How much drought is ‘just right’?
Spatial Differences in ‘Optimal Drought Severity’ for Drought Tolerant Maize

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ABSTRACT
The potential of agricultural biotechnology to produce seed traits that reduce yield risk generates widespread excitement. Hopes are high that in an era of tightening water constraints and climate change drought tolerant (DT) crop varieties will stabilize food production and allow for greater adaptation to changing production conditions. Although the DT agenda has united the public and private agricultural research system around concerns that seem to span rich and poor countries alike, the underlying crop-drought relationships differ substantially over space. We devise a methodology for characterizing these spatial differences in ‘optimal drought severity’ across two locations in Africa (Ethiopia and Mali) and one in the U.S. (Wisconsin) and analyze these differences to infer implications for the diffusion and impact of DT crop varieties. Drought-conditioned yield distributions for non-DT maize provide the benchmark against which we assess relative DT benefits in each setting. We construct a distribution of expected relative DT benefits as the product of the site-specific relative DT benefits distribution by rainfall and the site-specific rainfall distribution. We discuss how spatial differences in these expected relative DT benefit distributions may affect farmer decision making and welfare as well as agricultural adaptation to climate change.

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1. INTRODUCTION
The potential of agricultural biotechnology to produce seed traits that reduce yield risk has featured prominently in recent policy discussions related to climate change adaptation. Hopes are high that drought tolerant (DT) crop varieties will stabilize food production and facilitate adaptation to changing production conditions in a coming era of increasing water scarcity and troubling forecasts about the impact of climate change on agricultural production (Fedoroff, et al. 2010, Fischer and Shah 2005, Howden, et al. 2007, Mendelsohn and Tiwari 2000, Nelson, et al. 2009). As evidence of these high hopes, few agricultural research objectives have ever attracted as much attention and investment from private, public, academic, and philanthropic sectors as DT has in recent years: total investments in DT research in the past decade almost certainly surpass $1 billion.

With worrisome climate change forecasts, growing water scarcity and impending water disputes, the prospective welfare gains from effective DT varieties are enormous. Among the poor, gains from DT may limit catastrophic losses and help households recover. Some even promote DT as crop insurance that is built directly into seeds. With this built-in insurance concept in mind, many proponents further argue that poor adopters may feel less vulnerable to drought as a result of adopting DT crops and shift the rest of their household portfolio toward higher risk-higher return activities (so-called ‘positive moral hazard’). Whether the benefits of DT crops are akin to insurance and spark this positive moral hazard in practice depends crucially on the relationship between drought and crop production (Lybbert and Bell 2010), a point we build on in this paper.

While the structure of crop production for large-scale farmers in developed countries is often completely different, they too fear drought – and can suffer much larger monetary losses as a result. The prospective demand for DT crops in developed countries – especially Australia and the US – is consequently enormous and has fueled a bonanza of R&D among private agricultural firms. The fact that rich and poor farmers alike fear drought seems to suggest convenient ways to bring private R&D investments in DT research to bear on problems of the poor. Important private-public partnerships between the major private and public players have coalesced

1 See http://dtma.cimmyt.org/ (accessed May 2012).
precisely around this convenient complementarity. For example, the Drought Tolerant Maize for Africa (DTMA) project – which is led by CIMMYT and the International Institute of Tropical Agriculture (IITA) and funded by a mix of private foundations and official development agencies – coordinates public research and the private sector to develop and disseminate drought tolerant maize varieties and hybrids in 13 African countries. The other major DT initiative in Africa – the Water Efficient Maize for Africa (WEMA) project, which is led by the African Agricultural Technology Foundation (AATF) and involves a partnership with Monsanto – shares these broad objectives but embraces marker-assisted breeding and biotechnology as well as conventional breeding techniques. By facilitating the transmission of traits between varieties and crops, biotechnology-based breeding adds spatial versatility. Indeed, Monstano’s partnership in the WEMA project is evidence of this fact: The DT traits Monsanto is developing for profitable developed country markets are also relevant for very different production environments in Africa because biotechnology makes it easy to share these tools and traits. While these upstream complementarities in the research and development of DT crops are important, downstream differences will largely shape the adoption and diffusion of these crops. Specifically, as DT crops progress from the lab to the farmer, pronounced differences in crop-drought relationships in different settings may cause upstream complementarities to breakdown, with important implications for farm-level impacts. In this paper, we evaluate an important dimension of this spatial heterogeneity: the performance of DT crops relative to non-DT crops as a function of drought severity.

