Estimating the Impact of Climate Change on Agricultural TFP

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April 12, 2024

Abstract

Recent publications on the historical implications of climate change for agricultural TFP – and on GDP -- have found strong impacts. Large, negative impacts are important for the simulation modeling community because they should, if confirmed, suggest that currently there are understated likely future impacts by some combination of ignoring important impact channels or failing to appreciate the true magnitude of impact within included impact channels. In this paper we examine more carefully a model on which the recent publications are based, proposing an important modification, and critiquing the applications of this model in the noted papers.

While the model applies to both GDP and TFP, we focus empirically on agricultural TFP. Using two possible impact channels of climate on TFP/GDP, we test for their presence in a model which incorporates both, and then in subsequent regressions, estimate the magnitude of the impact of climate change with only the effect that is statistically significant. Using a flexible functional form, which reduces the bias that is usually imposed by researchers in choosing a linear or quadratic response function, we find that there is no statistically significant long-run (growth) effect of temperature or precipitation on TFP. We also find that while there is a short-run (level) effect of temperature, it occurs only in some temperature ranges and has resulted in a 1 percent reduction in average global agricultural TFP between 1976 and 2015. Finally, when the sample is split in half by income level, on average the higher-income countries show a large and negative long-run (growth) temperature effect on TFP while the lower-income countries have no long-run effect of temperature or precipitation and but do have a small negative short-run (level) effect.

Introduction

There have been several highly influential, high-profile articles published that claim extremely large impacts of relatively small increments of climate change on agricultural total factor productivity (TFP) (Ortiz-Bobea et al.) and on GDP (Burke et al 2015; Burke et al. 2018; Diffenbaugh et al. 2019). These struck us as being unreasonably large and unfortunately, they have been used by many well-meaning donors and decision-makers around the world to justify diverting resources to reduce the magnitude of the climate change impact. We fully embrace the fact that the climate is changing, and that the primary driver is greenhouse gas (GHG) emissions produced by human activity; however, over-valuing the real cost of climate change does not allow donors and governments to make optimal use of limited funds to address multiple needs. Decision-makers need the correct costs.

Both sets of analyses rely on the work of Dell et al. (2012) regarding the potential impact channels of climate on TFP/GDP. Because we intend to call into question how the assumptions each set of authors made drove the results, we will take time to develop the modeling framework. This paper will present results focusing on agricultural TFP, however, so the comments regarding GDP will be featured primarily within the section on modeling and very little will be found in the econometric analysis section.

While it is fairly common to model the impact of climate change on crop yields, that work has focused on a very limited number of crops sector (Lobell et al. 2011a; Lobell et al. 2011b; Schlenker and Roberts 2011; Rosenzweig et al. 2014; Jagrmeyer et al. 2021; Sulser et al. 2021). Much less is known about the impact on most fruits and vegetables, not to mention tree crops and other perennials, livestock, fish, and agricultural labor productivity. While these potential costs are not well-known, the extent of adaptation to the shocks is also not well-known, with locations where specific crops are grown changing, new varieties that are resilient to climate shocks and better adapted to the new climate being adopted, and farmers shifting planting dates to periods that are better suited.

That is why a study of the impact of climate change on agricultural TFP is extremely important: it incorporates the unknowns under a common umbrella and reveals the bottom-line impact on agricultural productivity. In this paper, we use a dataset assembled by Ortiz-Bobea et al. (2021), consisting of measures of country-level agricultural total factor productivity (TFP) for the entire world for 1961 to 2015 along with the mean temperature and precipitation in the growing season in the agricultural areas of each country.

Modeling climate impact on agricultural TFP

Following Dell et al. (2012), we investigate two possible avenues through which climate can affect GDP or TFP, one directly affecting the level of GDP or TFP, as if it were an input to the production function. The other affecting the growth rate of GDP or TFP, which is the technology advancement embedded within the production system.

