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Temperature change analysis in Viçosa-MG through time series

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ABSTRACT: The theme of global warming came into evidence at the end of the 20th century and beginning of the 21st century and is a recurrent theme of research, debates and studies around the world. Thus, the main objective of this work is to analyze the behavior of monthly averages of maximum and minimum temperatures in Viçosa-MG, with the interest of verifying if this region, with interior characteristics and with a good part of preserved biodiversity, also suffers from warming temperatures like the larger cities. Furthermore, it is desired to make a temperature forecast for the following year with the secondary objective of testing the quality of the model for this purpose. For that, the Box and Jenkins methodology was used to model the historical series through the SARIMA models, and for the variance, a model of the GARCH class was adjusted, which was shown to be necessary for the minimum temperature series, as it presents heterogeneous variance. It was found that Viçosa's region has been suffering impacts similar to the rest of the world, with one °C warming in the maximum temperature historical series and an increase above 1.5 °C in the minimum temperature in the last 50 years of data records, there is an even more accentuated increase in the last 20 years of the series. Therefore, this study can contribute a lot, as it shows that smaller cities, although it does not have nearby industries, are also suffering from climatic variations and that better city and regional planning will be needed to deal with the consequences imposed by global warming.

Keywords: SARIMA. ARCH. Prediction. Global warming

INTRODUCTION

Climate studies have been gaining more and more attention among scholars and researchers, especially those regarding temperature changes. The global warming phenomenon has caused concern, as its consequences are, in part, unknown. In terms of air temperature, two essential terms should not be confused: climate variability and climate change. According to Steinke et al. (2005), the climate variability term is used to describe climate variations due to natural effects, while climate change is used for changes that go beyond, motivated by human activity. It is not easy to conclude that specific climate changes are influenced by human action since climate variations on Earth are a natural process. Planet Earth undergoes countless climate variations, which constant and predictable effects can cause, or random effects, making prediction and understanding difficult. However, according to Silva et al. (2008), there is no doubt that the success or failure of given business activity is directly linked to temperature conditions in a region, country, or planet.

In Viçosa-MG, agriculture, animal production and reproduction, and energy supply are sectors directly affected by temperature changes. The population used to grow specific crops and raise specific animals may suffer losses if there are temperature variations. The energy supply sector is also impacted, as in warmer periods, the city consumes more energy, driven by the use of air conditioners, refrigerators, and freezers. Some climate studies in different parts of the world have already confirmed that time series models are good tools for climate data analysis. On their climate analysis, Gurudeo and Mahbub (2010) studied climate data of four weather stations in Queensland – Australia, through ARIMA time series models with regression variables to make predictions and conclude the inverse relationship between precipitation and temperature. Karner (2009) adjusted ARIMA models to analyze daily temperature data of fourteen weather stations, ten located in Europe and four in Asia. Asfaw et al. (2018) studied the temperature and precipitation of the Ethiopian historical series, finding a slight rise in a century. When referring to health and climatology, Li et al. (2020) carried out a time series study, finding an inverse correlation between temperature and the incidence of COVID-19 in the cities of Wuhan and XiaoGan, indicating that the highest levels of contamination occurred at lower temperatures. Guo et al. (2012) compared the high and low temperatures correlated with deaths through time series, identifying that high and low temperatures are correlated with deaths, with low temperatures indicating a more prolonged index.

Climate studies can be found in different parts of Brazil. Minuzzi et al. (2010) studied maximum and minimum air temperatures of several cities in Minas Gerais, Brazil, using time series models once more, reinforcing them as good modeling tools. Salviano et al. (2016) studied the historical series of temperature and precipitation for Brazil and identified that the average temperature showed a significant positive trend in much of Brazil throughout the year. By studying annual average maximum, mean, and minimum temperatures in Pelotas-RS, Brazil, from 1931 to 2011, through Box and Jenkins methodology (Box et al. (2008)), Gandra et al. (2014) showed that this is indeed an excellent approach to detect changes in air temperatures. Carvalho e Delgado (2020) analyzed climate data in the region of Ariquemes (RO), in which he compared the Box and Jenkins modeling with neural networks, showing other methodologies also effective in interpreting these data, in which they found a significant rise in temperatures in that region also in Carvalho et al. (2016). Blain (2010) studied the maximum temperature of eight cities in São Paulo, Brazil, through time series and detected significant temperature increase in four of them, whereas, for the other eight, there was neither a significant increase nor decrease. Kruel e Medeiros (2020) analyzed the historical series of Santa Maria (RS), not finding a trend towards minimum temperature and a downward trend of 0.01 °C for maximum temperature.

