Contemporary Issues in Estimating Yield Distributions

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Abstract : In the research area of crop yield density estimation and in particular in risk analysis, little emphasis has been given to the appropriateness of transformation methods (e.g., removing a linear trend) and how such transformations impact the reliability of the empirical distribution functions and the resulting probability estimates. Similarly, there is little consensus on the impact of environmental variables (e.g., rainfall and temperature) on empirical distributions of yields. Using historical county corn yield data for Arkansas and Louisiana and nonparametric methods, this empirical analysis shed light on the importance of data transformation in crop risk analysis. Results demonstrate that inappropriate data treatment can lead to misestimation of probability density estimates.

Keywords: Probability Density Estimation, Nonparametric, Kernel, Nonstationary, Unit Roots, Data Tranformations, Corn Yields, Weather.

I. Introduction

Crop yield density estimation has been the subject of much empirical research in risk analysis. Initial methodological efforts were confined to identification of parametric density functions, and these were later extended to the more flexible nonparametric methods. It seems that the bulk of the recent literature has converged to nonparametric methods, and these methods have found their way into the estimation premia in yield-based insurance programs. In fact, nonparametric estimation of yield densities via some sort of univariate ARIMA models appears to be the state-of-the art approach in risk analyses. While clear arguments tend to favor nonparametric methods, it still remains unclear whether the flexibility of these methods is vulnerable to the time series properties of historical yield data. Numerous papers have been published arguing for the existence of nonnormality, skewness, kurtosis, heteroskedasticity, stochastic trends, etc. Surprisingly, however, applications have been void of a rigorous analysis of the filtering procedures used prior to density identification either via parametric or nonparmetric methods in the context of time series data. Therefore, the modest contribution of this paper is to propose that the ambiguity in deciding which filtering methods are most appropriate can be solved through the application of unit-root testing procedures and that the reliability of density estimation can be enhanced through the adoption of these methods with historical yield data.

The paper is structured as follows. The second section provides a summary of the literature on crop density estimation and is broken down into three parts: 1) transformation techniques, 2) crop yield density estimation, and 3) impact of environmental variables. The third section describes the data, and section four explains the methodology for identifying time series properties and for the estimation of yield densities. Section five provides the results. The last section of the papers summarizes the findings via some empirical recommendations.

II. Literature review

1. Transformation techniques

The existence of (stochastic and deterministic) trends in crop yields have been addressed in numerous papers (e.g., Moss and Shonkwiler, 1993 inter alia). As underlined by Enders (1995) the assumption that an upward trend of a series can be represented by a linear time trend is "controversial". Unfortunately, it is often the case that crop yields are analyzed assuming a linear trend. A deterministic trend is basically a time trend that is often specified as linear and included as a regressor. The stochastic trend corresponds to a unit root process and is interpreted as a shock that has a permanent effect on the series. It is captured by the moving average operator. A process can also have both a stochastic and a deterministic trend. For instance, in the case of a random walk process:

$$(1) y_t = \alpha + y_{t-1} + \varepsilon_t$$

It is easily shown that this process can be represented as:

$$(2) y_t = y_0 + \alpha t + \sum_{i=1}^{t} \varepsilon_i$$

Thus, the deterministic trend is materialized by the term αt and the stochastic trend by $\sum_{i=1}^{t} \varepsilon_i$. The presence of one another trend makes the sequence non-stationary as the mean of the series is not constant, it is time-dependent. One of the elements of interest for this paper is the transformation associated with each trend. The usual technique to make a process containing a deterministic trend stationary is detrending while in the case of a stochastic trend, the appropriate transformation is taking the first differences. Hamilton (1994) mentions that “a final difference between trend-stationary and unit root processes that deserves comment is the transformation of the data needed to generate a stationary time series.” Enders (1995) also insists on this important fact by claiming that: “the form of the trend has important implications for the appropriate transformation to attain a stationary series.” Nelson and Kang (1981) have illustrated, carrying out a Monte Carlo experiment, the consequences of inappropriate transformations and in particular the spurious periodicity implied by detrending a random walk series. One of the first empirical and Monte Carlo studies illustrating the relevance of nonstationarity in yield data is that of Zapata and Rambaldi (1989) who found that an arbitrary transformation to commodity prices and yields data such as detrending can generate series with different properties than those of the underlying stochastic process. They were the first to suggest testing for unit roots to assess the appropriateness of the transformation to be employed. Surprisingly, however, the empirical literature to date has remained silent on this issue. Enders (1995) and Hamilton (1994) give several theoretical examples of erroneous transformations implications. For instance, the model:

$$(3)\ y_t = \alpha t + y_0 + \varepsilon_t$$

Contains a deterministic trend and taking the first differences will introduce a unit-root into the moving average component:

$$(4)\Delta y_t = \alpha + y_0 + \varepsilon_t - \varepsilon_{t-1}$$

In short, by taking the first differences the process implies shocks. The correct transformation is, as previously argued, detrending by subtracting the deterministic time trend αt from y_t or, as commonly done, by regressing y_t on a linear or polynomial trend. The residuals of this regression are stationary and become the variable of interest. Another empirically relevant point is that, considering again the random walk with drift model, if the series y_t is detrended, as noted by Hamilton (1994), the time-dependence of the mean is successfully eliminated but not the variance. Enders (1995) adds that the stochastic trend component is not removed and as a consequence the series remains non-stationary with the consequences implied.

It is well-known that non-stationarity is the cause of spurious regressions (Enders, 1995; Hamilton, 1994; Hill *et al.*, 2008) meaning that the regression appeared to be significant when in fact it is not. In other words, variables may be wrongly found to be highly related. Beyond this crucial issue, inappropriate transformation may be important in other cases and in particular in crop yield density estimation. It begins to become apparent, then, that probability density functions and the resulting probability estimates may be biased if the wrong transformation is applied.

