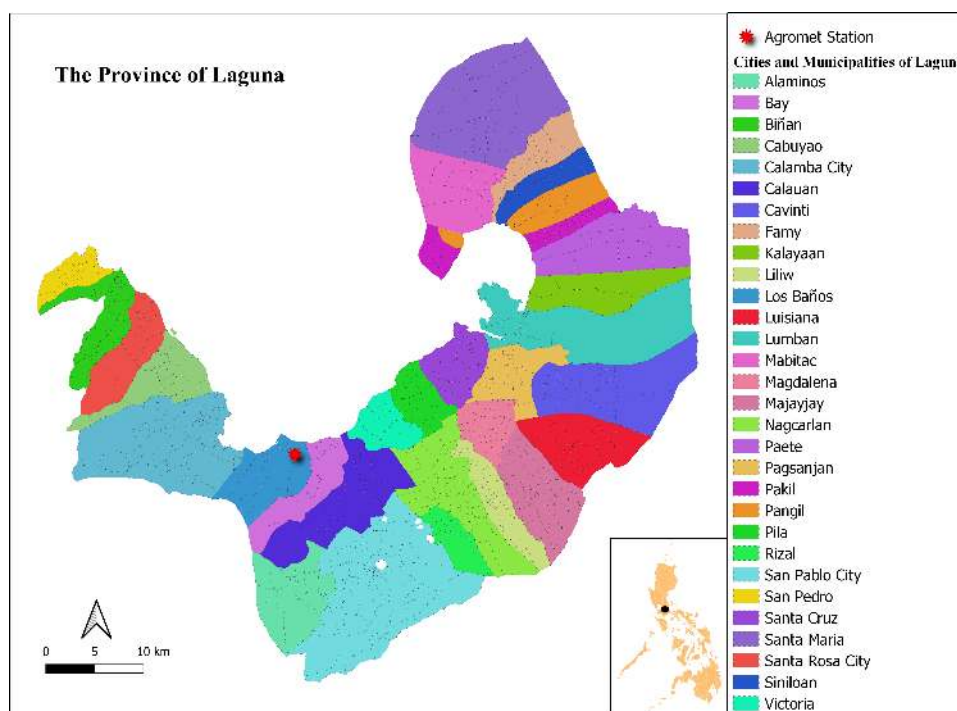
$$T_t = D_t + X_t; \tag{5}$$

Figure 1: Map of the Province of Laguna and the Location of the UPLB Agrometeorological Station.

where D_t is the seasonal component, while X_t is the stochastic component. These two components are modeled as follows:

The seasonal component, D_t, was modeled as a deterministic function given by

$$
\begin{aligned}
D_t \;=\;& g + at \\
&+ \sum_{h=1}^{3} \left[b_h \sin\left(\frac{2\pi}{365} s_h\right) + c_h \cos\left(\frac{2\pi}{365} s_h\right) + d_h \sin\left(\frac{2\pi}{7} s_h\right) + e_h \cos\left(\frac{2\pi}{7} s_h\right) \right];
\end{aligned}
\tag{6}
$$

with $s_1 = 1, s_2 = 2$ and $s_3 = 4$ and would capture the mid-week, weekly, quarterly, mid-year and annual temperature patterns. The goal would be to find the values of parameters g, a, b_h, c_h, d_h and e_h, for $h = 1, 2, 3$. However, in this study, only the results of parameters g and a would be highlighted. The parameters of D_t were estimated using the method of least-squares.

Next, the stochastic component, X_t, was modeled as an Ornstein-Uhlenbeck process, using (1). An explicit solution for (1) is given by

$$
X_t = X_s e^{-\alpha(t-s)} + \beta \left[1 - e^{-\alpha(t-s)} \right] + \sigma e^{-\alpha t} \int_s^t e^{\alpha u} \, dW_u;
\tag{7}
$$

where $s < t$. A discrete form of (7) is the equation

$$
X_{k+1} = X_k e^{-\alpha \Delta k} + \beta \left(1 - e^{-\alpha \Delta k} \right) + \sigma \sqrt{\frac{1 - e^{-2\alpha \Delta k}}{2\alpha}} \, \omega_k;
\tag{8}
$$

where $\{\omega_{k+1}\}$ is a sequence of independent and identically distributed (IID) standard normal random variables.