This study is critical to Viçosa, where the Federal University of Viçosa is located, since this institution is considered a role model in agricultural experimentation, with numerous works, many finished and others underway, in plant breeding of grown crop species nationwide. In this sense, the objective of this work is to analyze, through the modeling of Box and Jenkins (Box et al., 2008), the historical series of the monthly average of the maximum and minimum temperatures in Viçosa-MG, verifying the presence of possible alterations and historical patterns, to verify whether this region, which has biodiversity in a good state of preservation, has also been suffering from the effects of global warming.

Times series

Climate series typically have two common factors that time series models well explore the dependence between observations and factors that repeat themselves every period, called seasonality when the period is less than or equal to one year, and cyclicity otherwise. Therefore, it is quite common that climate studies involve time series modeling. According to Hamilton (2020), a time series is a collection of observations indexed by the date of each observation. We usually collect data starting on some specific date. According to Morettin and Toloi (2006), a time series can be divided into three non-observable variables: trend, seasonality, and random variable.

The presence of trend and seasonality in a time series can be identified through graph representations and consists of analyzing the general graph of the time series, the graph of the autocorrelation function (ACF), and the graph of the partial autocorrelation function (PACF), however, a more consistent analysis of such components is achieved through some tests.

An ACF and a PACF express the degree of dependency between observations in a given time t and the following times $t+i$. An ACF represents the dependency between observations considering the intermediate observations, while the PACF does not consider the intermediate observations. For the trend analysis, the augmented Dickey Fuller's test (ADF) (Dickey and Fuller 1979) requires the study of the following regression:

$$\Delta Z_t = \beta_1 + \beta_2 t + \pi Z_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Z_{t-i} + a_t, \quad (1)$$

where $\Delta Z_t = Z_t - Z_{t-1}$ is the first difference in the time series; ΔZ_{t-i} are the lagged values included in the test to eliminate serial autocorrelation of residuals; the m can be minimized by the Akaike information criterion (Akaike, 1974) or by the Bayesian information criterion (Schwarz, 1978) or even be done manually by trial and error, which consists of trying the smallest integer value so that the residuals of Equation (1) become white noise; β_1 represents the intercept; β_2 is the deterministic trend coefficient; π is the stochastic trend coefficient, and a_t is the white noise.

The seasonality of a time series can be understood as that factor that occurs in equal time intervals as long as this interval is less than one year. For Box et al. (2008), the residual autocorrelation function is not a sensitive seasonality indicator since several autocorrelations dilute seasonality effects. Therefore, the presence of seasonality and the seasonal lag size s will be verified in trend-free series through spectral analysis, which consists of decomposing the time series in the Fourier-frequency domain. Cryer and Chan (2008) define the intensities of Fourier frequencies as:

$$I(f_i) = \frac{2}{n}\left[\left(\sum_{t=1}^{n} Z_t \cos(2\pi f_i t)\right)^2 + \left(\sum_{t=1}^{n} Z_t \sin(2\pi f_i t)\right)^2\right]. \quad (2)$$

The Equation (2) graph was created to detect the periodicity of a time series. This graph has the Fourier frequencies on the x-axis and their intensities on the y-axis, and such a graph is called a periodogram.

In a periodogram, the critical frequency f_c, which is that frequency with the greatest intensity, is used to calculate the seasonality period given by the formula $s = 1/f_c$.

According to Morettin and Toloi (2006), a periodogram has several peaks is not enough to conclude beforehand that each peak corresponds to a periodic component of the Z_t series. That said, the statistical significance of a seasonal period S must be assessed, which can be done by the Fisher's G test (Fisher, 1929) through the following statistics:

$$G_{calc} = \frac{\max\left(I(f_i)\right)}{\sum_{i=1}^{n/2} I(f_i)}, \quad (3)$$

where $I(f_i)$ is defined in Equation (2). A p-value approximation suggested by the same author is given by:

$$P\left(G > G_{calc}\right) \approx n\left(1 - G_{calc}\right)^{n-1},$$

where n is the number of observations of a time series, and G_{calc} is given by Equation (3).