2. Crop yield density estimation

Foote and Bean (1957) followed by Day (1965) have first brought the issue of skewness in crop yield distributions. Their findings have been the starting point to a vast literature on crop yield density estimation ranging from parametric to non-parametric techniques. Researchers have naturally tried to use distributions that can capture the non-normality of crop yields. In the 80's Gallagher (1986, 1987) used a Gamma distribution to estimate corn and soybean yields and found evidence of negative skewness. Although the nature of the trend (deterministic or stochastic) was not tested and determined, Gallagher applied a detrending transformation to the data. Recently most of this literature has been developed for risk analysis purpose and in particular for crop insurance premia estimation. The controversy has been centered on the impact of the choice of the distribution on crop insurance premia. Nevertheless, little emphasis has been given to the appropriateness of transformation methods and their implication on crop yield density estimation. Nelson and Preckel (1989) opted for a beta distribution to estimate corn yield distributions conditional on fertilizer application. The beta distribution appears to be flexible enough to capture the first three moments of the distribution. Issues linked to non-stationarity have not been considered in this paper and, as a consequence non-stationarity tests and data transformations have not been performed. In 1990, Nelson compared the estimated crop insurance premiums from two distributions: normal and gamma. Although he recognizes the flexibility of the non-parametric approach, he did not consider this method in his study due to the lack of computational power at that time. Showing significant premium differences between the two distributions estimates, he brings for the first time the issue of the impact of the distribution choice on probability estimates. According to the authors, as they use farm level data the time-series were not long enough to detrend data. Hence, levels data have been used to compute crop yield distributions. Moss and Shonkwiler (1993) use a stochastic trend model to estimate corn yield distribution. In order to take into account the nonnormality of crop yields, the authors have applied an inverse hyperbolic sine transformation to the regression residuals. Such a transformation allows converting a non-normal distribution to a standard normal one (Moss and Shonkwiler, 1993). They found evidence of non-normality (negative skewness) and also of the presence of a stochastic trend in corn yields sequences. Goodwin and Ker (1998) have carefully determined the Data Generating Process (hereafter DGP) and found that an ARIMA (0,1,2) best represents the crop yield series and in consequence, have applied first differencing transformation to the data before generating non-parametric (Kernel) crop yield distributions. In line with the previous literature, they found negative skewness and significant evidence between Group Rate Program (hereafter GRP) premium rates from a non-parametric distribution compared to a parametric one. One limit to this work is that the DGP has been generalized to all the county/crop combinations. This choice was primarily practical but we believe that the DGP should not have been generalized to all counties and, as a consequence, first differences may have been, for some counties, inappropriate. Turvey and Zhao (1999) applied three parametric distributions (Normal, Gamma and Beta) and one non-parametric (Kernel) to five different crops farm-level yields. They conclude that, in the context of crop insurance premium estimation, the non-parametric approach is the most flexible and also the most efficient. However, they point out the complexity of such methods. For their estimation, they use detrended data ("since these data were already adjusted for trend by the [Ontario Crop Insurance] commission no further adjustments were made" (Turvey and Zhao, 1999)). Just and Weninger (1999) confront the evidence of crop yields non-normality. They interestingly depict the role of transformation methods in testing crop yield normality. Misspecified trends or inadequate detrending can "cause non-stationarity of yield deviations and incorrect assessment of skewness and Kurtosis" (Just and Weninger, 1999). Normality can be failed to be rejected when crop yield non-normality is today unquestionable. Ramirez *et al.* (2003) revisit these methodological problems raised by Just and Weninger along with enhanced techniques (allowing for different distributional characteristics) confirming nonnormal and left skewed Corn Belt corn and soybean yields. Later authors highlighted that "nonrejection does not prove yield normality, because the magnitudes of the type-two errors in their normality tests are unknown" (Ramirez *et al.*, 2003). In 2004, Norwood *et al.*, bring new elements that may close the debate around the distribution choice by comparing the out-of-sample six yield densities used in the literature. They found that the semi-parametric (Kernel) approach of Goodwin and Ker (1998) has the greatest performance in forecasting county average yields. This result constitutes the motivation for using non-parametric methods in the present research.

3. Impact of environmental variables

Few authors have considered including weather information in crop yield distribution and crop insurance coverage estimations. It is interesting to notice that most of the studies that have taken into account weather variables have included what we will characterize as long-term effect weather events (shocks) like El Niño and la Niña (e.g. Ker and McGowan, 2000). To our best knowledge, besides Kaylen and Koroma (1991), there is no study that has tried to determine the impact of environmental variables such as monthly temperature and precipitation, using weather station data, on empirical distributions of yields. Our hypothesis is that such approach has not been adopted because monthly weather data are not considered as exogenous and random variables in crop yield distribution estimation. We do not pursue a complete analysis of the effect of environmental variables on yield density estimation. The preliminary findings reported here are based on a regression model of yields on average, minimum and maximum temperatures and cumulative precipitation over the growing season. For additional literature on the subject, refer to Ker and McGowan (2000), Nadolnyak *et al.* (2008), Kaylen and Koroma (1991), Schlenker and Roberts (2006), Tannura *et al*. (2008), Martin *et al.* (2001), Vedenov and Barnett (2004), Turvey (2001), and Patrick (1988).

III. Data description

Although a complete analysis by crop and region would be appropriate, we confine the study to corn yields to illustrate the importance of filtering methods in density estimation. Corn yield (bushels/acre) data have been obtained from the National Agricultural Statistics Service (NASS) web site, for the period of 1960-2008 in Arkansas and Louisiana (two states crossed by the Mississippi river). Analyzed yields are indifferently irrigated or non-irrigated (Total for Crop). In Arkansas and Louisiana corn yields are characterized by an upward trend (figure 1).

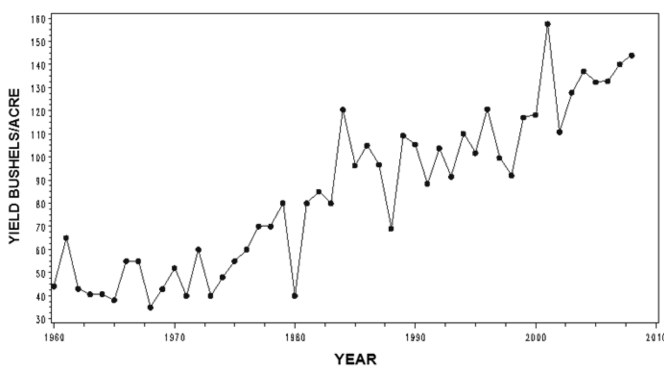


Figure 1: Corn Yield Overtime in Madison Parish, LA

In Louisiana, 19 counties have been studied for corn yields distribution estimation. The maximum yield (185 bushels/acre) has been reached in 2007 in Natchitoches Parish (county) while the minimum yield of the series corresponds to Washington Parish corn yield in 1960 (17 bushels/acre). The average yield of the series is around 76 bushels/acre. In Arkansas, 23 counties have been studied. The maximum and minimum corn yields are 191 (Lonoke, 2007) and 17 (Conway, 1964) bushels/acre. The average corn yield is higher than in Louisiana (80.21 bushels/acre).

