Chapter 5
Crop Responses to Climate: Time-Series Models

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Abstract Time series of annual crop production levels, at scales ranging from experimental trials to regional production totals, are widely available and represent a useful opportunity to understand crop responses to weather variations. This chapter discusses the main techniques of building models from time series and the tradeoffs involved in the many decisions required in the process. A worked example using United States maize production is used to illustrate key concepts.

5.1 Introduction

The task of predicting crop responses to climate would be easy if crop yield were determined by a single and simple biological process. The reality, of course, is more complex. Crop growth and reproduction are governed by many interacting processes that present an enormous challenge to efforts at prediction. Many of the most relevant processes have been outlined in Chapter 4, which describes efforts to develop models that capture the essence of each process without being too complex to prevent reliable model calibration and applications.

An alternative to this process-based approach is to rely on the statistical relationships that emerge between historical records of crop production and weather variations. In short, we observe the past and use it to build models to inform the future. From the outset, it should be clear that purely statistical approaches, whether based on time series as discussed in this chapter or cross-sectional data as discussed in the next, are not inherently better or worse than more process-based approaches. There are some disadvantages, such as difficulty in extrapolating beyond historical extremes, as well as some advantages, such as limited data requirements and the potential to capture effects of processes that are relatively poorly understood, such as pest dynamics.

It should also be clear that statistical approaches cannot proceed successfully without some consideration of the underlying processes. For example, the choice of which months of weather to consider will depend on the growing season of the

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crop, and the choice of what climate variables to use will depend on the processes thought to be most important. Such considerations will be explained in more detail below. The general point, and one that is often confused in the existing literature, is that the distinction between "process-based" and "statistical" models is somewhat arbitrary. All process-based models have some level of empiricism, and all statistical models have some underlying assumptions about processes.

This chapter seeks to describe time series based approaches to crop modeling, highlighting the important decisions that can affect the outcomes. Time series models have been widely used to evaluate the impacts of climate variability and change on crop production. They are particularly useful in situations where there is insufficient data to calibrate more process-based models, and where detailed spatial datasets are not available, both of which are accurate descriptions of the situation in many developing countries. Their main requirement is the availability of sufficiently long time series (at least 20 years) of both weather and crop harvests.

5.2 A Worked Example: U.S. Maize Yields

To help guide the discussion and illustrate the time series modeling process, we will use a dataset for US maize yields from 1950–2005. The United States Department of Agriculture (USDA) has recorded average yields for each county since early in the twentieth century, and in many cases since the late 1800s. In addition, the United States has arguably the most complete weather records of any country for the twentieth century. Here we have averaged yields over all counties east of the 100° W meridian, which separates mostly irrigated maize in the West from mostly rainfed maize in the East. The average was weighted by the area sown to maize in each county, so that yields in counties with high acreage were proportionally more important. Weather data from individual stations were similarly weighted.

5.3 Common Issues in Time Series Modeling

5.3.1 Spatial and Temporal Extent

The choice of restricting our time series to east of 100° W highlights one of the first decisions in time series modeling – the spatial extent over which yields and weather are averaged. This scale can range from individual fields (if the data are available) to entire regions. As scales become bigger, datasets are often more reliable and available. However, aggregating areas too large will result in combining fields that actually behave quite differently. Consider, for example, two adjacent areas, one of which prefers cooler climates and the other of which prefers warmer climates. If these two are combined, then the average yields could show no effect of climate variations even though there is a true response in each region. If the only goal is to understand yield responses at the broader scale, then one might be satisfied with this result. But, in general, we prefer when possible to work with regions that are relatively homogeneous in nature. Separating irrigated from rainfed crops is almost always a good idea, given the very different nature of response to rainfall.