Spatial differences in the relative performance of DT crops hinge on two important features of the relationship between drought and crop productivity. First, the relative benefits of DT peak with just the right amount of drought, then quickly fade as drought severity increases. In practice, this non-monotonicity and the ‘optimal drought severity’ it implies are potentially quite different in different production settings due to differences in soil types and joint probability distributions for rainfall and temperature. Second, in purely rainfed conditions, when the rains fail, crops fail – and the relative benefits of DT are zero. In contrast, in settings where supplementary irrigation is available, DT may outperform non-DT crops even when the rains fail.

2 The DTMA website describe this project in detail (see http://dtma.cimmyt.org/).
3 See http://www.aatf-africa.org/wema.
In this paper, we devise a methodology for characterizing spatial differences in ‘optimal drought severity’ across Africa and North America and analyze these differences to infer important implications for the diffusion and impact of DT crop varieties. We first construct a conceptual model to illustrate why and where different features of the relative benefits distribution for DT crops matter to farmer behavior and welfare. We then empirically explore key features of this conceptual model using (non-DT) maize production data from several locations in Africa and in the US. Distributions of yield conditional on drought stress provide the benchmark against which we assess relative DT benefits in each setting. We compile evidence from DT maize trials in our respective sites to suggest where, along the rainfall continuum in each site, DT maize is likely to deviate from our benchmark yield distributions. Since there is insufficient data to estimate DT maize production functions in the way we can for non-DT maize, we aim instead to characterize the essential differences between DT and non-DT maize. Finally, we construct a distribution of expected relative DT benefits as the product of the site-specific relative DT benefits distribution by rainfall and the site-specific rainfall distribution. Using our theoretical model as a guide, we discuss how cross-site differences in these expected relative DT benefit distributions may affect farmer decision making and welfare – and the likely returns on DT R&D investments and the major public-private partnerships that have grown around these investments.

Our analysis is intended to structure the policy discussion about DT crops in the context of climate change. This discussion – including the high profile public-private DT partnerships it has sparked in recent years – must take farmers’ perspective into account explicitly, which requires a characterization of expected DT benefits that is explicitly stochastic. Our methodology and the spatial comparison of these stochastic DT benefits aim to take a step toward such a characterization. Spatial differences in optimal drought severity have direct implications for a variety of other economic dimensions to the problem of agricultural production, climate change adaptation, and rural poverty. Given the increasingly global coordination of agricultural R&D and the potential role for future public-private partnerships, this paper sheds light on important spatial dimensions to features of technologies beyond DT crops.
2. Model of Optimal Drought Severity

In this section, we present a theoretical model to provide a framework for understanding optimal drought severity and its implications for farmers’ valuation of DT crops. We begin with the farmer’s unconstrained optimization problem. We assume that production and consumption decisions are separable so the farmer can maximize utility as a function of income:

$$\max_{x \geq 0} E u(z + y - w'x)$$
$$s.t. \quad y = y(x, \hat{D})$$

(1)

where $z$ indicates non-crop income, $y$ is stochastic crop income, $x$ is a vector of inputs, $w$ is a vector of associated input prices, and $\hat{D}$ is stochastic drought severity with probability density function (pdf) given by $g(\hat{D})$. Assume for now that $\hat{D}$ is a function of rainfall and temperature (e.g., the Palmer Drought Severity Index used to trigger drought relief programs in the U.S.). We assume for simplicity that crop price is exogenous and not influenced by drought severity (e.g., output markets are well integrated with many other regions producing the same crop).

In this unconstrained problem, the farmer chooses optimal input levels without worrying about liquidity constraints that might otherwise make the optimal input investment unaffordable or structural constraints that might otherwise make the optimal input level technically infeasible (e.g., access to supplemental irrigation). As the solution to this problem, we denote the optimal input vector as $x^*$. Thus, the maximized expected utility is given by

$$Eu^* = \int_0^\infty u \int f(y^* | x = x^*) w(y(x^*, \hat{D}) - w'x^*) df(y^*).$$

(2)

where $f(y^*) = f(y | x = x^*)$ is the pdf of crop income conditional on $x = x^*$ such that optimal stochastic crop income is $y^* = y(x^*, \hat{D}) = y(\hat{D}|x = x^*) = y'(\hat{D})$. In reality, farmers often modify their input choices throughout the growing season as $\hat{D}$ is revealed. While our empirical approach implicitly allows for these intraseasonal input adjustments, we assume a sequential structure in this theoretical model in which $x^*$ is chosen before $\hat{D}$ is observed to simplify the model. The core intuition remains unchanged.