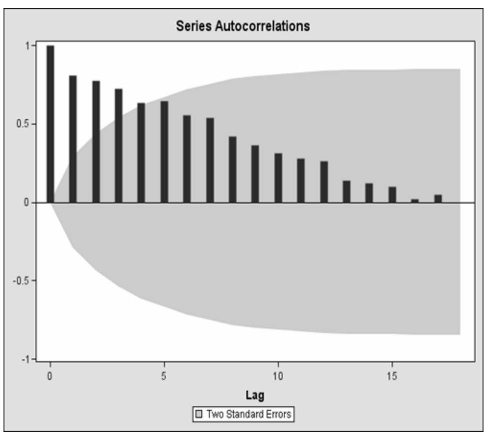
Climate data are from the U.S. National Weather Service (NCDC) stations of Arkansas and Louisiana counties during the 1960-2008 period. The Thompson model (1969).uses monthly data and is ideal in explaining the influence of weather on yield. Indeed, in the agronomic literature, we can find that weather variables have a different effect on crop yields according to the stage of development of the crop. For example, precipitations have the greatest impact on yield during the corn flowering. Even if calendar months do not correspond exactly to plant growth stages, the use of monthly weather variables can capture the uneven impact of weather variables over the growing season. However, in the present work, because yields are estimated by county, it has been impossible to include monthly weather variables. The number of exogenous variables would have been too high compared to the number of observations and thus reducing unacceptably the degrees of freedom. Unlike the Thompson model, pre-season weather has not been taken into account as most of studies showed that weather variables have a much greater influence on crop yields during the growing season (Tannura *et al*, 2008). For all these reasons weather variables have been averaged over the growing season. Growing season minimum, maximum and average surface air temperatures (Fahrenheit) as well as cumulative precipitation (Inches) have been used. In this study, the minimum temperature corresponds to the minimum daily temperature that has been registered during the growing season. Similarly the maximum temperature corresponds to the maximum daily temperature that has been registered during the growing season. The average temperature has been computed by first calculating monthly temperatures averaging the daily minimum and maximum temperatures over a month and then by averaging the monthly temperatures over the growing season. County climate data have been calculated by averaging the data over the weather stations belonging to a same county. For reasons that will become clear further, only the counties that have at least 30 years of observations have been studied.

The minimum and maximum temperatures that have been registered since 1960 in Louisiana are respectively 47.7 (Madison, 1973) and 102.4 (Bossier, 1998) Fahrenheit. It is important to notice that this exceptionally high temperature that occurred in Bossier corresponds to an unusually low yield (46.9 bushels/acre). The average temperature is 76.57 Fahrenheit. Concerning rainfall, the average cumulative precipitation is 23.51 inches. The minimum cumulative precipitation is 7.65 inches (Franklin, 1965) while the maximum is 51.6 inches (East Baton Rouge, 1989). In Arkansas, the maximum, minimum and average temperatures are respectively: 106.5 (Conway, 1983), 29 (Conway, 1989) and 74.1 Fahrenheit. The average cumulative precipitation is 19.85 inches. The minimum and maximum cumulative precipitations are 1.03 (Conway, 1989) and 43.77 (Ashley, 1975) inches.

IV. Methodology

In order to generate crop yield densities and the corresponding probability estimates, an adequate DGP for yields has to be identified. The Box-Jenkins model selection (1976) is a common strategy to select a model (Enders, 1995; Maddala and Kim, 1998). All the models can be generalized as an ARIMA model and the focus of the Box-Jenkins methodology is to specify the ARIMA model. The first step, also called as the identification stage corresponds to a visual analysis of series time plot. This step allows identifying the presence of non-stationarity. If the series shows a trend or seems to wander with no real pattern, it may be a sign of non-stationarity.

The autocorrelation and partial autocorrelation functions (hereafter ACF and PACF) of the series can also be computed. Enders (1995) summarizes the different processes with their corresponding ACF and PACF. For example, a correlogram with a gradual decay is characteristic of a non-stationary time series. This is the case of Madison Parish, LA (figure 2) and most of the counties in Arkansas and Louisiana.



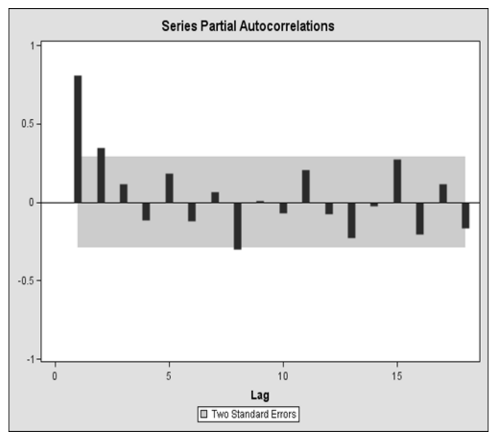


Figure 2: ACF Corn Yield, Madison, LA **Figure 3:** PACF Corn Yield, Madison, LA

The visual inspection of non-stationarity is however not rigorous enough and the use of formal test is necessary to determine the presence of a trend and if the trend is stochastic or deterministic. Enders (1995) proposes to use of unit-root test to identify nonstationary properties of time series. One test statistic is the Augmented Dicky-Fuller test (hereafter ADF). It is a test for unit-root and trends as it allows determining the presence of a unit-root, a unit-root with a drift or a unit-root with a drift and a trend. One of the issues linked to unit root tests is the choice of the regression equation. Based on Doldado *et al.* (1990), a strategy has been developed to test for unit root when the DGP is not known. In the first step of this procedure the most complete model (trend and drift) is used to test for the presence of a unit root. For details of this procedure, refer to Enders (1995). Additionally, as suggested by Hamilton (1994), the choice of the test (three equations for Dickey Fuller tests) also depends “on a plausible description of the data.” In our case, due to the well known 20^{th} century technological advancements in agriculture, the presence of stochastic trends in corn yields is almost unquestionable. However, there is no theory that would justify the presence of a deterministic time trend in weather variables sequences although some research, suggest that temperatures are globally increasing. To verify the “climatic theory”, we have plotted cumulative precipitations, average, maximum and minimum temperatures over time. It turns out that out of these four weather variables, only minimum temperature series seem to exhibit a (upward) deterministic time trend (figure 4).