Following the method presented by Tang and Chen [15], the paramaters of X_t are estimated by the following equations

$$\hat{\alpha} = -\log(\gamma_1), \ \hat{\beta} = \gamma_2 \text{ and } \hat{\sigma} = \sqrt{2\hat{\alpha}\gamma_3(1-\gamma_1^2)^{-1}} \tag{9}$$

where

$$\gamma_1 = \frac{n^{-1}\sum_{i=1}^{n} X_i X_{i-1} - n^{-2}\sum_{i=1}^{n} X_i \sum_{i=1}^{n} X_{i-1}}{n^{-1}\sum_{i=1}^{n} X_{i-1}^2 - n^{-2}\left(X_{i-1}\right)^2}, \tag{10}$$

$$\gamma_2 = \frac{n^{-1}\sum_{i=1}^{n}\left(X_i - \gamma_1 X_{i-1}\right)}{1-\gamma_1}, \text{ and} \tag{11}$$

$$\gamma_3 = n^{-1}\sum_{i=1}^{n}\left[X_i - \gamma_1 X_{i-1} - \gamma_2(1-\gamma_1)\right]^2. \tag{12}$$

Temperature from the whole observation period, 1960 to 2018, was modeled. Moreover, temperatures from 1970 to 2018, 1980 to 2018, 1990 to 2018, 2000 to 2018, and 2010 to 2018 were also modeled so to give an idea on the rate of increase/decrease in temperature during the recent years. This would offer insights on how fast climate is changing, and if compared to anthropogenic activities in the area, could also offer insights on how these activities affect the climate (however, this would not be done in this study).

Calculation of Temperature Anomalies

Temperature anomaly was calculated by comparing the daily temperature of the whole observation period to the average daily temperature from 1980 to 2000, which is the median period. Temperature anomaly is the difference from a baseline temperature. This parameter offers insights if there is increase or decrease in temperature when compared to a reference value [8].

Error Analysis

The error metrics considered in this study were mean-squared error (MSE), root-mean-squared error (RMSE), absolute-mean error (MAE), and relative-absolute error (RAE). Values that are closer to zero are better.

If X_k is the exact value and $\hat{X}_k$ is the estimated value at time k, $\underline{X}$ is the mean of all the X_k's, then the following formula were used for the error metrics:

$$MSE = \frac{\sum_{k=1}^{K}\left(X_k - \hat{X}_k\right)^2}{K}; \tag{13}$$

$$RMSE = \sqrt{\frac{\sum_{k=1}^{K}\left(X_k - \hat{X}_k\right)^2}{K}}; \tag{14}$$

$$MAE = \frac{\sum_{k=1}^{K} \left| X_k - \hat{X}_k \right|}{K}; \text{ and} \tag{15}$$

$$RAE = \frac{\sum_{k=1}^{K} \left| X_k - \hat{X}_k \right|}{\sum_{k=1}^{K} \left| \underline{X} - \hat{X}_k \right|}. \tag{16}$$

3. Results

Summary of the Temperature Data

The collected data shows that, in the 58-year period, the average minimum temperature is 22.95°C, the average maximum temperature is 31.67°C. The temperature varies from these means by 1.54°C and 1.54°C for minimum and maximum temperature, respectively. The months of April to June are the hottest months, while the months of December to February are the coldest months. The highest recorded maximum temperature is 39°C, recorded on 24 Jan 1999, while the lowest is 23.10°C, recorded on 20 Nov 1964. On the other hand, the highest recorded minimum temperature is 33.80°C, recorded on 31 Jan 1986, and the lowest is 15°C, recorded on 28 Oct 2000.

Results of Regression of the Deterministic Model D_t

The result in the regression of the deterministic model in equation (6) is shown in Table 1. As previously mentioned, only the results of parameters for a and g are shown.

Table 1: Regression Parameters for Deterministic Model .

	Minimum Temperature		Maximum Temperature	
Years	a	g	a	g
1960-2018	6.51×10^{-5}	22.25	2.58×10^{-5}	31.39
1970-2018	7.52×10^{-5}	22.37	1.05×10^{-5}	31.66
1980-2018	6.77×10^{-5}	22.72	-3.41×10^{-5}	32.09
1990-2018	9.83×10^{-5}	22.76	-4.03×10^{-5}	32.00
2000-2018	6.71×10^{-5}	23.22	-6.13×10^{-5}	31.72
2010-2018	1.33×10^{-4}	23.36	1.47×10^{-4}	31.44

To show the goodness-of-fit of the deterministic model to the actual temperature, an illustration for the minimum and maximum temperature for years 2010 to 2018 are given in Figure 2. The blue lines are the actual temperature while the red line is result of the deterministic model. A good fit of the deterministic model to the actual temperature can be seen. This fit would be verified in the later sections, in the error analysis.