The scale issue also extends to the temporal dimension. Just as maize in California may be functionally a very different crop than maize in Georgia, maize in 1950 was potentially very different in its climate response than maize in 2000. For example, Zhang et al. (2008) demonstrate that the correlation between rice yields and temperature in China switched from being negative before 1980 to positive after 1980. The explanation in this instance was that irrigation was much more widespread after 1980, allowing crops to take advantage of the drier, sunnier conditions that led to water stress for rainfed crops. The time period for time series analysis should therefore be restricted to periods over which management was reasonably constant, particularly management factors such as irrigation that can strongly influence climate responses. One approach to ensure a stationary relationship between climate and yields is to perform the analysis for the first and second half of the record, and then compare the results.

5.3.2 Trend Removal

Figure 5.1a shows average yields over the study period. The most obvious feature of this time series, and time series of yields for most crops in most regions, is the highly significant positive trend with time. This trend results largely from improvements in technology, such as adoption of modern hybrid cultivars and increased use of fertilizer. Given that so much of yield variation between years in different parts of the record occurs because of technology differences, the effect of climate is difficult to discern from the raw yield data. For that reason, one nearly always performs a de-trending of the data to remove the influence of technology. There are several ways to do this, none of them clearly optimal. The first is to approximate the trend in technology with a polynomial fit, and take the yield anomalies from this trend. For most crops the technology trend can be approximated with a first order polynomial (linear trend).

Figure 5.1b illustrates the yield anomalies from a linear trend for the maize time series. The anomalies are much larger in absolute value for the latter part of the record, a common occurrence in yield time series. This change in variance from the beginning to end of the record, known as heteroskedasticity, violates some of the basic assumptions of many statistical techniques such as linear regression. To correct for this, yields are often expressed on a log basis, which means that anomalies represent percent differences from the trend line rather than absolute differences, since log (a) − log (b) = log (a/b). As shown in Fig. 5.1c, use of log yields rather than absolute yields removes most of the problem with heteroskedasticity.[1]

[1] However, note that if the yield anomalies in Fig. 5.1b showed no sign of heteroskedasticity, then introducing the log transformation could lead to heteroskedasticity by suppressing values at the beginning of the record.