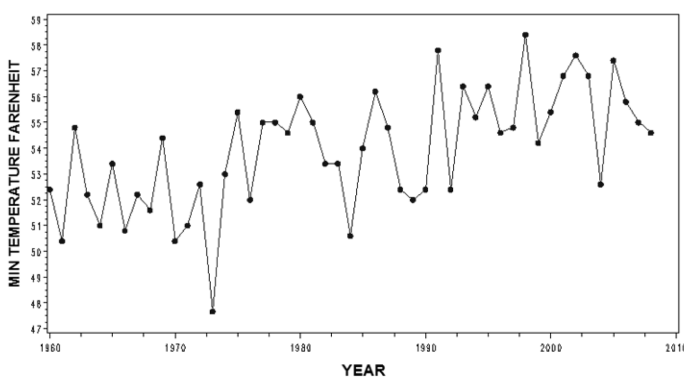


Figure 4. Minimum Temperature Overtime, Madison, LA

In short, unit root tests allow determining the presence of unit root while giving guidance on the appropriate transformation to be applied to the data. The procedure has been followed for the crop yield series as well as weather series. Once the data have been transformed, the researcher has to decide if the adequate process is an AR(p), MA(q) or ARMA(p,q). This can be done by examining the ACF and PACF of the transformed data. For univariate ARIMA model, a moving average (MA) process typically presents an ACF with a spike at the first lag and a PACF with an oscillating decay. An AR(p) process has an ACF that decays toward zero and a PACF with spikes up to lag p. Finally an ARMA process has an ACF that decays up to lag q and a PACF that declines beginning at lag p (Enders, 1995). In the next steps of the Box-Jenkins methodology, the estimation of the ARMA model and forecasting of future values of the crop yield series are computed which is not the purpose of this paper. We have chosen to use Kernel density estimation technique to estimate crop probability distribution functions because of its popularity in empirical work of crop insurance programs. We believe that the effect of inappropriate transformations will be more visible if a flexible distribution is used. A Kernel density estimate includes a variable Y (crop yield) and a symmetric weighting variable W. For n identically independently distributed (i.i.d.) observations of a univariate series, the Kernel density estimate is given by:

$$(5)\hat{f}(y) = \frac{1}{\sum_{i=1}^{n} W_i} \sum_{i=1}^{n} W_i \, \varphi h \, (y - Y_i)$$

There are different methods to choose the appropriate smoothing scale (bandwidth -*h* in the equation-), in this paper bandwidth selection is carried through plug-in formula as recommended by Jones *et al*. (1996).

$$(6)h = \left[\frac{R\varphi}{nR\hat{f}''{}_{g(h)}(\int Y_2 \, \varphi(Y)dy)^2}\right]^{\frac{1}{5}}$$

Where $R(\varphi) = \int \varphi(y)dy$. This equation is solved by first evaluating it on a grid of values spaced equally on a log scale. The largest two values from this grid that bound a solution are then used as starting values for a bisection algorithm" (SAS Institute, 2003). If the density turns out to be normal then the model simplifies to:

$$(7)\ h = \hat{\sigma}[4/(3\mathrm{n})]^{1/5}$$

The impact of data transformation is measured by computing and comparing probability estimates. The best way is to calculate the probability that a low yield occurs, particularly important in risk management analysis. In this paper, we decided to adopt a slightly different methodology than the one used by Goodwin and Ker (1998) who have computed the probability that crop yields fall below a certain percentage of the county average yield using the trapezoidal rule. Instead, we calculate different percentiles of the distribution. The results are as useful as the traditional methodology in illustrating the effect of data transformations but also the implication for risk analysis and in particular crop insurance rating. In order to show the impact of inappropriate transformations, the methodological framework has been based on the following scenarios (table 1):

Table 1. Methodological Framework (scenarios)

True process	Correct transformation	Wrong transformation
Random walk	Differencing	Detrending
Random walk + drift	Differencing	Detrending
Random walk + drift + linear trend	Differencing	Detrending
Trend stationary	Detrending	Differencing
Stationary	None	Differencing

The random walk scenario in table 1 implies that if actual yields follow a random walk process then the appropriate transformation is first differencing and not detrending. We assess what happens to the empirical density functions under these two transformations and calculate the "percent error" which is the percentile difference between the two transformations. Other scenarios are analyzed similarly.

Percentiles estimates calculated based on distributions of correctly transformed data are compared to the ones computed from distributions of crop yield series that have been inappropriately transformed. The hypothesis is that percentiles estimates will be significantly different if a wrong transformation is used.

One of the objectives of this paper is to determine if the inclusion of weather variables was relevant in probability density estimation using non-parametric techniques. The simplest way is to generate crop yield distribution conditional on weather variables. According to Nelson and Prekel (1989), linear regression models with crop yields regressed on input can be considered as conditional probability distribution of crop yields. Consequently, weather is taken into account by regressing weather variables (also appropriately transformed) on crop yields.

V. Results

Unit root tests have been carried out on crop yield and weather variables series. Tables 2 and 3 summarize the results of the unit root tests on corn yield series. In Louisiana, 21% of the studied counties are characterized by corn yield series that are trend stationary while 79% present random walk sequences. In Arkansas, 13% of the studied counties are characterized by trend stationary corn yield sequences, 65% by random walk sequences and finally 22% by random walk plus drift plus linear trend sequences. Also note that in four Arkansas counties (Arkansas, Lee, Lonoke and White) and one Parish in Louisiana (Ouachita) two differences were needed to achieve stationary in corn yields.