In equation (6), the parameter g gives the average temperature over the reckoning period, while the parameter a gives the linear trend of the temperature or in other words the expected increase or decrease in temperature per day. Looking at the biggest data
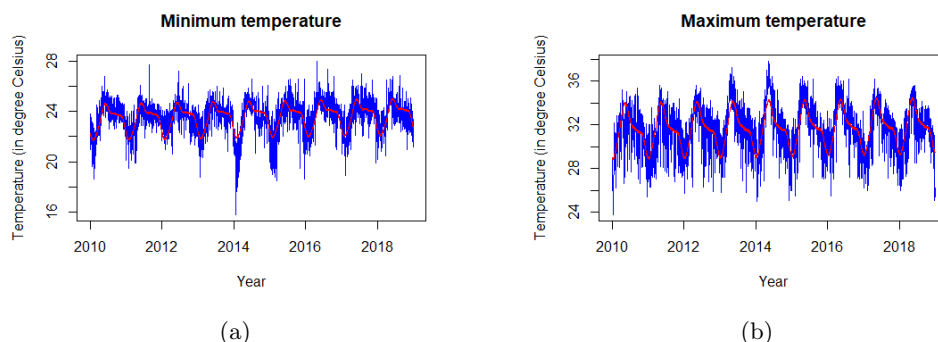
Figure 2: Regression of Minimum (a) and Maximum Temperature (b) from year 2010 to 2018.

set which covers 1960 to 2018, the results for parameter a show that there is a slow but steady increase of 6.51×10^{-5} (6.26×10^{-5}°C to 6.77×10^{-5}°C, 95% confidence interval) in the daily minimum temperature. On an annual basis, this is equivalent to an increase of 0.02°C, which means that the province of Laguna saw an increase of 1.16°C since 1960. The years from 2010 to 2018 saw the highest daily increase of 1.33×10^{-4}°C (9.72×10^{-5}°C to 1.69×10^{-4}°C, 95% confidence interval), which corresponds to 0.05°C annually.

The 1960 to 2018 model of the maximum temperature shows that there is an increase of around 2.58×10^{-5}°C (2.21×10^{-5}°C to 2.96×10^{-5}°C, 95% confidence interval) per day which translates to an overall increase of 0.55°C within the time period. Considering narrower time periods such as 1980 to 2018, the model sees a decline in the maximum temperature. The trend would then reverse and start to increase again within 2010 to 2018. In fact, there is a very steep increase in the trend from to 2010. Figure 3 shows the trends of minimum and maximum temperature as the time periods are shortened. Over here, one can see that the average minimum temperature as the time periods shorten increases. This is another indicator of increasing minimum temperature.

Following Table 2, the mean reversion coefficients α of both the minimum and maximum temperature show a general increase as time periods are shortened. This indicates that in the recent years, temperature reverts to the average temperature less and less. This could imply that temperature gets noisier, or difficult to predict, as time goes on.