In this model, X_{it} is the aggregate input for country *i* and year *t*, and this is an essential component of the definition for TFP. However, in work on GDP, researchers typically ignore X, so the model is applicable to both TFP and GDP, as long as the reader is willing to simply forget about the existence of X in translating this work to the study of climate impact on GDP.

We begin with the basic model, given in (1). Let

$$Y_{it} = A_{it} e^{h(Z_{it})} X_{it} \quad (1)$$

where Y_{it} is aggregate agricultural output, Z_{it} is the corresponding climate (in our analysis, a vector accounting for temperature and precipitation), $e^{h(Z_{it})}$ is the effect of climate on the level of output, and A_{it} is the measure of technological knowledge embodied in producing the output.

Following Dell et al. (2012), we assume that $ln(A_{it})$ may also be affected by climate Z_{it} , growing at the rate given by

$$ln(A_{it}) = ln(A_{it-1}) + \alpha_{i0} + f(Z_{it}) \quad (2)$$

where α_{i0} is the exogenous country annual growth rate of A_{it}. Taking the log of (1), rearranging, and substituting in (2) gives

$$ln(TFP_{it}) \equiv ln(Y_{it}) - ln(X_{it}) = ln(A_{it-1}) + \alpha_{i0} + f(Z_{it}) + h(Z_{it}) \quad (3)$$

Noting the recursive nature of (2), we can also write,

$$ln(TFP_{it}) = ln(A_{i0}) + \alpha_{i0} t + \sum_{s=1}^{t} f(Z_{is}) + h(Z_{it}) \quad (3')$$

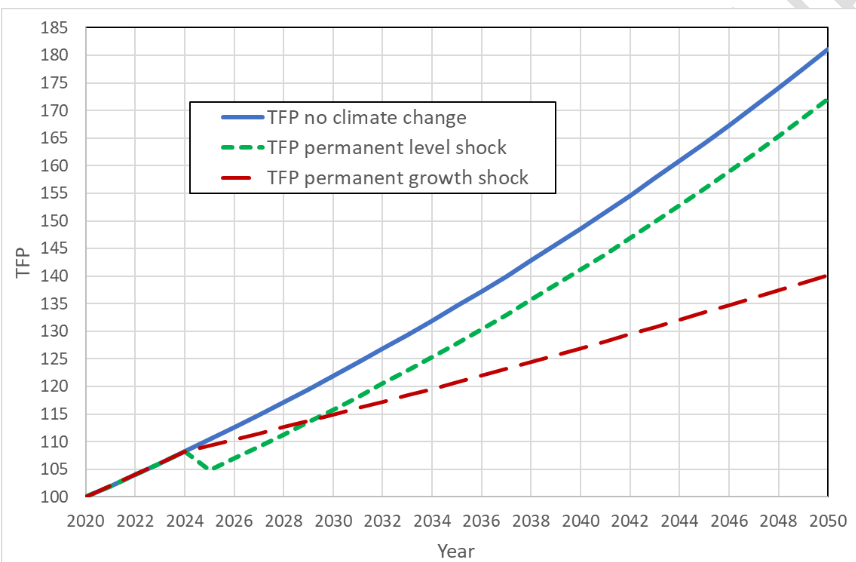
This tells us that if $f(Z_{it})$ is different than 0, a change in climate in any period affects the TFP level in any future period. Subtracting the log of (1) evaluated at time t-1 from (3) gives us

$$g_{it} = \Delta ln(TFP_{it}) = \alpha_{i0} + f(Z_{it}) + \Delta h(Z_{it}) \qquad (4)$$

where Δ is the difference operator. In (4), we see that $f(Z_{it})$ affects the growth rate in TFP directly, and that is why Dell et al. (2012) call it the "growth effect". A consequence of climate acting through the growth rate is that a one-period shock changes all future levels of TFP (or output) and is therefore considered a long-run effect. It also implies that a longer time horizon leads to a larger accumulated loss (gain). The level effect can be thought of as the short-run effect because its impact on TFP only affects TFP during one period.