Tables 4 and 5 summarize the results of the unit root tests on weather variables. Overall, in Louisiana (Arkansas), 84% (74%) of the cumulative precipitation series are stationary and 16% (26%) are best represented by a random walk. For average temperature, 58% (70%) of the series are stationary, 5% (0%) trend stationary while 37% (30%) are random walk. For maximum temperature 74% (61%) of the series are stationary, 5% (0%) trend stationary and 21% (39%) are random walk. Finally, 63% (39%) of the minimum temperature series are trend stationary, 5% (9%) stationary while 32% (52%) are random walk. This uneven repartition of the processes confirmed the hypothesis of spatial heterogeneity in terms of crop yield estimation. This shows the importance of not generalizing a process to an ensemble of series (for example counties of a same region) without testing rigorously before and in particular without carrying out unit root tests. As explained in the methodology, percentiles estimates of yield series inappropriately transformed have been compared to percentiles estimates of yields correctly transformed based on rigorous tests. Tables 6 and 7 summarize these results and present the percentage error of applying a wrong transformation to the series. The first important result is that the use of wrong transformations to estimate probability density functions of time series implies considerable percentage error that is sometimes larger than 10%. Another interesting result is that it seems that the direction of the error is characteristic of the type of process. For both Arkansas and Louisiana series, applying an inappropriate transformation to a random walk process will most of the time lead to an underestimation of the percentile estimates. On the contrary, when a trend stationary process is wrongly transformed, the percentiles will tend to be overestimated. Percentile estimates errors are also produced in the case of conditional distributions of corn yield on weather. However, a clear pattern of the direction of the misestimation does not appear when the effect of weather is included.

Table 2. Unit Root Test Results, Corn Yields, Arkansas

County	Conclusion /Process	Transformation
Arkansas	Random Walk	Differencing II
Ashley	Random Walk+drift+linear trend	Differencing
Benton	No unit root	Detrending
Clark	Random Walk	Differencing
Clay	Random Walk	Differencing
Conway	No unit root	Detrending
Craighead	Random Walk	Differencing
Cross	Random Walk	Differencing
Desha	Random Walk	Differencing
Independence	Random Walk	Differencing
Jackson	Random Walk+drift+linear trend	Differencing
Jefferson	Random Walk+drift+linear trend	Differencing
Lee	Random Walk	Differencing II
Logan	Random Walk	Differencing II
Lonoke	Random Walk	Differencing
Miller	Random Walk	Differencing
Mississippi	Random Walk+drift+linear trend	Differencing
Monroe	Random Walk	Differencing
Phillips	Random Walk	Differencing
Prairie	No unit root	Detrending
Randolph	Random Walk+drift+linear trend	Differencing
White	Random Walk	Differencing II
Yell	Random Walk	Differencing

Note: Differencing II means that the yield series required second order integration to achieve stationarity.
10% critical values (τ_τ, $\phi_{3,}$ τ_μ, $\phi_{1,}$ τ) were used.

Table 3. Unit Root Test Results, Corn Yields, Louisiana

County	Conclusion /process	Transformation
Allen	Random Walk	Differencing
Avoyelles	Random Walk	Differencing
Beauregard	Random Walk	Differencing
Bossier	Random walk	Differencing
Caddo	Random Walk	Differencing
East Baton Rouge	Random Walk	Differencing
East Carroll	Random Walk	Differencing
Franklin	Random Walk	Differencing
Iberville	Random Walk	Differencing
Lafayette	Random Walk	Differencing
Madison	Random Walk	Differencing
Morehouse	No unit root	Detrending
Natchitoches	No unit root	Detrending
Ouachita	Random Walk	Differencing II
Pointe Coupee	Random Walk	Differencing
Saint Landry	No unit root	Detrending
Tangipahoa	Random Walk	Differencing
Tensas	No unit root	Detrending
Washington	Random Walk	Differencing

Note: Differencing II means that the yield series required second order integration to achieve stationarity.
10% critical values (τ_τ, $\phi_{3,}$ τ_μ, $\phi_{1,}$ τ) were used.

Table 4. Unit Root Test Results, Weather (Cumulative Precipitation, Average Temperature, Maximum Temperature and Minimum Temperature), Arkansas

Variables	**Cumulative Precipitation**		**Average Temperature**		**Maximum Temperature**		**Minimum Temperature**	
County	**Conclusion /process**	**Transf-Ormation**	**Conclusion /process**	**Transf-Ormation**	**Conclusion /process**	**Transf-Ormation**	**Conclusion /process**	**Transf-ormation**
Arkansas	No unit root	None	No unit root	None	Random walk	Differencing	No unit root	Detrending
Ashley	No unit root	None	No unit root	None	No unit root	None	Random walk	Differencing
Benton	No unit root	None	No unit root	None	Random walk	Differencing	Random walk	Differencing
Clark	No unit root	None	No unit root	None	Random walk	Differencing	Random walk	Differencing
Clay	Random walk	Differencing	No unit root	None	Random walk	Differencing	Random walk	Differencing
Conway	Random walk	Differencing	Random walk	Differencing	Random walk	Differencing	No unit root	None
Craighead	No unit root	None	Random walk	Differencing	No unit root	None	Random walk	Differencing
Cross	Random walk	Differencing	No unit root	None	No unit root	None	No unit root	Detrending
Desha	No unit root	None	No unit root	None	No unit root	None	Random walk	Differencing
Independence	Random walk	Differencing	No unit root	None	No unit root	None	Random walk	Differencing
Jackson	No unit root	None	No unit root	None	No unit root	None	No unit root	Detrending
Jefferson	No unit root	None	No unit root	None	No unit root	None	No unit root	Detrending
Lee	No unit root	None	No unit root	None	No unit root	None	Random walk	Differencing
Logan	No unit root	None	Random walk	Differencing	Random walk	Differencing	Random walk	Differencing
Lonoke	No unit root	None	Random walk	Differencing	Random walk	Differencing	No unit root	Detrending
Miller	No unit root	None	No unit root	None	No unit root	None	No unit root	None
Mississippi	No unit root	None	No unit root	None	No unit root	None	Random walk	Differencing
Monroe	Random walk	Differencing	Random walk	Differencing	Random walk	Differencing	No unit root	Detrending
Phillips	Random walk	Differencing	Random walk	Differencing	Random walk	Differencing	No unit root	Detrending
Prairie	No unit root	None	No unit root	None	No unit root	None	Random walk	Differencing
Randolph	No unit root	None	No unit root	None	No unit root	None	No unit root	Detrending
White	No unit root	None	No unit root	None	No unit root	None	Random walk	Differencing
Yell	No unit root	None	Random walk	Differencing	No unit root	None	No unit root	Detrending
Arkansas	No unit root	None	No unit root	None	Random walk	Differencing	No unit root	Detrending

Note: 10% critical values (τ_τ, ϕ_3, τ_μ, ϕ_1, τ) were used.