For the minimum temperature, the volatility parameter σ shows decrease as the time periods are shortened. This means that data dispersion decreases, which can imply that if there is an increase in temperature in one day then it can be expected that the following days are also hot days. For maximum temperature, it can be noted that there is a big decline (comparing to the other periods) in σ, which implies that data dispersion in this period decreased.
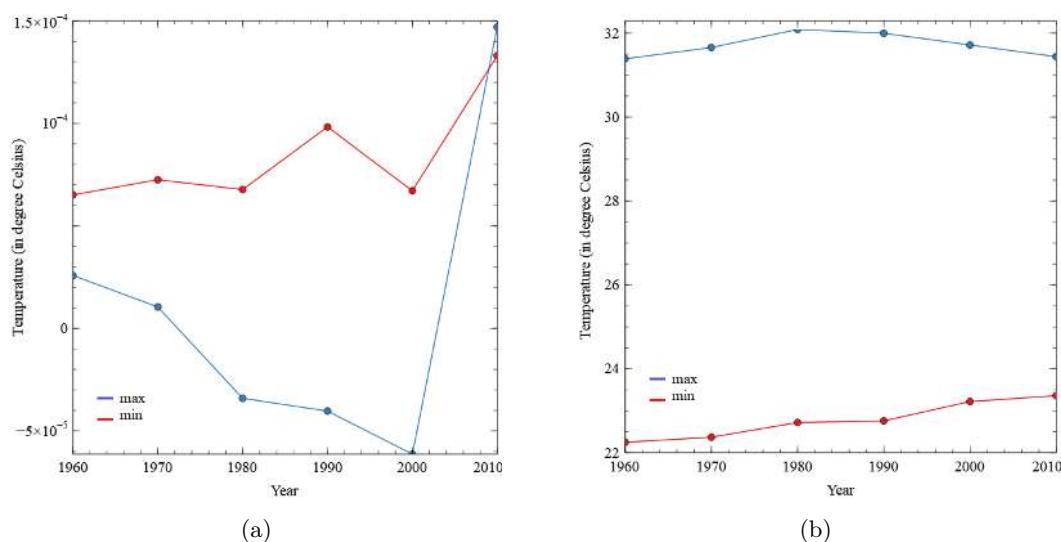
Figure 3: Trend of Minimum and Maximum Temperature According to (a) Parameter a and (b) Parameter g with Respect to Shortening Time Periods.

Table 2: Parameters for the Stochastic Model.

	Minimum Temperature			Maximum Temperature		
Years	α	β	σ	α	β	σ
1960-2018	0.574	-0.0001	1.269	0.585	0.0001	1.881
1970-2018	0.556	-0.0001	1.263	0.588	-0.0002	1.884
1980-2018	0.551	0.0002	1.279	0.612	-0.0003	1.885
1990-2018	0.702	0.0002	1.285	0.624	-0.0006	1.884
2000-2018	0.743	-0.0003	1.237	0.631	-0.0006	1.881
2010-2018	0.759	0.0002	1.220	0.622	0.0003	1.802

Performance of the Model

In this section, different measures of error for the model will be obtained. From (8), the expectation, $\mathbb{E}[X_{k+1}]$, is given by

$$\mathbb{E}[X_{k+1}] = X_k e^{-\alpha} + \beta \left(1 - e^{-\alpha}\right). \tag{17}$$

The above equation will be used to compute for the predicted values of X_k and the deseasonalized data will be used as the actual value of X_k. Using the obtained paramaters from the stochastic process, Table 3 gives the summary of the error metrics. It shows that the minimum temperature model outperforms the maximum temperature model across all time periods. The values for the MSE, RMSE, MAE and RAE are closer to zero for the minimum temperature model compared to the maximum. In this case, this means that the predicted values given by (17) have better accuracy.

Table 3: Error Metrics.

Years	Minimum Temperature				Maximum Temperature			
	MSE	RMSE	MAE	RAE	MSE	RMSE	MAE	RAE
1960-2018	0.9570	0.9783	0.7236	1.5037	2.0874	1.4448	1.0905	1.4451
1970-2018	0.9623	0.9810	0.7222	1.5181	2.0880	1.4450	1.0920	1.4504
1980-2018	0.9908	0.9954	0.7279	1.4716	2.0490	1.4314	1.0830	1.4998
1990-2018	0.8877	0.9422	0.7038	1.7219	2.0285	1.4243	1.0775	1.5277
2000-2018	0.7965	0.8925	0.6730	1.8376	2.0117	1.4183	1.0796	1.5438
2010-2018	0.7652	0.8748	0.6640	1.8828	1.8576	1.3629	1.0434	1.5267