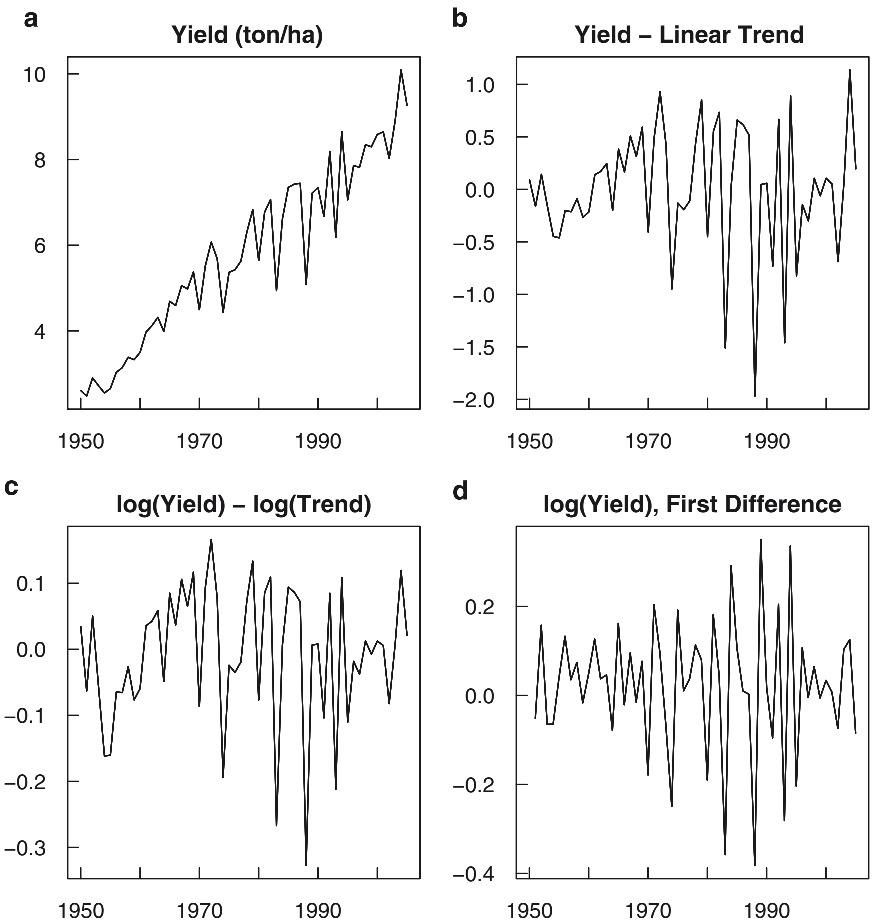

Fig. 5.1 (**a**) Time series of maize yields in US for counties east of 100° W, shown with three common methods of detrending (**b–d**)

It is frequently the case that yield trends are obviously not linear, as demonstrated for two cases in Fig. 5.2. In this situation, fitting a linear trend may cause serious errors, and one can resort instead to higher order polynomials. A more flexible approach, and one that is commonly used in time series analysis, is to transform the data to first-differences as shown in Fig. 5.1d, where from each value one subtracts the value in the previous year. In this case, the subsequent analysis focuses only on year-to-year changes so that effects of long-term trends are minimized. Any predictor variables must then also be transformed to first-differences in order to compare with yields.

A final approach to account for technology is not to remove a trend, but rather to include a term for year (and possibly year-squared) in subsequent regression analysis. One could also include explicit technology proxies, such as fertilizer rate or percent of growers using modern cultivars.

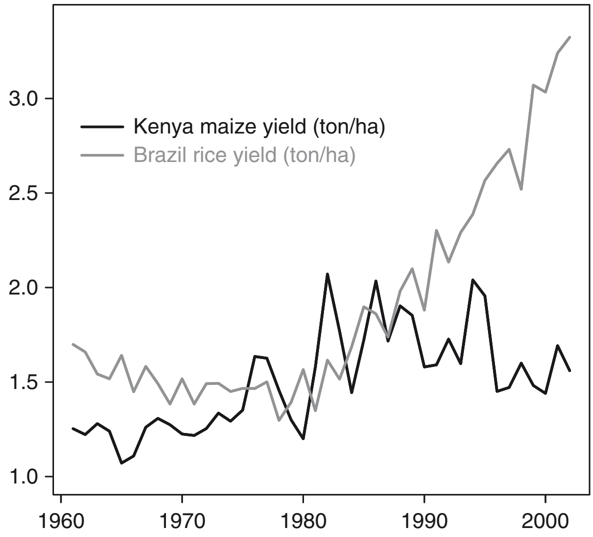

Fig. 5.2 Time series of yields in two cases with a nonlinear trend

Table 5.1 Summary of regression model results for different methods of detrending

Response variable	Predictor variable(s)	Model R^2	Yield sensitivity (mean ± 1 s.d.% °C^{-1})
Yield	Avg. temperature and year	0.92	−3.8 ± 2.0
Log (Yield)	Avg. temperature and year	0.90	−4.5 ± 2.5
Yield–Trend	Avg. temperature	0.06	−3.7 ± 1.9
Log (Yield)–Log (Trend)	Avg. temperature	0.10	−4.4 ± 1.9
Yield, first difference	Avg. temperature, first difference	0.16	−7.6 ± 2.4
Log (Yield), first difference	Avg. temperature, first difference	0.16	−6.8 ± 2.3

In summary, for any yield time series of considerable length, accounting for technology trends is essential, and many approaches exist toward this end. How important is this decision in the final analysis? Table 5.1 summarizes the results of simple linear regressions with average growing season (April–September) temperature as the predictor variable and various representations of yield as the response variable. The model R^2 indicates that regressions using first differences tend to have higher explanatory power than those based on anomalies. Models that use raw yields and include a time trend have, of course, much higher R^2 because the effect of technology has not been previously removed but is included in the model.