Table 5. Unit Root Test Results, Weather (Cumulative Precipitation, Average Temperature, Maximum Temperature and Minimum Temperature), Louisiana

Variables	**Cumulative Precipitation**		**Average Temperature**		**Maximum Temperature**		**Minimum Temperature**	
County	**Conclusion /process**	**Transf-Ormation**	**Conclusion /process**	**Transf-ormation**	**Conclusion /process**	**Transf-ormation**	**Conclusion /process**	**Transf-ormation**
Allen	Random Walk	Differencing	No unit root	None	No unit root	None	No unit root	None
Avoyelles	Random Walk	Differencing	No unit root	None	Random Walk	Differencing	No unit root	None
Beauregard	Random Walk	Differencing	No unit root	None	No unit root	None	No unit root	None
Bossier	Random Walk	Differencing	No unit root	None	No unit root	None	Random Walk	Differencing
Caddo	Random Walk	Differencing	Random Walk	Differencing	No unit root	None	Random Walk	Differencing
East Baton Rouge	Random Walk	Differencing	Random Walk	Differencing	No unit root	None	No unit root	None
East Carroll	Random Walk	Differencing	No unit root	None	Random Walk	Differencing	No unit root	None
Franklin	Random Walk	Differencing	No unit root	None	No unit root	None	No unit root	None
Iberville	Random Walk	Differencing	No unit root	None	No unit root	None	No unit root	None
Lafayette	Random Walk	Differencing	No unit root	None	No unit root	None	No unit root	Detrending
Madison	Random Walk	Differencing	No unit root	None	Random Walk	Differencing	No unit root	None
Morehouse	No unit root	Detrending	No unit root	None	No unit root	Detrending	No unit root	None
Natchitoches	No unit root	Detrending	Random Walk	Differencing	Random Walk	Differencing	No unit root	None
Ouachita	Random Walk	Differencing2	No unit root	None	No unit root	None	No unit root	None
Pointe Coupee	Random Walk	Differencing	Random Walk	Differencing	Random Walk	Differencing	Random Walk	Differencing
Saint Landry	No unit root	Detrending	No unit root	None	Random Walk	Differencing	Random Walk	Differencing
Tangipahoa	Random Walk	Differencing	No unit root	None	Random Walk	Differencing	No unit root	None
Tensas	No unit root	Detrending	No unit root	None	No unit root	None	No unit root	None
Washington	Random Walk	Differencing	No unit root	None	No unit root	None	No unit root	None

Note: 10% critical values (τ_τ, $\phi_{3,}$ τ_μ, $\phi_{1,}$ τ) were used.

The results would not have meaning without an applied context. One illustration would be to ask: what does a 10% percentage error means for a farmer buying crop insurance? In the U.S., several different types of crop insurance policies are available. In order to well illustrate our empirical results, we will refer to the GRP insurance as it is based on county yield. This type of coverage provides an indemnity to the farmer if the county average yield falls below a trigger yield or yield coverage that represents a percentage (70-90%) of the expected county yield (Kim *et al.,* 2007). The level of coverage is chosen by the farmer. Let's suppose that a farmer producing corn in Beauregard parish, LA buys a GRP insurance and chooses a 85% coverage level. If a correct transformation has been applied to the corn yield sequence and an unconditional distribution is generated, the expected yield for this county is 58.25 bushels/acre (table 7). A 85% coverage level would correspond to a trigger yield of 49.51 bushels/acre. Moreover, if the correct transformation is used, the 25th percentile is 51.41 bushels/acre (table 7) which corresponds to 88% of the expected yield (51.41/58.25=88%). On the other hand, the expected yield based on the distribution generated with the inappropriate transformation, in this case detrending, is 56.31 bushels/acre. If the same farmer chooses a 85% coverage level, the trigger yield will be 47.86 bushels/acre. Finally, the 25th percentile in this case is 46.68 bushels/acre which represents 83% of the expected yield (46.68/56.31=83%).

Table 6. Unconditional Kernel Probability Estimates (Percentile Values), Arkansas

County	Differences to RW			Detrending to RW			Percentage Error (%)		
	Percentiles								
	25	50	75	25	50	75	25	50	75
Arkansas[a]	74.51	86.01	98.51	70.39	87.44	101.00	-5.85	1.64	2.47
Ashley	62.37	73.37	80.37	55.11	70.05	81.03	-13.17	-4.74	0.81
Clark	41.69	50.99	65.69	38.77	47.22	62.29	-7.53	-7.98	-5.46
Clay	93.38	105.00	116.00	93.10	101.00	109.00	-0.30	-3.96	-6.42
Craighead	84.86	91.96	104.00	80.16	90.65	103.00	-5.86	-1.45	-0.97
Cross	65.18	72.18	77.08	56.81	68.16	78.76	-14.73	-5.90	2.13
Desha	81.24	92.54	106.00	76.39	92.65	101.00	-6.35	0.12	-4.95
Independence	71.08	80.08	91.68	63.11	79.57	94.93	-12.63	-0.64	3.42
Jackson	82.13	92.13	105.00	83.71	90.86	103.00	1.89	-1.40	-1.94
Jefferson	80.70	90.70	103.00	76.67	89.18	99.79	-5.26	-1.70	-3.22
Lee[a]	68.07	82.67	106.00	72.20	88.15	100.00	5.72	6.22	-6.00
Logan[a]	59.37	73.37	86.37	50.55	73.05	85.17	-17.45	-0.44	-1.41
Lonoke	80.47	90.97	100.00	74.47	84.43	101.00	-8.06	-7.75	0.99
Miller	55.83	65.83	73.83	52.92	60.98	70.88	-5.50	-7.95	-4.16
Mississippi	84.74	97.74	108.00	86.01	94.19	108.00	1.48	-3.77	0.00
Monroe	80.56	90.21	101.00	71.92	85.38	98.65	-12.01	-5.66	-2.38
Phillips	76.54	86.19	93.54	69.10	79.93	100.00	-10.77	-7.83	6.46
Randolph	80.31	90.71	102.00	77.07	90.72	102.00	-4.20	0.01	0.00
White[a]	54.75	71.75	84.75	58.99	67.45	78.64	7.19	-6.38	-7.77
Yell	61.63	71.63	80.13	58.89	67.56	74.41	-4.65	-6.02	-7.69
	Detrending to Trend Stationary Process			**First Differences to Trend Stationary Process**			**Percentage Error (%)**		
Benton	41.70	52.18	58.94	46.55	53.05	61.55	10.42	1.64	4.24
Conway	67.56	75.13	85.57	65.67	76.67	88.67	-2.88	2.01	3.50
Prairie	78.86	91.20	103.00	86.59	92.59	104.00	8.93	1.50	0.96

Note: 10% critical values (τ_τ, ϕ_3, τ_μ, ϕ_1, τ) were used.