Results of Temperature Anomalies

Temperature anomalies are computed. Results shows that had been a 1.38°C increase in minimum temperature or a 0.0238°C per year increase; and, a 0.55°C increase in maximum temperature or a 0.0094°C per year increase within the last 58 years. Figure 4 shows the temperature anomalies. The positive-sloping trend-lines (in red) of the anomalies also suggest a continuing increase in temperature. It should be noted that the slope of the trend line for minimum temperature is steeper. This indicates that increasing in minimum temperature is higher than that of maximum temperature.
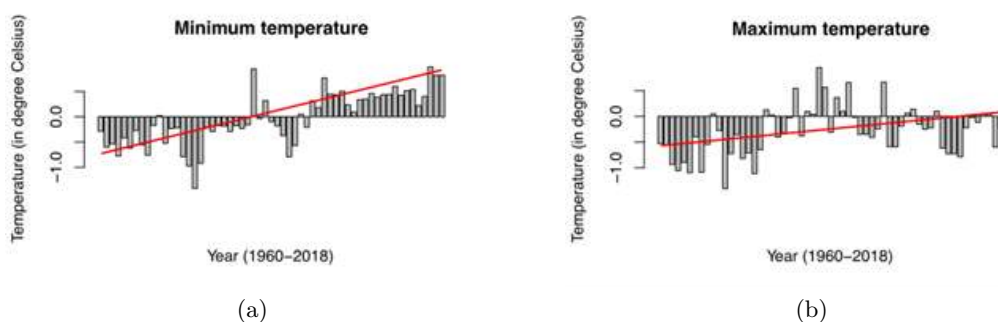

(a)   (b)

Figure 4: Anomalies for Minimum (a) and Maximum Temperature (b) from Year 1960 to 2018.

Comparison with Other Studies

It can be noted that the 1960 to 2018 minimum temperature model reports a slow annual increase of 0.02°C; while the maximum temperature reports a 0.009°C annual increase. Comparing these values to the results of the temperature anomalies, it can be said that the regression models give a good measurement of the actual temperature.

Using again the 1960 to 2018 models, there can be a 2.11°C increase in minimum temperature and a 0.83°C increase in maximum temperature by 2050. Meanwhile, PAGASA estimated that average temperatures in all areas in the country are expected to increase by 1.8°C to 2.2°C by 2050. Once more, even though this study considers minimum and

maximum temperatures while PAGASA considers average temperature, the results of the studies are close to each other. Another agency that released temperature predictions is the USAID, which affirms the predictions of PAGASA.

Discussion

In the results of the study, it can be seen that both the minimum and maximum, has been increasing since 1960. The results show that there will be a slow but steady increase of the minimum and maximum temperatures, and a narrowing of the range between the minimum and maximum temperature. These scenarios do not offer a positive outlook to the different industries mentioned earlier that are vulnerable to the increase in temperature.

Following the 1960 to 2018 model and should the parameters remain unchanged in the next 40 or so years, the results of this study may provide an early view of the possible temperature pattern in Laguna, and help government and non-government agencies to device contingency measures. Agriculture can be particularly threatened by these forecasts. As mentioned earlier, sterility of palay, which is the top agricultural product of the province, can be triggered by temperature higher than $31°C$. Furthermore, the increasing minimum temperature is more alarming for rice producers. In 2004, a study highlights that there can be as much as 10% yield decline for every $1°C$ increase in minimum temperature during the dry season [11]. This, partnered with other meteorologic and economic factors, would be detrimental in rice production and ultimately food security in the future.

Research on high-temperature resistant rice can commence followed by production and distribution of the seeds to vulnerable farmers. Aside from this, research can also be done on shifting the cropping calendar to mitigate the effects of the increasing temperature [12]. Poultry farms can invest in temperature-controlled rooms to optimize production [14]. Aquaculture in the Laguna Lake area may opt to utilize fish tanks wherein they can control the level of dissolved oxygen in the water instead of relying primarily on the lake itself [13]. These will drive production costs, but these alternatives will also drive sustainability and continued output of important products to help the province of Laguna and the greater region become ready for the 21st century and beyond.

4. Conlusion

This study is one of the pioneering temperature studies in the Philippines that considers a more localized setting, particularly in Laguna. Doing research in a regional or provincial context can help local decision makers, especially the industries that are sensitive to temperature. The study gives a model for minimum and maximum temperatures and offers projection of temperature for the next few years. As a lot of industries in Laguna are vulnerable to increase in temperature, adaptation strategies should be placed immediately. Such can greatly improve everyone's quality of life in the future.

However, despite the good fit, these models also have their weaknesses such as it does not take into consideration a change in emission or land use, which could have heavy

implications on temperature. Thus, this study can be extended by interested researchers to consider other temperature models that involve these factors. The study can also be improved by finding the reasons for the possible cooling during the 1990 to 2000. While the authors maintain that the models in this study may improve by involving more variables in a future study, continued monitoring and modeling of the temperature in a local setting is a step in the right direction.

Acknowledgements

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