The key aspect of these models is the predicted response to temperature, which is expressed as the % change in yield for a 1°C increase. The results can vary by a factor of 2, with the smallest effect found when using raw yields with a time term, and the biggest effect using first differences of raw yields. Note that the effect of using log relative to absolute yields can either increase or reduce the model R^2 and inferred yield sensitivity, while the effect of using first-differences tends to increase both in this example.

5.3.3 Climate Variable Selection

The above example used average growing season temperature, which is indeed a very common measure of growing season weather. However, there are many other defensible variables to use in place of or in addition to this value. We distinguish here between two main choices: variable type and temporal scale. Variable type decisions involve, for instance, whether to include a term related to temperature, one for precipitation, and/or one for solar radiation or some other meteorological variable. Temporal scale decisions include extent (i.e., what length of growing season to consider) and resolution (i.e., how many intervals within the growing season to include). For example, while we defined the growing season as April–September, one could argue that March–August or June–September is a better definition. For resolution, many have argued that intra-seasonal variations in weather can be as important as averages (e.g., Thompson 1986; Hu and Buyanovsky 2003; Porter and Semenov 2005). Heat or rainfall during critical flowering stages for example, may be as or more important than average conditions. Again, while this is certainly true to some extent, the key question is how much the final analysis is affected by this decision.

One aspect of intra-seasonal variation is the length of time the crop spends above critical heat thresholds. For maize, it is commonly thought that temperatures above 30°C are particularly bad for crop development and growth (see Chapter 4). With hourly data, one can compute the number of hours spent above some threshold for the entire growing season in addition or in lieu of using growing season averages. Such decisions depend a great deal on the availability of fine scale meteorological measurements. In many parts of the world, reliable data are only available for monthly averages (briefly discuss here the approach to deriving degree days).

Figure 5.3 illustrate three climate variables for US maize: average growing season temperature and precipitation, and degree days above 30°C (GDD30), all plotted against each other and yield anomalies. The numbers below the diagonal in Fig. 5.3 indicate the correlation coefficient between the pair of variables. In this example, average temperature shows a significant correlation with yields, but less so than GDD30. Precipitation exhibits a slight positive correlation with yields and negative correlations with both temperature measures.

An important point illustrated in Fig. 5.3 is that different climate variables are often highly correlated with each other, such as average temperature and GDD30 in this example. Thus it is impossible to say exactly how much of the observed correlation between yields and average temperatures is due to a real effect of average conditions, and how much is due to a real effect of very hot days or reduced precipitation that happens to be correlated with average temperatures.