After analyzing the presence of trend and seasonality in a time series, the next step is to choose a model for the series modeling process. In this study, the Box and Jenkins modeling process was chosen (Box et al., 2008). The SARIMA (Seasonal Autoregressive Integrated Moving Average) model is used to model time series with trend and seasonality components. This model contains autoregressive and moving average polynomials of order p and q, respectively, in addition to autoregressive and moving average polynomials of seasonal components of order P and Q. The model $SARIMA(p,d,q)\times(P,D,Q)$ is defined by Box et al. (2008) as:

$$\phi_p(B)\Phi_P(B)\Delta^d(B)\Delta_s^D Z_t(B) = \theta_q(B)\Theta_Q(B)a_t,$$ where

$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ is the autoregressive polynomial;

$\Phi_P(B) = 1 - \phi_1 B^s - \phi_2 B^{2s} - \cdots - \phi_p B^{Ps}$ is the seasonal autoregressive polynomial of lag size s;

$\Delta^d(B) = (1 - B)^d$ is the difference polynomial;

$\Delta_s^D(B) = (1 - B^s)^D$ is the seasonal difference polynomial;

$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$ is the moving average polynomial;

$\Theta_Q(B) = 1 - \theta_1 B^s - \theta_2 B^{2s} - \cdots - \theta_Q B^{Qs}$ is the seasonal moving average polynomial;

a_t are the white noise errors.

Following Box and Jenkins modeling process (Box et al., 2008), there are four steps: model selection, identification of its parameters, parameter estimation, and verification of the fitted model.

After choosing the SARIMA model, parameter identification was performed according to the Bayesian Information Criterion (BIC) proposed by Schwarz (1978), given by the expression:

$$BIC = -2\ln L(\hat{\theta}) + p\ln(n).$$

Where $L(\hat{\theta})$ is the likelihood function for the maximum-likelihood estimator $(\hat{\theta})$, p is the number of parameters, and n is the number of observations of a time series.

Emiliano et al. (2014) assessed the Akaike - AIC (Akaike 1974), corrected Akaike – cAIC (Sugiura, 1978) and BIC (Schwarz, 1978) information criteria through data simulation, and found out that for time-series studies, the BIC stabilized at about 96%

correct answers while for the other two it stabilized at 85%. Therefore, BIC will be the criterion used here to select model parameters, which consists of creating several models and choosing the one with the lowest BIC estimate. After selection, parameters were estimated using the *Stats* package from the R software (R, 2017). For more details, see Morettin and Toloi (2006).

The last step of modeling consisted of verifying the chosen models. The Ljung and Box's test (Ljung and Box, 1978) is widely used and must be applied twice, first to the residuals to check if the time-series correlation was well adjusted, and second to the squared residuals to check if the model's residual variance is homogeneous.
Suppose the model does not eliminate serial correlation in the residual analysis. In that case, it is recommended to adjust another model, whereas, if the model does not have homogeneous variances, its variance must be modeled using a heteroskedastic model; in this case, the GARCH(r ,s) can be used.

The ARCH model was proposed by Eagle (1982) for estimating the variation of inflation in the United Kingdom and its generalization. The GARCH models were proposed by Bollerslev (1986). Morettin and Toloi (2006) define the $GARCH(r,s)$ model as:

$$a_t = \sqrt{\left(\alpha_0 + \sum_{i=1}^{r} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j h_{t-j}\right)} \varepsilon_t,$$

where a_t is the residue observation in the time t, α_i and β_j with $i = 0,1,2,\ldots,r$ and $j = 0,1,2,\cdots,s$ are the model parameters to be estimated, ε_t is the residue which has normal distribution, Student's t or yet GVE (generalized distribution of extreme values). For this work, we used $\varepsilon_t \sim N(0,1)$.

MATERIAL AND METHODS

The time series we studied here contains information of maximum and minimum temperatures of Viçosa-MG, Brazil, from a conventional weather station database, with coordinates -20.76 latitude and -42.86 longitude, located in the Department of Agricultural Engineering at Federal University of Viçosa (UFV, 2016). More specifically, our data consisted of daily maximum and minimum temperature observations from which we calculated monthly averages between Jan/1968 to Jul/2016.