Now, suppose the farmer has the choice of two different crop varieties, the traditional variety (0) and a drought tolerant variety (DT). The value of each of these crop varieties is given by the certainty equivalent (CE) as follows:
The farmer’s relative valuation of the DT crop can be expressed as the premium

$$\eta = \frac{CE_{DT} - CE_0}{CE_0}.$$  

In this model, the value of the DT crop relative to the traditional crop hinges on how the optimal input vector changes from \(x_0^*\) to \(x_{DT}^*\) and how the conditional pdf changes from \(f_0(y_0^*)\) to \(f_{DT}(y_{DT}^*)\). Our empirical approach remains agnostic about changes in the optimal input vector and focuses instead on changes in the conditional pdf.

To explore \(f_k(y_k^*)\), consider the expected crop income associated with optimal input vector \(x_k^*\), which is given by \(E y_k^* = \int y_k^*(\tilde{D}) dg(\tilde{D})\). Obviously, the full conditional pdf \(f_k(y_k^*)\) is similarly composed of the conditional crop income function \(y_k^*(\tilde{D})\) and the pdf for drought severity \(g(\tilde{D})\). This decomposition provides a useful guide for assessing potential spatial differences in farmers’ DT crop premium \(\eta\). Although a naïve perspective on DT crops might suggest that the value of DT would increase as optimal crop income becomes more sensitive to drought and as the probability of drought increases, this is not necessarily the case. Because even DT crops require water to grow, a severe enough drought will lead to total crop failure in both DT and traditional crops. This implies that relative DT benefits are potentially non-monotonic in drought severity and that these benefits are highest at some optimal drought severity defined as \(\tilde{D}^* = \arg \max \left[ \Delta y^*(\tilde{D}) \right]\), where \(\Delta y^*(\tilde{D}) = y_{DT}^*(\tilde{D}) - y_0^*(\tilde{D})\).

To allow for spatial variation in \(\tilde{D}^*\) in this unconstrained model, we must allow either the pdf for drought severity or the conditional crop income function or both to differ spatially: \(g_s(\tilde{D})\) or \(y_{sk}^*(\tilde{D})\) where \(s\) indexes location \(s\). In practice, there are dramatic spatial differences in \(g_s(\tilde{D})\). Thus, even if \(y_{sk}^*(\tilde{D}) = y_{hk}^*(\tilde{D}) = y_k^*(\tilde{D})\) \(\forall s, h\) (i.e., the same varieties, growing conditions, agronomic practices, and input and output market conditions prevail across all locations), the probability of experiencing optimal drought – given by \(g_s(\tilde{D}^*)\) – will vary widely across space. Based on these spatial differences alone, farmers in some locations may experience relative DT benefits that are essentially monotonic in drought severity, whereas farmers in other locations may frequently experience drought severity well beyond \(\tilde{D}^*\). To be more precise,
spatial differences in $g_s(\tilde{D})$ relative to $\tilde{D}^*$ translate into differences in the probability that $\Delta y^*(\tilde{D})$ is increasing or decreasing in $\tilde{D}$ or zero:

$$\Pr\left( \frac{\partial \Delta y^*}{\partial \tilde{D}} > 0 \right) = \int_{\tilde{D}}^0 g_s(\tilde{D}) = \lambda_s$$

$$\Pr\left( \frac{\partial \Delta y^*}{\partial \tilde{D}} < 0 \right) = \int_{\tilde{D}}^{\tilde{D}^0} g_s(\tilde{D}) = \theta_s$$

$$\Pr\left( \frac{\partial \Delta y^*}{\partial \tilde{D}} = 0 | \Delta y^* = 0 \right) = \int_{\tilde{D}}^{\tilde{D}^0} g_s(\tilde{D}) = 1 - \lambda_s - \theta_s$$

where $\tilde{D}^0$ indicates a level of drought severity that causes DT (and non-DT) crops to fail. In locations where $\lambda_s \approx 1$, relative DT benefits are approximately monotonic (see Figure 1 left panel). In locations where $\theta_s < 0$, these benefits are non-monotonic (and the probability of DT benefits declining in drought severity is given by $\theta_s$). In locations where $\lambda_s + \theta_s < 1$, there is a chance that drought will be so severe that even DT crops are not worth harvesting. Figure 1 (right panel) depicts this last case. In contrast to Figure 1, the definitions in equation (5) allow for $\Delta y^* < 0$ when drought is low, which would be the case if the DT trait entails a yield penalty when optimal growing conditions (without drought) prevail.