Table 7. Unconditional Kernel Probability Estimates (Percentile Values), Louisiana

County	Differences to RW			Detrending to RW			Percentage Error (%)		
	Percentiles								
	25	50	75	25	50	75	25	50	75
Allen	39.67	44.87	50.27	38.30	46.56	50.82	-3.58	3.63	1.08
Avoyelles	78.19	91.99	104.00	76.80	85.29	102.00	-1.81	-7.86	-1.96
Beauregard	51.41	58.31	71.41	46.68	56.51	63.12	-10.13	-3.19	-13.13
Bossier	42.23	52.23	64.23	42.68	47.99	62.86	1.05	-8.84	-2.18
Caddo	65.00	76.50	93.20	63.93	76.43	87.63	-1.67	-0.09	-6.36
East Baton Rouge	59.65	66.65	72.15	54.35	64.19	72.07	-9.75	-3.83	-0.11
East Caroll	76.77	90.77	101.00	79.12	90.03	99.33	2.97	-0.82	-1.68
Franklin	87.53	99.68	110.00	82.17	93.65	106.00	-6.52	-6.44	-3.77
Iberville	68.77	83.77	98.77	67.64	83.86	93.06	-1.67	0.11	-6.14
Lafayette	59.50	67.55	73.95	52.84	66.99	75.13	-12.60	-0.84	1.57
Madison	77.13	87.98	98.18	76.25	86.56	92.14	-1.15	-1.64	-6.56
Ouachita[a]	57.16	67.16	87.16	56.94	73.28	82.14	-0.39	8.35	-6.11
Pointe Coupee	92.43	104.00	122.00	90.88	97.05	116.00	-1.71	-7.16	-5.17
Tangipahoa	58.23	65.83	81.63	56.71	68.21	74.70	-2.68	3.49	-9.28
Washington	52.70	66.80	77.70	55.95	63.98	74.42	5.81	-4.41	-4.41
	Detrending to Trend Stationary Process			**First Differences to Trend Stationary Process**			**Percentage Error (%)**		
Morehouse	72.83	82.87	94.28	71.06	85.36	105.00	-2.49	2.92	10.21
Natchitoches	67.50	77.88	89.04	68.12	79.82	99.02	0.91	2.43	10.08
Saint Landry	77.83	86.80	97.76	84.64	88.99	98.84	8.05	2.46	1.09
Tensas	76.47	83.95	96.73	72.55	86.80	106.00	-5.40	3.28	8.75

Note: 10% critical values (τ_τ, ϕ_3, τ_μ, ϕ_1, τ) were used.

Figures 5 and 6 summarize the issue just raised. We can see that if the GRP contract is based on a distribution misestimated because of inappropriate data transformations, the probability of falling beneath the trigger yield (47.86 bu/ac) is greater than 25% (figure 5). However, if the GRP contract is based on a correctly estimated distribution, the probability of falling below the trigger yield would be less than 25% (figure 6). In short, if a crop yield series corresponding to a random walk process is detrended instead of differenced, the probability of falling below the yield coverage is overestimated, and this has important implications for the insured and the insurance company. The contrary seems to be true: if a trend stationary crop yield sequence is differenced instead of detrended, the probability of falling below the trigger yield is underestimated.

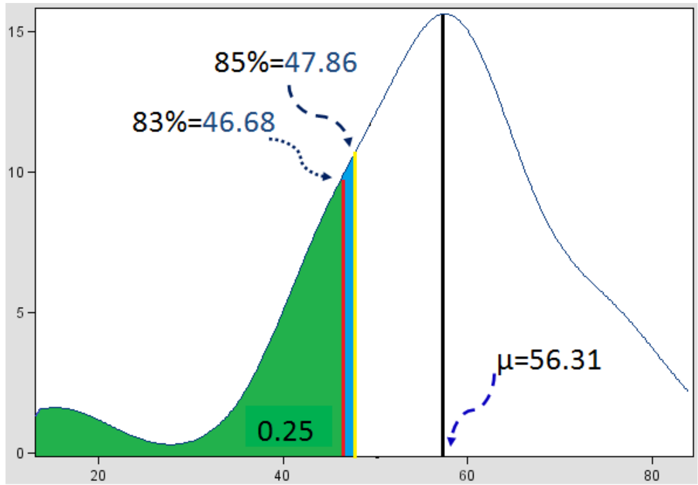


Figure 2. Estimated Kernel PDF out of Inappropriately Transformed Corn Yield Series for Beauregard County, LA

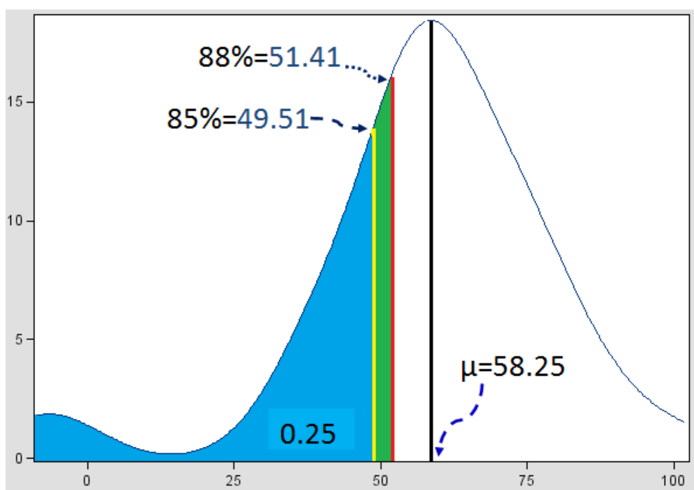


Figure 3. Estimated Kernel PDF out of Appropriately Transformed Corn Yield Series for Beauregard County, LA

A final objective of this paper was to assess the relevance of including weather variables in the estimation of crop yield probability density functions. Comparing the percentile estimates of the unconditional and conditional distributions (tables 8 and 9) we can see that there is a significant difference between the two sets of estimates. Furthermore, the percentile estimates based on a conditional distribution seem to be generally lower than the ones computed from an unconditional distribution. If the inclusion of weather variables improves the estimation of corn yields or not is a question that was not in the scope of this paper but that could be answered by generating in-sample forecasts that would be compared to the actual crop yields.