Often shocks are thought of as short-lived, perhaps just a single period (e.g., a drought or heatwave). But climate change is a permanent shock. A permanent shock has a much greater impact through a growth effect compared to a level effect (see Figure 1). A permanent level effect shifts the curve, but the rate of growth is unaffected, and the new path is roughly parallel to the unshocked path. A permanent growth effect shifts the slope of the curve, and over time, the changed slope causes a much greater impact than a shifted curve.

Figure 1. Illustration of the permanent shock with a level and growth effect



The level effect is the more intuitive concept of the two: climate affects output directly. Low rainfall lowers the crop yields for the current year, but normal rainfall in the following year restores yields to the normal level. An example of how climate might act through the growth effect is more difficult to hypothesize.

In studies on the impact of climate change on GDP (Burke et al 2015; Burke et al. 2018; Diffenbaugh et al. 2019), the authors do not allow for a level effect, imposing the assumption that climate can only act through the growth effect, and thus forcing the model to predict extremely large costs of climate (they find a half-degree difference in temperature results in a loss of $20 trillion by 2100, in part due to the long time horizon of their accounting).

One important thing that has not been well addressed in the literature is the assumption concerning the functional form for the level effect and growth effect. Dell et al. (2012) only estimated a linear function for climate, though they do interact the linear terms with a term that distinguishes rich countries from poor countries. Most subsequent studies have relied on the quadratic form, including Ortiz-Bobea et al. (2021) and Burke and colleagues (Burke et al 2015; Burke et al. 2018; Diffenbaugh et al. 2019). But there is no reason to assume that in the aggregate, the response of production would be either linear or quadratic. Schlenker and Roberts (2009) estimate a flexible functional form for the effect of temperature on agricultural yield and show that it is not well-approximated by a quadratic function. We therefore propose using a flexible functional form for the climate impact on TFP. We choose a piecewise linear function with nodes chosen to allow sufficient data to inform each section. We select the end nodes so that roughly 10 percent of the observations are in both the top and bottom of the distribution of temperature and precipitation, and a reasonable spacing that kept 10 to 20 percent in each segment in between the ends. In the end, we use 3 degrees per segment for the temperature distribution, but we also test the robustness of such an approach by off-setting the original starting and ending values by a half-degree and using a spacing of 2 degrees. The results for the original and the alternate are qualitatively very similar, with each line segment having similar slopes, allowing for differences in the location of the nodes.

Results

Regression results using all countries in sample

We begin by running regressions that include both long-run and short-run climate terms, with one regression using quadratic functions and the other regression using piecewise linear functions. We estimate the data as a panel which allows each country to have a different growth rate. Furthermore, we control for global economic shocks by having a categorical variable for each year. We find that the long-run climate effects are not jointly significant in either regression.