To consider spatial differences in the conditional crop income function $y^*_{sk}(\tilde{D})$, we introduce two additional features to the simple model: (i) input constraints that are potentially input-specific and (ii) a two-stage production function with potentially limited input flexibility.

$$\max_{x \leq 0} E \left[ u + z + y - w_1'x_1 - w_2'x_2 \right]$$

s.t. $y = y_1(x_1, \tilde{D}_1), y_2(y_1, x_2, \tilde{D})$

$x_i \leq c_i, t = 1, 2 \ \forall i$

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4 In practice, “crop failure” is inherently an economic concept as it indicates a crop yield that is too low to justify the costs of harvesting. Thus, crop failure need not imply that yield is zero – only that yield is too low to be worth harvesting.

5 Biotechnology-based breeding seems to reduce these yield penalties by enabling breeders to introduce DT traits genetically and directly into any crop variety. This would be especially true if a single trait conferred DT (as with pest resistance (Bt)). The fact that DT is likely to be a multi-gene trait may introduce more complex interaction effects that could make these yield penalties a problem (REFs).
where 1 and 2 denote the first and second intra-seasonal stages (e.g., early and late growing season), $\tilde{D}_i$ indicates the drought severity in the sub-season 1, $y_i$ is (unharvested) crop output from sub-season 1, and $c_{it}$ is the exogenous input-specific constraint on input $i$ in sub-season $t$.

While it is perhaps easiest to think of these input-specific constraints as technical or structural constraints such as irrigation infrastructure and input market infrastructure, a slight modification to the model could accommodate endogenous liquidity constraints. To simplify notation, we assume for now that these constraints reflect both technical/structural and liquidity constraints.

With this expanded and constrained model in mind, compare grower A with few constraints and complete flexibility to adjust input levels in both sub-seasons to a second grower B with tighter input constraints and less flexibility. Specifically, suppose that

$$
\begin{align*}
\mathbf{x}^*_1 &= \arg \max_i \mathbb{E} \left[ E_i u_k^A \right], \quad \mathbf{x}^*_2 &= \arg \max_i \mathbb{E} \left[ E_i u_k^B \right] \\
\mathbf{x}^1_2 &= \arg \max_i \mathbb{E} \left[ E_i u_k^A \right], \quad \mathbf{x}^2_2 &= \arg \max_i \mathbb{E} \left[ E_i u_k^B \right]
\end{align*}
$$

(7)

where $E_i$ indicates that expectations are formulated in sub-season $t$. In this case, grower A is better able to respond to drought as it occurs. Grower B, in contrast, faces input constraints that may lead to sub-optimal input choices and has to lock in sub-season 2 input choices before observing $\tilde{D}_i$. Even if these growers are growing the same variety, face the same growing and market conditions and have the same degree of risk aversion, these added features imply that, $y_{sk}^A(\tilde{D}) \neq y_{sk}^B(\tilde{D})$ and $\Delta y^A(\tilde{D}) \neq \Delta y^B(\tilde{D})$. Figure 2 depicts how these differences in input constraints and flexibility may affect the relationship between drought severity and relative DT benefits.

In sum, this simple theoretical framework highlights some of the ways that pervasive spatial differences may translate into important differences in the relative gains associated with DT crops. In the empirical portion of the paper, we explore how spatial differences affect non-DT maize yields and use this baseline and qualitative results from DT crop trials to test whether spatial differences in these relative DT benefits are likely to matter in practice.

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6 Although it is technically the physical crop output from the first sub-season that matters to ultimate crop production value (e.g., crop establishment, root development, etc.), we retain this output value notation to simplify the exposition.
3. DATA & EMPirical METHODOLOGY

We use data from several sites in Ethiopia, Mali and Wisconsin to explore spatial differences in drought sensitivity of maize yields. This section describes these data sources and our empirical approach.

Ethiopia

We compile data from several sources to construct our Ethiopian data. First, the bulk of the data comes from IFPRI's Ethiopian Rural Household Survey. This panel dataset covers several villages in each agroclimatic zone and includes several rounds of data collection in the past 20 years. Second, we use data from the Ethiopia Nile Basin Climate Change Adaptation Dataset collected by the Ethiopian Development Research Institute. Third, we added some data from IFPRI’s Sustainable Land Management in the Ethiopian Highlands project (19998-2000).