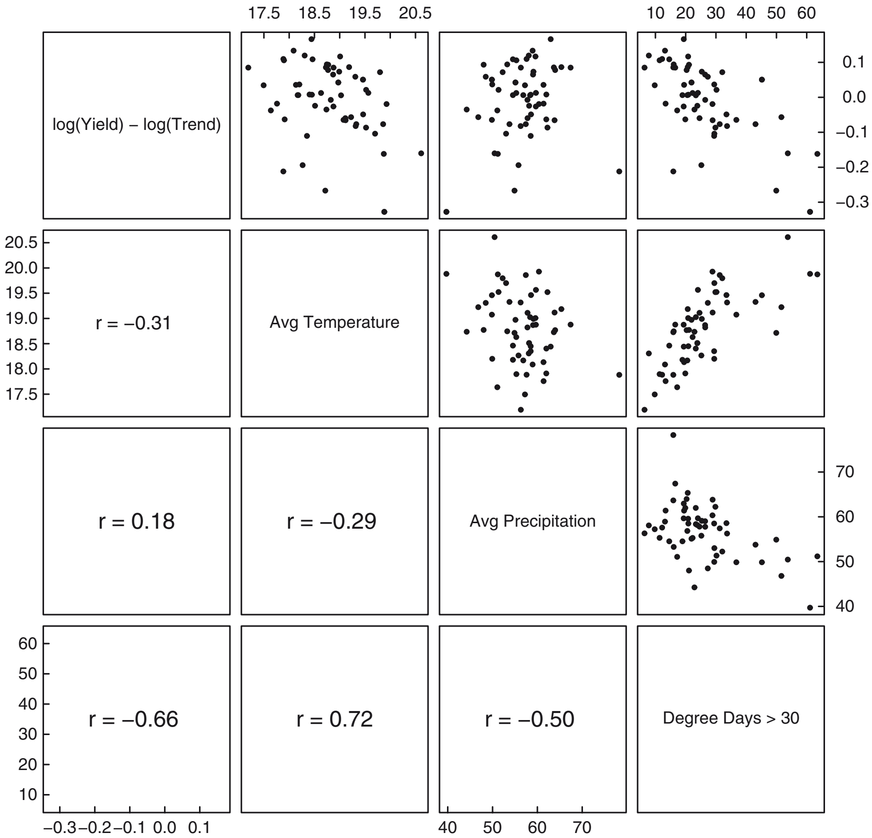

Fig. 5.3 Scatterplot of data for the US maize example

This problem of colinearity is common in statistical analysis, and often makes it impossible to attribute yield changes to a single climate variable. The obvious risk is that one may attribute yield losses to one variable when in fact another variable is the true culprit. The best approach to minimizing colinearity is to obtain samples where the climate variables are not highly correlated. For example, although growing season daytime and nighttime average temperatures are often very highly correlated, there are some locations in the world where this is not the case. Lobell and Ortiz-Monasterio (2007) focused on three such regions to evaluate the response of wheat yields to night and day temperatures.

A useful method for gauging the effect of colinearity is to evaluate partial correlation coefficients, i.e., the correlation between yield and a climate variable after the correlations with all other variables have been removed. Similarly, one can compute regressions between a variable and the residuals from a regression of yield on all other variables. Comparison of this value with the coefficient from an ordinary multiple regression will provide some measure of the role that colinearity plays.

Overall, colinearity is perhaps the biggest obstacle to time series modeling. In some cases it may be possible to distinguish between apparent and true effects on yield with knowledge of biological processes. More likely, this distinction is subjective and subject to disagreement. In an analysis of experimental rice yield responses to warming, for instance, Peng et al. (2004) reported a roughly 10% loss of yield for each degree of nighttime warming based on time series analysis. A subsequent analysis by Sheehy et al. (2006) used the rice process-based model ORYZA2000 to demonstrate that roughly half of the perceived effect of temperature could actually be due to changes in solar radiation, which are negatively correlated with nighttime temperature in this location. Similarly, Lobell and Ortiz-Monasterio (2007) compared statistical models with CERES-Wheat simulations to show that correlations of solar radiation and nighttime temperature can confound interpretation of statistical models. In the end, only controlled experiments can be used to uniquely identify the effect of a single variable when all others are held constant.

A related point illustrated by Fig. 5.3 is that omission of important variables can bias results. Maize yield correlates much more strongly with GDD30 than average growing season temperature in this region. Yet measures of exposure to extreme heat such as GDD30 have not been widely used, with most studies focused a priori on weekly or monthly averages. The choice of which variables to consider is often dictated by data availability – there are few regions in the world where reliable sub-daily data on temperatures extend back prior to 1980. There are similarly few good datasets on solar radiation, which as discussed above can be an important omitted variable because it is often correlated with temperature and rainfall.

Only by comparing results with and without the inclusion of variables such as GDD30 or solar radiation can we estimate the bias that their omission introduces in specific locations. Moreover, only by repeating these studies for a large number of locations can we make more general statements about the importance of these factors for future impacts, although strong claims for the importance of extreme events are frequently heard (Easterling et al. 2007).[2] It should also be clear that the importance of different variables may depend on the time scale for which projections are being made. For example, GDD30 may initially increase slowly as temperatures rise but more rapidly as average temperatures approach 30°C.