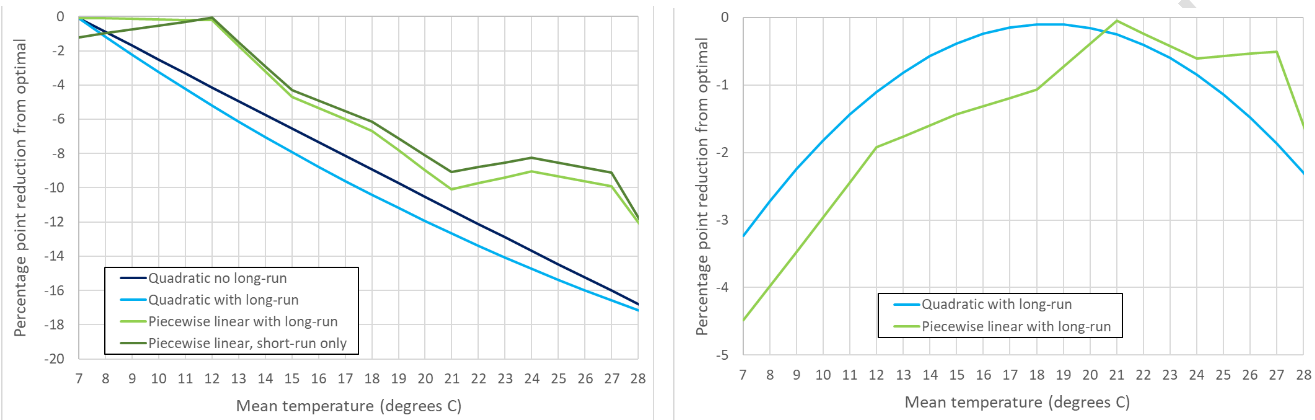
We then remove the effects that are not statistically significant – i.e., the long-run effects -- and re-run the two regressions with only short-run climate terms. Note that the quadratic with only short-run effects is the regression used by Ortiz-Bobea et al. (2021). Impact of temperature on TFP level (short-run effect) and TFP growth (long-run effect) for the four regressions are shown in Figure 2. We show both sets of regression results in the figures, but our strategy is to estimate the regressions with both effects to see whether either or both effects had any explanatory power, then to re-estimate the equation with only the effect(s) that have explanatory power, from which we get the parameter values for the true model. Only the second set of regression results are reported in Table 1.

While the short-run effect estimated with the quadratic appears generally similar to the short-run effect estimated with the piecewise linear – in that they are both generally downward sloping and even parallel in certain temperature ranges -- there are important and noteworthy differences. Firstly, the piecewise linear has areas that are significantly flat – at temperatures less than 12 degrees and those between 21 and 27 degrees. Upon testing with both a bootstrap and an F-test, we find that these flat areas have slopes that are not significantly different than 0, and therefore conclude that temperature change does not appear to affect TFP when initial temperature is in these ranges. It also implies that the imposition of a quadratic functional form without a strong prior belief that the response function must be quadratic can lead us to the wrong conclusion about the effect of temperature on TFP. We also see in the piecewise linear specification that above 27 degrees there is a significant decline in TFP.

The long-run effect shown in Figure 2 seems to suggest that there are temperature ranges for which the slopes are large and statistically significant; however, bootstrap and F-tests indicate that they are not. A histogram of temperatures for the countries of the world can be found in the Appendix.

Figure 2. Effect of temperature on agricultural TFP in analysis of full sample

Short-run effect   Long-run effect



Note: These graphs show percentage point yield losses relative to an optimal temperature. The best way to use the graph to interpret the impact of climate change is to note the change in percentage points between a country's starting mean temperature and ending mean temperature. This represents the change in level of TFP (in the case of the short-run effect) or the growth rate of TFP (in the case of the long-run effect). For example, in the "quadratic with long-run" in the short-run effect graph, an increase of 3 degrees from 23°C to 26°C lowers the level of TFP by 2 percentage points. In the "Piecewise linear with long-run" in the long-run effect graph, a 1-degree change from 27°C to 28°C slows the annual growth rate by roughly 1 percentage point.

To create counter-factual temperatures representing the absence of climate change, we removed the climate trend after 1976. Similar to Ortiz-Bobea, we used these along with actual temperatures to determine the effect of climate change between 1976 and 2015 on the TFP levels in 2015. Because TFP is computed as an index, to summarize global total, we chose to average TFP across all countries and calculate the percentage difference for the sample, as Ortiz-Bobea et al. (2021) did. The climate impact on agricultural TFP is presented in Table 1.