For some missing data, interpolation was used, which considered previous observations to infer a $Z_t$value, and if these observations contain a seasonality factor, this factor is incorporated into the interpolation model to obtain better precision. After data processing, a general graph was built for each series, in which we could make a visual analysis of the time series and try to identify some series features and identify likely necessary tests.
Dickey and Fuller's test was used to detect the trend component, and then the periodogram was used to identify the presence of seasonality and its size.

We found out that a SARIMA model would be appropriate to adjust the time series. Model parameters were then chosen based on the BIC criterion. Next, parameters were estimated using the *Stats* package from the R software (R, 2017). Model verification, the last step in the methodology proposed by Box and Jenkins, was performed via Ljung and Box's test first applied to residuals and, next, to squared residuals. The model selected to adjust the monthly average maximum temperature time series was appropriate. In contrast, the model selected to adjust the monthly average minimum temperature time series was inappropriate, so we used an ARCH model, which is a GARCH-derived model, to adjust the heterogeneous residual variance. The last step was to predict temperature using the selected models to adjust the time series.

RESULTS

Maximum temperature in Viçosa-MG was 26.6 °C on average, with a standard deviation of 2.1 °C, and special attention given to February 2002, when average maximum temperature was highest (32.4 °C), and July 1976 when average maximum temperature was lowest (22.2 °C). The minimum temperature was 15.4 °C on average, with a standard deviation of 3 °C, and special attention should be given to January 2003, when average minimum temperature was highest (20.2 °C) and June 1968, when average maximum temperature was lowest (7.3 °C). Figure 1 shows the time series of monthly average maximum and minimum temperatures as well as their trendlines. In Figure 1, we can observe the time series behavior and the trendline slopes. Visual analysis shows that there has been a more significant rise in temperature from the beginning of the 21st century.

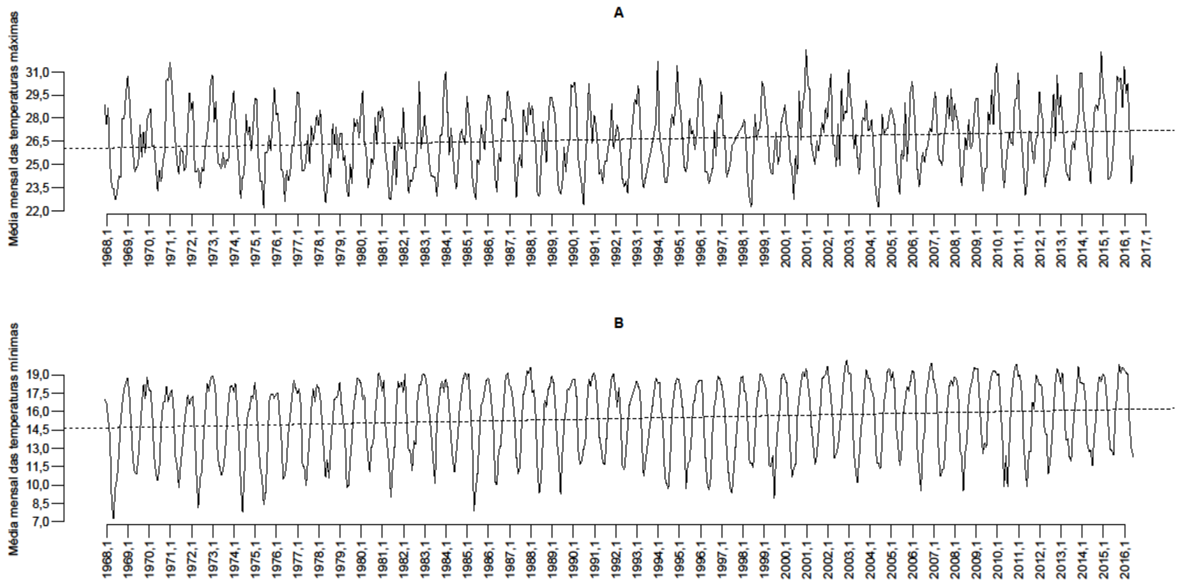

Figure 1: A – Monthly average maximum temperature of Viçosa-MG and its trendline (round dots). B – Monthly average minimum temperature of Viçosa-MG and its trendline (round dots)

