2014 American Control Conference (ACC)
June 4-6, 2014. Portland, Oregon, USA

How Good is Bad Weather?

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Abstract— **Accurately identifying key parameters in complex systems demands sufficient excitation, so that the resulting data will be informative enough to reveal hidden parameter values. In many situations, however, users choose inputs that attempt to optimize the system response, not necessarily those that yield more informative data. This leads to the classic trade-off between exploitation and exploration in learning problems.**

Farmers face a similar issue. Although they would like to identify key soil parameters affecting the growth of their crops, market pressures force them to manage their product to maximize yield, resulting in less informative data. This suggests that weather, and bad weather in particular, may play a critically important role in creating informative data for crop systems by driving them into low-yield regimes that no farmer would otherwise choose to explore.

This paper investigates these issues using a standard computational model for corn and real weather data. Two model-based measures characterizing any year's weather pattern are introduced. The first measure characterizes how well a particular year's weather pattern *produces* corn, according to the model. The second measure characterizes how well a particular year's weather pattern *distinguishes* the way different soil types affect corn growth. We then use these measures to show that, from the perspective of corn, bad weather can indeed be very good for distinguishing soil type.

I. INTRODUCTION

Control of uncertain systems involves a classic dilemma known as the exploitation vs. exploration trade-off [1]. That is, at each time step the controller must determine whether to choose the control action that optimizes performance based on the best current understanding of the system to be controlled (i.e. exploitation), or to choose a control action designed to discover more information about the system (i.e. exploration). This trade-off is easily understood in the context of choosing a restaurant: is it better to go to your favorite restaurant or try something new? Whenever decisions are made in real time without perfect information, an explicit or implicit choice is made regarding this trade-off.

Farmers face the control of an uncertain system when they manage their crops. Given a particular plot of land, with a corresponding climate and environmental context, farmers choose which crops to plant year after year, as well as how much and when to irrigate, apply fertilizer, apply pesticides, and weed or apply herbicides. They also manage a host of financial decisions, such as when to sell their crop and how to invest in equipment, labor, and insurance.

In all of these decisions, farmers face the exploitation vs. exploration trade-off. Nevertheless, rarely do they have the luxury of experimenting with their crops to estimate scientific models of their particular plot of land and how it responds to the various management decisions they might make; exploration is typically too expensive and risky a prospect to consider.

Instead, farmers historically have used almanacs, rules-of-thumb, and qualitative judgement to drive their system, as best they can, into the most profitable position possible. This exploitation-bias results in management decisions that are extremely conservative, such as over-fertilizing to hedge against the risk of rainy weather leeching an early application and leaving the crop nitrogen starved. The result, however, is that many different soils and growing conditions end up producing strong yields, while the subsequent nitrogen pollution in freshwater streams and rivers creates a growing crisis. Every year over-fertilization pollutes the Mississippi River, creating seasonal hypoxia, or a "dead zone," in the Gulf of Mexico; in 2013 this "dead zone" was about the size of the state of Connecticut [2]. Solving this pollution problem without sacrificing productivity will demand better information about specific soils and crop growth conditions so that less conservative management decisions can be successfully deployed.

Understanding the nature of how a particular plot of land affects crop growth, however, is a difficult task. For some crops, years of agronomic research have accumulated in the development of computerized models designed to simulate plant growth under specific conditions. Calibrating these simulations to model the behavior of a specific farm growing a particular crop in a specific year typically demands the specification of four types of inputs: cultivar genetic parameters, management decisions, weather, and soil parameters. Cultivar type and management decisions are control inputs and are typically chosen by the farmer to maximize profits (as much as possible) according to an exploitation-bias. Weather is an uncontrolled and highly variable disturbance, typically highly uncertain until within a nominal forecast window of about a week. Soil parameters, on the other hand, are also typically unknown, but, unlike weather, they are typically constant. Thus, one would like to accurately identify soil parameters, but choosing cultivars or management decisions to experiment with the farm is not generally economically viable.