Table 1. Point estimates of percentage change in TFP in 2015 due to climate change (1976-2015)

Function	Effect used in regression	Sample	Effects estimated	All	Higher income	Lower income
Quadratic	Short-run only	All	Short-run	-0.9	-0.9	-0.9
Piecewise linear	Short-run only	All	Short-run	-0.8	-0.8	-0.9
Piecewise linear	Long-run only	All	Long-run	-15.2	-12.8	-17.8
Piecewise linear	Long-run only	Higher income	Long-run	NA	-15.4	NA
Piecewise linear	Short-run only	Lower income	Short-run	NA	NA	-1.0

In that table we note that despite having some significant differences in slope between the quadratic and piecewise linear forms, the estimates for aggregate TFP change in 2015 are remarkably similar for the regressions [1]. These show less than 1% reductions, and the reductions are almost identical in higher-income and lower-income countries.

As a technical matter, it is important to reiterate that long-run variables accumulate, generating large impacts over time in counterfactual scenarios. To illustrate what would happen if researchers estimated this data with only a long-run effect (even when we have shown that the long-run effect is not statistically significant in the full sample when a short-run effect is included), they would find that the long-run effect is statistically significant and would project very large losses due to climate change – 15.2% in 2015 – even though the regression suggested that there is no long-run effect. It would also project greater losses in lower-income countries, reaching almost 18%, and a 13% reduction in higher-income countries.

Results from splitting the sample into higher- and lower-income countries

We now investigate whether TFP responds to climate differently in higher-income countries than in lower-income countries. The former tend to have smaller agricultural sectors relative to the rest of the economy and can access more-expensive agricultural technologies that may allow for faster adaptation to climate change. Furthermore, higher-income countries tend to be in higher latitudes where it is cooler. We therefore split the sample based on average income over the entire period and run regressions on each group using piecewise linear long-run and short-run terms. For the higher-income countries, only the long-run terms were statistically significant while for the lower-income countries, only the short-run terms were statistically significant. Hence, we also present regressions dropping the insignificant set (e.g., short-run terms for higher-income countries). Figure 3 shows results.

For higher-income countries, despite the long-run effect being jointly significant for temperature, bootstrapping the regression showed that the effect was only statistically different from zero in the 12-15 degree and > 27-degree range. And, despite not being jointly significant in the short-run effect, temperatures in the range of 12-15 degrees and 18-21 degrees were statistically significant. When we limited the regression to only the long-run effect, the temperatures tested jointly significant, yet the only individually significant temperature range was for the > 27-degree range. In Figure 3, the steep decline above 27 degrees is readily observed.

For lower-income countries, neither the long-run temperature variables nor the long-run precipitation variables – nor both together – were jointly significant. Surprisingly, the short-run temperature variables were not jointly significant either, though the estimates were significant in the 12–18-degree range and for temperatures greater than 27 degrees. The short-run precipitation variables were, however, jointly significant, as were the short-run temperature and precipitation variables together. When we dropped the long-run variables and re-ran the regression, the temperature variables were jointly significant, as were the precipitation variables, and the temperature and precipitation variables together.

Table 1 shows that lower-income countries seem to have only experienced a 1% reduction in agricultural TFP by 2015 relative to what would have happened if there had been no climate change after 1976. However, higher-income countries appear to have a 15% lower agricultural TFP as a result of the climate change that has happened up to 2015.

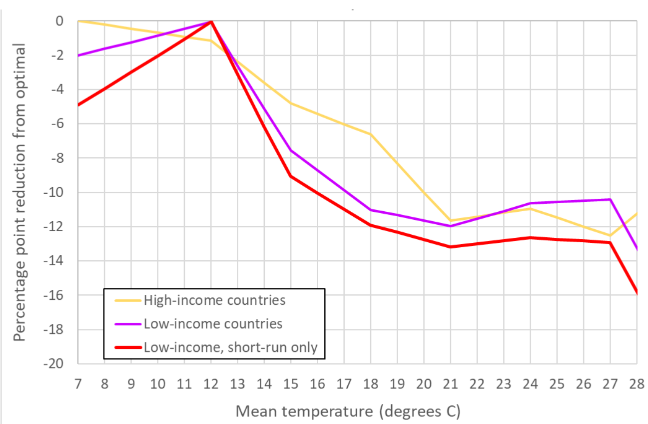
[1] While we reproduce the regression estimates of Ortiz-Bobea et al. (2021), we believe that they made a mistake using their climate projections.