Table 8. Comparison of Probability Estimates Generated out of Unconditional and Conditional Yields, Arkansas

County	Unconditional			Conditional on Weather			Percentage Error (%)		
	Percentiles								
	25	50	75	25	50	75	25	50	75
Arkansas	81.56	86.06	97.76	72.33	91.33	98.41	-12.76	5.77	0.66
Ashley	62.37	73.37	80.37	60.65	71.23	76.23	-2.84	-3.00	-5.43
Benton	41.70	52.18	58.94	42.96	50.09	58.46	2.93	-4.17	-0.82
Clark	41.69	50.99	65.69	40.90	51.36	62.01	-1.93	0.72	-5.93
Clay	93.38	105.00	116.00	89.70	102.00	113.00	-4.10	-2.94	-2.65
Conway	67.56	75.13	85.57	67.59	76.00	83.40	0.04	1.14	-2.60
Craighead	84.86	91.96	104.00	78.13	89.57	103.00	-8.61	-2.67	-0.97
Cross	65.18	72.18	77.08	62.68	71.51	76.71	-3.99	-0.94	-0.48
Desha	81.24	92.54	106.00	78.46	89.25	104.00	-3.54	-3.69	-1.92
Independence	71.08	80.08	91.68	64.71	80.23	94.55	-9.84	0.19	3.04
Jackson	82.13	92.13	105.00	77.62	92.68	104.00	-5.81	0.59	-0.96
Jefferson	80.70	90.70	103.00	79.89	87.18	97.60	-1.01	-4.04	-5.53
Lee	81.57	88.67	100.00	67.96	80.62	103.00	-20.03	-9.99	2.91
Logan	65.37	74.37	82.37	59.12	69.56	78.66	-10.57	-6.91	-4.72
Lonoke	80.47	90.97	100.00	74.95	89.15	99.49	-7.36	-2.04	-0.51
Miller	55.83	65.83	73.83	52.39	60.61	75.26	-6.57	-8.61	1.90
Mississippi	84.74	97.74	108.00	80.59	93.29	108.00	-5.15	-4.77	0.00
Monroe	80.56	90.21	101.00	78.28	87.33	96.27	-2.91	-3.30	-4.91
Phillips	76.54	86.19	93.54	76.17	81.05	91.71	-0.49	-6.34	-2.00
Prairie	78.86	91.20	103.00	83.51	89.62	103.00	5.57	-1.76	0.00
Randolph	80.31	90.71	102.00	78.38	87.92	100.00	-2.46	-3.17	-2.00
White	61.80	73.30	79.55	49.65	65.99	82.67	-24.47	-11.08	3.77
Yell	61.63	71.63	80.13	57.41	67.58	77.35	-7.35	-5.99	-3.59

Table 9. Comparison of Probability Estimates Generated out of Unconditional and Conditional Yields, Louisiana

County	Unconditional			Conditional on Weather			Percentage Error (%)		
	Percentiles								
	25	50	75	25	50	75	25	50	75
Allen	39.67	44.87	50.27	38.97	44.45	52.26	-1.80	-0.94	3.81
Avoyelles	78.19	91.99	104.00	77.64	91.30	101.00	-0.71	-0.76	-2.97
Beauregard	51.41	58.31	71.41	46.83	54.70	66.94	-9.78	-6.60	-6.68
Bossier	42.23	52.23	64.23	43.44	51.31	61.41	2.79	-1.79	-4.59
Caddo	65.00	76.50	93.20	58.43	75.04	88.23	-11.24	-1.95	-5.63
East Baton Rouge	59.65	66.65	72.15	52.05	65.15	77.14	-14.60	-2.30	6.47
East Caroll	76.77	90.77	101.00	76.16	88.22	103.00	-0.80	-2.89	1.94
Franklin	87.53	99.68	110.00	83.84	97.26	104.00	-4.40	-2.49	-5.77
Iberville	68.77	83.77	98.77	73.08	81.80	95.01	5.90	-2.41	-3.96
Lafayette	59.50	67.55	73.95	58.30	67.65	72.19	-2.06	0.15	-2.44
Madison	77.13	87.98	98.18	76.28	85.15	96.24	-1.11	-3.32	-2.02
Morehouse	72.83	82.87	94.28	65.78	79.79	90.82	-10.72	-3.86	-3.81
Natchitoches	67.50	77.88	89.04	67.15	78.31	89.53	-0.52	0.55	0.55
Ouachita	57.16	67.16	87.16	52.76	68.44	84.44	-8.34	1.87	-3.22
Pointe Coupee	92.43	104.00	122.00	92.43	98.70	113.00	0.00	-5.37	-7.96
Saint Landry	77.83	86.80	97.76	77.72	88.28	97.16	-0.14	1.68	-0.62
Tangipahoa	58.23	65.83	81.63	53.73	65.80	77.19	-8.38	-0.05	-5.75
Tensas	76.47	83.95	96.73	76.10	84.18	97.91	-0.49	0.27	1.21
Washington	52.70	66.80	77.70	53.22	63.64	72.52	0.98	-4.97	-7.14

VI. Conclusion

Whereas the probability theory for nonstationary data is clear on the appropriate transformation techniques to use in identifying data generation processes for time series, the empirical adoption of these techniques are not pervasively used in empirical risk analysis research. The results from this very preliminary research, lead to some empirical guidance for current and future research and can be outlined as follows. First, ADF tests (or other unit-root tests such as Phillips-Perron) should be adopted in identifying time series properties of historical Parish/county level crop yields. Unit-root tests are objective tools of analysis and are widely available in most commercial econometric software. Second, the application to historical corn yields for Arkansas and Louisiana suggest that, given the complex unit-root behavior and deterministic trends, there is not one single transformation technique for universal adoption in risk analysis and that the insured and insurer are to benefit from case-specific analyses. In other words, inappropriate data transformation can lead to large “percentile errors” in calculating risk premiums off yield distributions. Lastly, this study points to future Monte Carlo simulation work that should be designed to uncover the reliability of density estimation based on the empirical findings on the time series properties of yield data for all crops and counties in the South. One value of this research would be in the analysis of feedstocks yields used in ethanol production. The analysis can also be extended to the study of revenue densities in the assessment of feasible technologies for biofuel production.

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