To summarize, time series methods are hampered by frequently high correlations between climate variables. In cases where two correlated variables are both included in the model, attribution of yield changes to any single variable is difficult if not impossible. In cases where an important variable is omitted, there is risk of attributing too much importance to a correlated variable included in the model. Even when the omitted variable is not correlated with included variables, there is a risk that its omission will miss an important effect of climate on yields.

[2] The recent IPCC Fourth Assessment Report states that "Projected changes in the frequency and severity of extreme climate events will have more serious consequences for food and forestry production, and food insecurity, than will changes in projected means of temperature and precipitation (high confidence)."

One may wonder at this point why we do not typically just include all possible climate variables in a regression analysis. As already stated, one common reason for omitting variables is lack of reliable data. More fundamental is the fact that increasing model complexity by adding more and more variables will eventually result in a model that is over-fit to the data, including the noise present in the data, and has worse predictive skill than a model with fewer variables. The balance between including enough but not too many variables is known in statistics as the bias-variance tradeoff, and places a premium on choosing variables wisely. As mentioned, knowledge of the biological processes that control crop growth and reproduction can be of tremendous value in the search for the "right" variables.

5.3.4 Functional Forms

Functional form refers to the type of relationship specified between a predictor variable, X, and a yield response variable, Y. The form could be a polynomial relationship, such as Eqs. (5.1) and (5.2), or an exponential relationship such as Eq. (5.3).

$$Y = \beta_0 + \beta_1 X \tag{5.1}$$

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 \tag{5.2}$$

$$\mathrm{Log}(Y) = \beta_0 + \beta_1 X \tag{5.3}$$

Several other classes of equations could also be used, such as regression trees, neural networks, or Mitscherlich equations. The most common forms used for modeling yield responses to weather are the linear model of Eq. (5.1) and the quadratic model of Eq. (5.2).

A useful way to determine the appropriate functional form is to examine a scatter plot of the data, such as in Fig. 5.3. One can also use statistical tests to determine whether a squared term significantly improves the model. A squared term can be very useful when there is an optimum temperature or precipitation amount that falls within the observed data. Thompson (1986), for instance, found that yields were reduced for departures from average June temperatures in five Corn Belt states, whether the departures were towards cooler or warmer weather.

Adding a squared term does not always help, however, as it is adds to the model complexity and can lead to overfitting and lower predictive skill. In general, we have found that higher order terms are more useful as the range of temperatures or precipitation that the crop experiences becomes wider. The reason is illustrated in Fig. 5.4: although no weather variable ever has a truly linear effect,[3] a linear approximation can be appropriate over a limited range of the weather variable. In this example, yield exhibits a nonlinear response to temperature, but this response is well approximated

[3] Extremely low and high values are nearly always bad for crops, so that the optimum value is found somewhere between.

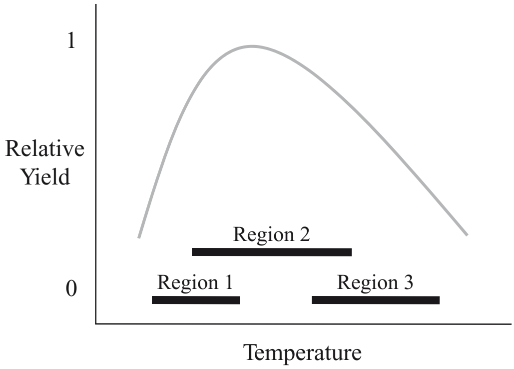

Fig. 5.4 A hypothetical relationship between temperature and yield. The range of temperatures experienced in a region will determine whether a linear approximation is appropriate

in regions 1 and 3 by a linear fit, since they are always on the cool and warm side of the optimum, respectively. In contrast, region 2 includes both temperatures where warming is strongly beneficial and temperatures where warming is quite harmful. Thus, a non-linear function would be necessary in region 2 but not the others.