Discussion

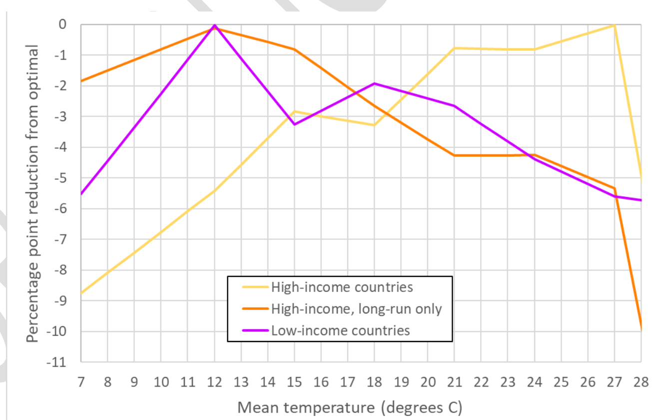
We have shown how the two pathways for climate to influence TFP (and GDP) differ in importance when assessing potential damages and losses. The pathway that affects the level of TFP can be seen as a short-run effect and the magnitude of losses through this effect, while important, are relatively small compared to the second pathway. That pathway, which affects the growth rate for TFP, is a long-run effect. It is persistent – it never disappears. Furthermore, it accumulates in such a way that the longer the time horizon, the bigger the cost, penalty, or loss. Therefore, it is not surprising that in the split sample, higher-income countries, for which climate seemed to act through the growth pathway, had a very large loss from climate change, while lower-income countries, for which climate seemed to act through the level pathway, had a very modest loss. Furthermore, in the combined sample, the statistical analysis rejected the growth pathway, leaving only modest losses from the level pathway.

Figure 3. Effect of temperature on agricultural TFP in analysis of split sample

Short-run effect



Long-run effect



Note: Interpreted in the same manner as Figure 2.

What shall we conclude about the value of the flexible functional form compared to the more-often-used quadratic? It appears that the quadratic poorly represents the impact of climate change on agricultural TFP, and therefore the flexible functional form is an important innovation for this type of analysis. On the other hand, one wonders whether it is actually the climate effect that drives the shape of the curve or the characteristics of the particular countries that are located in each temperature band? While the best answer might be found empirically by making a bigger dataset, perhaps by including states and provinces of some of the geographically-larger countries, we can at least note that even in the split sample, the flat areas and sloped area that were found in the full sample were also there in the split sample for both higher-income and lower-income countries, suggesting but not proving that perhaps it is a real effect of how climate impacts agricultural TFP.

Our split sample analysis suggests that there might be a genuine structural difference between agriculture in higher-income and lower-income countries. If that is the case, it is unclear how to think about the future impact of climate change on lower-income countries. Will lower-income countries continue in a regime in which climate affects TFP only through the level effect, or as they continue growing economically, will they switch into the higher-income regime, for which climate impacts TFP through the growth effect, thus exposing them to large impacts on their agricultural sectors?

The main goal of this paper was to determine how much climate change had impacted agricultural TFP by 2015 by accounting for two climate pathways, the long-run rate (growth) effect and the short-run level effect. For lower-income countries, the answer is almost surely far less than the approximately 21% reduction proposed by Ortiz-Bobea et al. (2021). In both the full sample and the split sample, lower-income countries were estimated, on average, to have only lost 1% (or less) of their agricultural TFP to climate change by 2015. On the other hand, higher income countries may have lost only 1% -- based on the full sample – or over 15% -- based on the split sample. That latter value is approaching the level estimated by Ortiz-Bobea.