By evaluating the monthly average maximum temperature series trendline, we observed an increase of 0.0229 °C in the monthly mean per year, which resulted in a total increase of over 1 °C at the end of the studied period. As for monthly average minimum temperature, an even greater annual temperature increase was detected (0.0313 °C), which resulted in a total increase of over 1.5 °C at the end of the studied period. Salviano et al. (2016) found similar results in some Brazilian historical series, while Asfaw et al. (2018) found a rise of 0.6 °C in a century in the historical series for Ethiopia, showing a smaller but significant rise. Finally, Sanches et al. (2017) studied the series of Viçosa-MG through analysis of covariance (ANCOVA) and found a variation of 1 °C and 1.4 °C for the minimum and maximum temperatures respectively.

Trend analysis using Dickey and Fuller's test confirmed the results, suggesting that both series have a deterministic trend. For the maximum temperature series, $\hat{\beta}_2 = 0.0010$ with $p = 0.0067$, indicating that the trend effect was significant. With $\hat{\beta}_2 = 0.0013$ and $p = 0.0004$, trend effect was also significant for the minimum temperature series. We needed to apply a simple difference to the data in both series to eliminate the trend effect. We also detected seasonality in both series, which was already expected since we are dealing with climate data. In both series, seasonality was $s \approx 12$. $p - value$ of Fisher's G test was lower than 0.0001 in both series, indicating the presence of annual seasonality. The seasonality effect in both series was removed by applying the seasonal-lag difference to the series. After acknowledging the presence of trend and seasonality components, it is time to choose a model that can adjust these two features so that we used $SARIMA(p,d,q)\times(P,D,Q)$ with $d = D = 1$ since a simple difference was applied to eliminate trend and seasonal difference to eliminate seasonality. Table 1 shows some of the models created. We selected the model with the lowest BIC estimate, so for both series, we chose the $SARIMA(1,1,2) \times (0,1,1)$ model as the most appropriate to adjust our temperature data series.

Table 1: Model selection for maximum and minimum temperature time series

Model	BIC for the maximum temperature time series	BIC for the minimum temperature time series
SARIMA(1,1,0)x(0,1,0)	2279.489	1951.104
SARIMA(2,1,0)x(0,1,0)	2267.859	1929.888
SARIMA(2,1,1)x(0,1,0)	2160.795	1846.041
SARIMA(2,1,2)x(0,1,0)	2164.43	1850.777
SARIMA(2,1,2)x(0,1,1)	1848.929	1540.279
SARIMA(2,1,2)x(0,1,2)	1855.275	1546.542
SARIMA(2,1,2)x(1,1,1)	1855.275	1546.548
SARIMA(1,1,2)x(0,1,1)	**1847.699**	**1534.037**
SARIMA(1,1,2)x(1,1,1)	1854.044	1540.298
SARIMA(1,1,2)x(0,1,2)	1854.444	1540.29

Residual analysis results for the two models are shown in Table 2. For the fitted model on monthly average maximum temperature series, the null hypothesis was not rejected by the Ljung-Box tests for both residuals and squared residuals, confirming model fitness. The model adjusted for monthly average minimum temperature series had the hypothesis of homogeneity of variances rejected by the Ljung-Box test applied to the squared residual.

Table 2: A – Model's residual analysis for monthly average maximum temperature time series. B – Model's residual analysis for monthly average minimum temperature time series

	A		B	
Test	Statistics	p-value	Statistics	p-value
Ljung-Box for residuals	135.2900	0.7220	7.7640	0.9330
Ljung-Box for squared residuals	20.8090	0.1430	30.7370	0.0107

As the hypothesis that the residuals are not autocorrelated from the Ljung-Box test applied to the residuals was not rejected, we can assume that the model properly adjusted the serial correlation, however as the $SARIMA(1,1,2) \times (0,1,1)$ model's variance is not homogeneous, modeling for this variation is also required.