It follows from the fact that the appropriateness of linear approximations depends on the range of weather experienced that the appropriateness will vary with the choice of model scale, since averages over large regions will show less variation from year to year than will averages over smaller areas. Linear models are therefore usually more appropriate when looking at national or regional time series than when looking at individual counties or states. As a case in point, the relationship between temperature and yield in Fig. 5.3 appears roughly linear even though at the state scale maize yields can exhibit strong nonlinear relationships with weather (Thompson 1986; Schlenker and Roberts 2006). Thus, as with the previous issues, the best choice for functional form will vary with the particular crop, location, and scale of interest.

5.3.5 Data Quality and Regression Bias

The example of US maize yields represents perhaps the most accurate long (50+ years) time series available on both crop yield and climate anywhere in the world. In many countries of prime interest for food security, the quality of data can be considerably worse. The crop production database of the Food and Agriculture Organization of the United Nations (FAO), for instance, contains an enormous wealth of information but much of it is visibly suspect. Reported yields are often identical for 3 or more years in a row, and areas can change dramatically in a single year. Errors in the response variable tend to inflate the standard error of coefficients in a regression model, but as long as the errors are random they should not introduce bias into the estimation procedure (Chatfield 1996). Errors in the predictor variables - in our case climate measurements – are a more serious concern because they tend to bias the coefficients towards zero. This phenomenon is known as regression bias, and though several methods exist to attempt to correct for it (Frost and Thompson 2000) its effects are often not well understood.

5.4 Projecting Impacts of Climate Change with Time Series Models

Once a model has been calibrated with time series data, it can be used to predict yield responses to any hypothetical amount of climate change. (Chapter 3 describes approaches for downscaling climate projections for input into crop models.) For example, temperature and precipitation changes from climate model simulations can be used to generate new values of the relevant predictor variables, which the regression model then translates to yields.

There are, however, three extremely important caveats to the use of time series models for simulating yield responses to climate change, even for the analyst who has successfully navigated the issues described in the previous section. The first is common to all cases of statistical model prediction, and relates to the problem of extrapolating the model beyond the range of calibration data. In particular, as the climate warms growing season temperatures may increasingly exceed the warmest year contained in the historical data used to fit the statistical model. Figure 5.5 illustrates this for the current example: as temperatures rise fewer and fewer predictions will reside in the calibration domain.

The simplest approach to avoiding extrapolation errors is to use statistical models only for the relatively near term where the vast majority of years have historical precedents. For example, if we set an arbitrary threshold that no more than 25% of

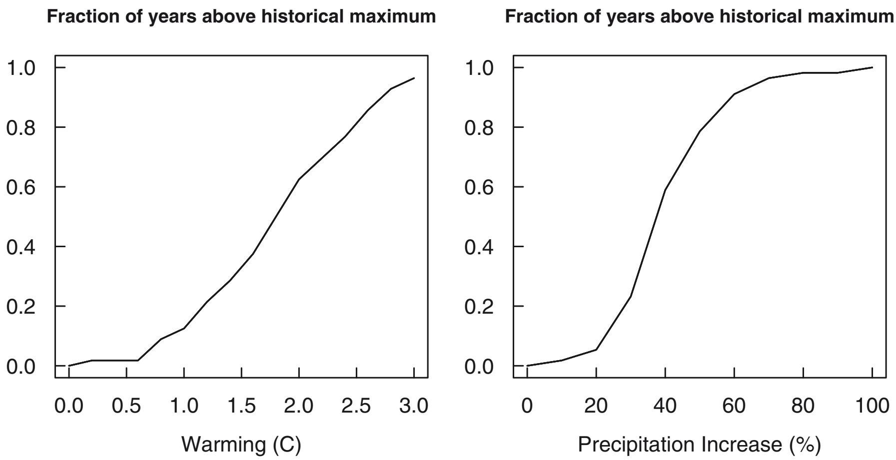

Fig. 5.5 Fraction of years that exceed historical maximum for the US maize example when temperature (*left*) or precipitation (*right*) is increased by different amounts

years should be warmer than the warmest year on record, then based on Fig. 3.5 we would only make projections out to 1.3°C. This corresponds roughly to average projections for 2030, which is still a useful period to analyze. However, using time series based models to make projections to 2080 – where climate model projections commonly exceed 3°C of warming – would be misguided, and in that case other approaches would be more appropriate.