While we have reported on average impact on agricultural GDP, both Figure 2 and Figure 3 show steep reductions in TFP above 27°C. Therefore, the limited number of countries with temperatures above that will indeed have larger reductions in agricultural TFP as a result of climate change. With rising temperatures, more countries will shift into that range, suggesting that some lower-income countries will experience steeply rising costs of climate change even without a regime shift, especially if emissions cannot be curtailed soon.

While our results provide a basis for less pessimism about the ability of agricultural systems in lower-income countries (and higher-income countries, if we are more prone to believe the results of the full sample) to withstand the warming that is baked into the climate systems over the next 30 years or so, they provide no basis for complacency. Rather, they highlight the need for investment to build resilience to shocks and to maintain or accelerate underlying productivity growth rates through time. Investment in productivity growth rates could compensate, in part or in full, future reductions in productivity from climate change.

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Acknowledgments

This work was undertaken as part of the CGIAR Initiative on Foresight.

Appendix

Distribution of countries by temperatures used in regressions

Figure 1. Histogram of observed temperatures for full sample

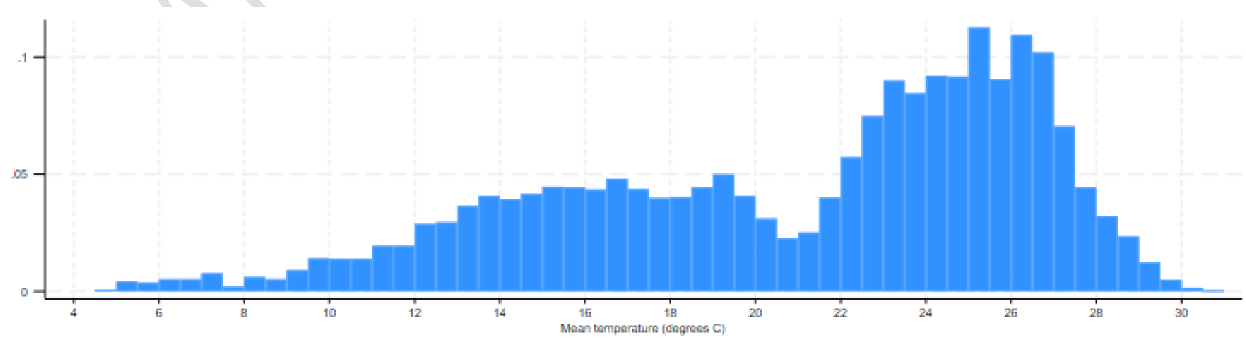

Figure 2. Histogram of observed temperatures for above median income countries

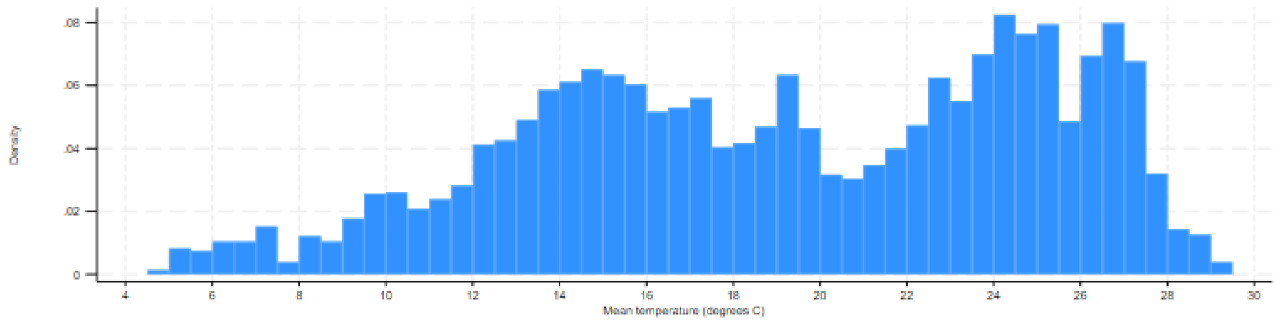

Figure 3. Histogram of observed temperatures for below median income countries