Mali

We use a 17-year panel data set (1994-2010) for over 100 farm households from 12 villages located in Mali’s southern maize belt. The Malian agricultural research organization Institut d’Economie Rurale (IER) started collecting these data in 1988 from 149 farmers spread across 12 villages in 3 different communes in the Sikasso region. The data set starts with 149 farmers in 1988 and ends with 84 in 2010 due to sample attrition, primarily of villages rather than farmers. IER researchers chose the villages to represent different agro-ecological zones within the Sikasso region and the farmers to represent different types of farms stratified by farm assets. IER researchers collected the data primarily for agronomic studies and they most closely resemble the kind of data one might get from farm trials, except that they come from individual farmers. With their level of agronomic detail and long time series, these micro-level panel data can answer questions that aggregate and cross-sectional data are unable to tackle. They have details such as daily rainfall data that can solve a number of the econometric problems that cause difficulties for many productivity studies. The data set contains disaggregated fertilizer and chemical input data by input type and by crop.

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7 For a complete description and details, see http://www.ifpri.org/dataset/ethiopian-rural-household-surveys-erhs.
**Wisconsin**

We use maize trial data collected in field trials in 11 locations throughout the state of Wisconsin. These trials were conducted from 1990-2010 and include nearly 5,000 different hybrids. These trial data allow us to understand the relationship between yield and precipitation in a controlled environment, but have the disadvantage of not capturing any behavioral responses of farmer. Specifically, with trial data we do not pick up the effect of input constraints or other inflexibilities. We are therefore working to supplement these trial data with farm-level yield data.

**Empirical Methodology**

Our empirical methodology consists of (1) assessing the drought sensitivity of non-DT maize varieties (and hybrids) in each location, (2) comparing the drought sensitivity of non-DT maize yields across the locations, (3) projecting how drought sensitivity may differ for DT maize varieties relative to these baseline non-DT varieties using recent DT maize trials, and (4) comparing the differences between non-DT drought sensitivity to (projected) DT drought sensitivity. In this preliminary draft, we present preliminary results for steps (1) and (2) in this methodology. Analysis for steps (3) and (4) is on-going. We are currently processing summary information from DT trials in Africa and elsewhere in order to project possible DT differences. Only when we finish processing this information will we be able to complete the analysis.

**4. RESULTS**

We opt in this draft to rely exclusively on graphical depictions of our preliminary analysis. Figure 1 displays kernel densities for total rainfall during the maize growing season for Ethiopia, Mali and Wisconsin – with all locations in each pooled together. The horizontal (rainfall) but not the vertical (density) axis shares a common scale. Based on these densities, our research sites in Mali have the highest average rainfall, Ethiopian sites have the most variable rainfall, and the Wisconsin sites have the lowest average and least variable rainfall. Since these figures mix variability over years and across space, in each location we disaggregate by site and estimate site-specific kernel densities. Figure 2 shows quite dramatic differences between the five Ethiopian sites. Figure 3 shows more similarities between the three Mali sites, although one (Koutiala) appears to be more drought prone judged on total rainfall alone. Figure 4 shows
rainfall distributions for 12 sites in Wisconsin, which are much more similar than either the Mali or Ethiopia sites.

Next, we begin our exploration of the sensitivity of maize yields to drought using some simple nonparametric regressions of maize yield (kg/ha) on total rainfall (mm). When we pool all the sites within each location together, we see some remarkable spatial differences (Figure 5). Again, we scale the axes so the horizontal but not the vertical (yield) axis shares a common scale because we are more interested in comparing drought sensitivities across sites (i.e., relative maize yield effects) rather than absolute differences in yield. We note in passing, however, that the maize yields in Wisconsin are nearly an order of magnitude larger than Ethiopian and Malian yields, which is due to the substantial differences in agronomic practices (e.g., seeding rates), in hybrid maize rates (100% in Wisconsin), and to the fact that the Wisconsin data is trial data whereas the other locations are based on farm data.

With these magnitude differences in mind, we shift to a discussion of relative differences in drought sensitivity. First, whereas both Ethiopia and Wisconsin display an expected non-monotonic relationship between yield and rainfall, Mali – surprisingly – displays a monotonically decreasing relationship. We are exploring these differences in ongoing analysis. Second, whereas yields in Wisconsin peak with about 700 mm of seasonal rainfall, in Ethiopia they peak at roughly double this amount. Finally, since we are interested in the sensitivity to drought, we are interested in this relationship at low rainfall levels. The Mali regression is difficult to interpret from this point of view as it suggests that among low rainfall seasons even less rainfall is better than more. In the other two locations, low rainfall outcomes clearly affect yields, but at least on average these yields are certainly not zero – and are almost certainly above the economic crop failure level (i.e., the yield at which harvesting is not profitable). We are exploring how yield sensitivity to rainfall at lower quantiles compares to this sensitivity at the mean.