Another approach to address extrapolation error is to implement several different methods of extrapolation to gauge whether results are sensitive to predictions made outside the calibration domain. For example, one can contrast a conservative approach of truncating yields to historical extremes, with a more aggressive approach of allowing yields to extrapolate to zero (Lobell et al. 2006). The point at which the two methods diverge provides a measure of when the time series model is on shaky ground.

The second caveat is another common one in statistics and involves the assumption of stationarity – that relationships observed in the past also apply to the future. As crop varieties and management systems change, however, the response of yields to variations in weather may also change. An example already mentioned is when irrigation is introduced into currently rainfed areas. As with extrapolation, the assumption of stationarity becomes more questionable as the time horizon of projections extends further into the future.

The final and perhaps most serious caveat is the use of models based on year-to-year variations in weather to predict responses to gradual changes in climate. An economist would refer to this as equating short-run and long-run effects, which ignores the ability of humans to adapt to system shocks. For agricultural systems, we attribute the difference between weather and climate responses to the ability of farmers to (1) perceive and (2) adapt to a changing climate. Some have gone so far as to argue that the response to climate can be opposite in sign to that for weather (Hansen 1991), while others argue that adaptation will be very difficult and not entirely effective.

A detailed discussion of adaption is presented in Part 3 of this book. The only point made here is that applying time series based models to projection of climate change implicitly assumes that no adaptation will take place. Note that this assumption does not have to be true for the projections to be useful. One goal of projections, for example, can be to identify where the biggest threats are to agriculture if we do not adapt, in order to guide short-term investments in adaptation (Lobell et al. 2008). Also, comparing time series based projections with those that incorporate adaptation can provide a useful measure of the potential impact of adaptation, a point explored further in the next chapter.

5.5 Summary

Time series can be an invaluable resource for understanding the aggregate response of crop production to variations in climatic conditions. Models based on time series depend not only on the data, but on several choices faced in the modeling process.

Most prominent among these are choosing the spatial and temporal extent of the time series data, method of detrending, types and temporal resolution of climatic variables, and the specification of the functional relationship between climate and yield. Poor choices for any of these can potentially lead to invalid estimates of climate responses.

Two general principles are especially useful for time series models. First, the analyst should always plot the data at each step, to examine features such as colinearity, heteroskedasticity, and nonlinearities, rather than rely exclusively on model summaries provided by common software packages. Second, when a choice between two alternatives is not apparent, the analysis should be tried both ways and the results compared. This is analogous to using multiple process-based models that have different but equally defensible assumptions to evaluate model uncertainty.

Users of time series models should be keenly aware that adaptation can, in principle, cause fundamentally different responses to weather and climate. As time series models are based on year-to-year variations in weather, their application to future scenarios of climate change embody an assumption of no adaptation. This can be useful in many situations, especially when results are contrasted with estimates of impacts that include adaptation, but the assumption should be kept explicit at all times.

A summary of the key points of this chapter are given below.

- Time series models can be extremely useful for projections for the next 20–30 years, when adaptation is likely to be small and climate is not too far from current conditions. Beyond that, the extrapolation of past relationships to the future becomes more tenuous.
- The most pervasive challenge in time series modeling is co-linearity between the major climate variables known to affect crops, namely temperature, precipitation, and solar radiation.
- There is no single best approach to time series modeling, as optimal decisions will depend on location, crop, and scale. Comparison of results from multiple alternative specifications can be a useful measure of uncertainty.

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