The ARCH model was selected the same way as the SARIMA model, by creating several models and selecting the lowest BIC estimate. The $ARCH(2)$ model was chosen, with $BIC = 1496.8930$. For the other tested models, $BIC > 1497$. After adjusting the variance using the $ARCH(2)$ model, model residuals became non-self-correlated, and their variances became homogeneous, suggesting a good fit. Therefore, the monthly average maximum temperature time series was modeled by $SARIMA(1,1,2) \times (0,1,1)$, while the monthly average minimum temperature had its correlation modeled by $SARIMA(1,1,2) \times (0,1,1)$ and its residuals adjusted by $ARCH(2)$. We predicted air temperature in Viçosa-MG for the next 12 months with these models.

Table 3 shows air temperature predictions followed by their respective confidence intervals for the next 12 months (from August 2016 to July 2017) in Viçosa-MG. Particular attention should be given to February 2017, in which the average maximum temperature was over 30 °C, and June and July, the coldest months, with average minimum temperatures of 12° C and 11 °C, respectively.

Table 3: A – Prediction of monthly average maximum temperatures for Viçosa-MG, Brazil. B - Prediction of monthly average minimum temperatures for Viçosa-MG, Brazil

A				B			
Month	Prediction	Confidence Interval		Month	Prediction	Confidence Interval	
Aug/16	26.4551	24.2603	28.9743	Aug/16	11.4097	11.0139	14.4611
Sep/16	27.2116	25.0867	29.9964	Sep/16	14.0669	13.1357	16.7171
Oct/16	28.1462	25.8277	30.7714	Oct/16	16.8001	15.2965	18.9596
Nov/16	27.7839	25.5919	30.5387	Nov/16	18.0071	16.6035	20.3191
Dec/16	28.7096	26.4384	31.38	Dec/16	19.0737	17.5346	21.2823
Jan/17	29.3654	27.1725	32.0805	Jan/17	18.6623	17.5909	21.3605
Feb/17	30.2605	28.0189	32.9736	Feb/17	18.7801	17.4334	21.2179
Mar/17	29.1307	26.9389	31.8453	Mar/17	19.1671	17.1262	20.9211
Apr/17	27.9333	25.7009	30.701	Apr/17	18.6035	15.568	19.3706
May/17	25.6222	23.417	28.3615	May/17	14.9948	12.4675	16.2757
Jun/17	24.6834	22.4784	27.4483	Jun/17	12.0781	10.5781	14.3916
Jul/17	24.8016	22.5893	27.5203	Jul/17	11.1088	10.0091	13.8261

DISCUSSION

In the studied period, we detected an increase in monthly average maximum and minimum temperatures, with minimum temperature increase being slightly higher than maximum temperature increase, showing to be more sensitive to the external factors affecting climate. Air temperature increase above 1 °C is a matter of concern since the population can change their habits if this rising pattern continues. The presence of seasonality is already expected, as this is a climate time series, but the trend identified in both series is the one relevant for the region. Experiments with plants and animals are developed on a large scale in Viçosa-MG, many of them without environmental control. Such temperature increase may influence some research areas, especially plant breeding, which requires many years to develop a variety. The monthly average minimum temperature series,

after being adjusted by a $SARIMA(1,1,2) \times (0,1,1)$ model, showed heterogeneous variance, so it was necessary to adjust its residuals with an $ARCH(2)$, the model that proved to be a good alternative, in this case, making predictions better and meeting the assumptions of Box and Jenkins methodology for time series modeling.
Considering the temperature predictions estimated by such models, most months had temperature estimates above the time series general average. Only August 2016, May, June, and July 2017 were below the general average for the maximum temperature series. For the minimum temperature series, the lowest minimum temperature was observed in June 1968 and has not been repeated since then. In the last 17 years, the monthly average minimum temperature below 10 °C was observed only five times.

CONCLUSION

This study concludes that Viçosa-MG follows the same pattern of significant temperature increase found in many other places. However, we cannot assume that such an increasing pattern is due to a global phenomenon since this study considers data from just one city. Global phenomena, on the other hand, cannot be ignored. Therefore, temperature increase in this city may result from the city's growth and development, including industrialization, street paving, and an increased vehicle flow. Our results are essential to Viçosa citizens, especially those who depend directly on climate to perform their business activities. Considering that the city has been suffering a constant rise in temperature, it becomes necessary to rethink how we carry out activities and act appropriately to contain this phenomenon.

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