Figures 6, 7 and 8 disaggregate these nonparametric regressions for each location by site. Although a few of the sites display the expected inverted U relationship, there are more sites that do not. Furthermore, there are substantial differences in these regressions between sites in a given location. Our ongoing analysis will explore and control for these intra-location differences.
5. **Next Steps**

There are several additional steps we must take to refine this analysis to the point that it can shed light on differences in drought sensitivity in practice – and ultimately inform the diffusion of DT crops. In this section, we briefly highlight these next steps.

First, we need to do more to better characterize drought in each location. While total seasonal rainfall provides a point of departure in this draft, we plan to extend this simple depiction of drought in two ways. By weighting monthly or decadal (i.e., 10 day) rainfall according to its influence on maize yield at harvest, we can more accurately characterize drought. By incorporating temperature, we could similarly improve the accuracy of our drought measure. We are exploring possibilities for adding temperature to our rainfall measures and evaluating whether a relatively crude approach to combining the two is better than simply using total rainfall.

Second, we need to do more to leverage differences between farm and trial data. In this preliminary draft, we use a preliminary data set that is not well matched for doing this. Ideally, we would have farm and trial data on maize yields in all three locations and possibly more. We are hunting for additional data to complement the dataset we use in this draft. Assuming we can access acceptable farm and trial data in each location, we will be able to estimate the contribution of behavioral farmer responses to drought sensitivity. To the extent that this behavioral sensitivity has an important a spatial component, being able to tease apart the behavioral from the technical components may be important to drawing implications for the uptake and diffusion of DT crops.

Third, the analysis in this draft is essentially descriptive. In order for the analysis of non-DT yields to provide a solid basis for the subsequent evaluation of relative DT benefits, this analysis must be more rigorous and must control for other factors that influence yield – including those that interact in important ways with drought severity. We have estimated several regression models as an initial exploration of parametric approaches to this problem. These appear promising, but will require more work to refine.

The final next step we showcase here relates to the impact of DT on maize yield distributions. In some sense, it is precisely the difficulty of this task that motivates this research project. The potentially non-monotonic relative DT benefits can pose a real challenge for breeders when designing and conducting field trials. Each prospective DT trait or variety may
have a different relative benefit curve as a function of drought severity. Thus, a test of a single
drought severity level may not be sufficient to characterize the complete relative benefit
distribution. The DTMA project mentioned in the introduction uses a uniform definition of
drought stress for its maize trials and describes these trial results in a summary report each year.
While these reports would seem to be a useful starting point for sizing up the relative benefit
distribution, their usefulness is limited by the uniform definition of drought stress: with little
variation in drought severity it is difficult to estimate the broader relative benefit distribution. We
are currently searching for other DT trial data that explicitly varies drought severity in order to
estimate this distribution. We know such data exist and – assuming we can access these data –
are confident that even a handful of data points from the right field trial would be sufficient to
construct prototypical DT benefit curves to lay on top of the non-DT yield sensitivity measures
we are estimating. Once we can put these two pieces together, we are equally confident that we
will be able to make an important contribution to the flurry of research and popular interest in
DT crops.
REFERENCES


Figure 1 Differences in distribution of drought severity between two locations imply that one site (left) experiences monotonic relative DT benefits and the other (right) non-monotonic and, over a range of extreme drought, no relative DT benefits.

Figure 2 Differences in input constraints and flexibility between two locations imply that one site (left, grower A) is more likely to experience relative DT benefits that increase monotonically in drought severity relative to another site (right, grower B).
Figure 1 Rainfall distributions in Ethiopia, Mali and Wisconsin
Figure 2 Rainfall distributions by region in Ethiopia
Figure 3 Rainfall distributions by region in Mali
Figure 4 Rainfall distributions by region in Wisconsin
Figure 5 Nonparametric regressions of maize yield on total rainfall in Ethiopia, Mali and Wisconsin
Figure 6 Nonparametric yield regressions for Ethiopia by region
Figure 7 Nonparametric yield regressions for Mali by region
Figure 8 Nonparametric yield regressions for Wisconsin by location