As a result, weather becomes a critically important source of excitation for the system in order to identify key parame-

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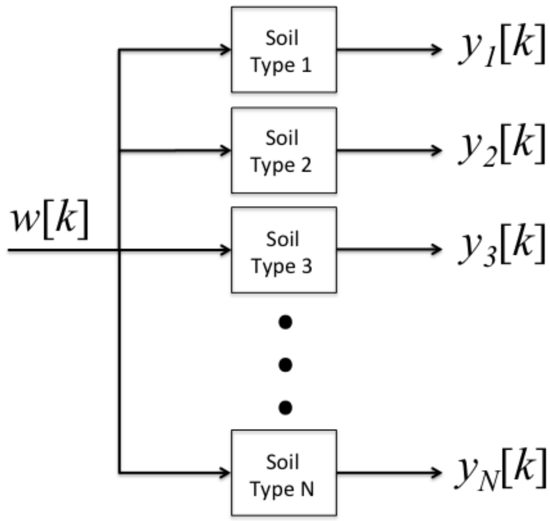

Fig. 1. Driving multiple simulations of different soil types, in parallel, with the same year's weather pattern, $w[k]$, generates a vector of yields for that year, $y[k]$. Measures of productivity and distinguishability on $y[k]$ then characterize $w[k]$ for year k.

ters, especially those associated with the soil at a particular geographic location. While it is well known that weather is critical to the understanding of a crop system, this research quantifies the information in a particular weather pattern corresponding to a specific year.

To accomplish this, we employ a specific open-source crop model for corn called CERES-Maize [3]. Using this model, we introduce a measure quantifying how effective a particular year's weather pattern is at producing corn in a variety of soils. This *productivity measure* allows us to describe how "good" a particular weather-year is for growing corn.

Next, we use the model again to quantify how a particular year's weather pattern distinguishes one soil's yield from another. This *distinguishability measure* describes the information about soil, quantified in bits, available from a particular weather pattern's affect on crop growth, according to the CERES-Maize simulation. Note that these measures are model-based, in the sense that the same measures referencing different corn simulators, such as APSIM [4], may lead to different results. Figure 1 illustrates the computational set up generating these measures.

Finally, using these measures, we then explore which weather patterns, according to the productivity measure, are most informative, according to the distinguishability measure. The main result, encapsulated in Figure 6 and Figure 7, illustrates that bad weather is, in fact, very good for distinguishing soil types, according to the CERES Maize crop simulator.

II. BACKGROUND

The measures introduced in this paper consider weather from the perspective of a particular crop simulation for corn. This section introduces the computational crop model, along with brief tutorials on the impact of soils and weather on crop systems.

A. CERES-MAIZE

The Decision Support System for Agrotechnology Transfer (DSSAT) is a set of software tools developed in the 1980's by researchers attempting to apply a systems approach to agronomic research. The main DSSAT program is made up of several submodules that handle various agronomic processes, such as weather, soil and crop growth. CROPGRO is the submodule of DSSAT that handles many aspects of the crop growth processes, such as photosynthesis, plant nitrogen demand and pest damage [5]. In this paper, we use DSSAT version 4.0.

CROPGRO, however, is only a generic crop growth simulator; it does not cater for the various nuances associated with different crop types. Separate submodules were created to handle the dynamics of specific crop types correctly. These sub-modules include CERES-Maize (Crop Environment Resource Synthesis), CERES-Wheat, and CERES-Rice, among others. In this paper we focus on the corn growth process, which utilizes the CERES-Maize submodule. CERES-Maize is a predictive, deterministic model designed to simulate corn growth for a single field for one growing season [3].

CERES-Maize requires information about a farm's location, planting data, weather data, irrigation data, cultivar genetic data, and soil data. A comprehensive list of input parameters for CERES-Maize can be found in Table 2 of [6]. Given the requested input parameters, CERES-Maize simulates the corn growth and outputs dry matter yield, antithesis date, maturity date, leaf nitrogen concentration, soil nitrate concentration, soil moisture, and others [7].

In this paper, we assume no irrigation is utilized to mitigate the effects of drought. We also choose a planting date and cultivar genetic parameters that are consistent with the location where weather is measured. Since we use weather measured in various parts of Missouri, we chose a planting date and genetic parameters for a cultivar commonly used in Missouri. Thus, all simulations in this work use the same genetic parameters and management decisions, allowing us to study the relationship between weather and soils.

B. SOIL

Crop growth is heavily influenced by the soil type on any given farm. Soil not only reflects the physical context of a seed and the roots of a plant, but it also characterizes chemical and biological dynamics of the environmental setting for a plant. Soil is composed of particles of varying sizes, and its texture refers to the relative proportions of the particles, where the particles are classified as either sand (between 0.05 and 2mm), silt (between 0.002 and 0.05mm), and clay (less than 0.002mm), (see Figure 2).

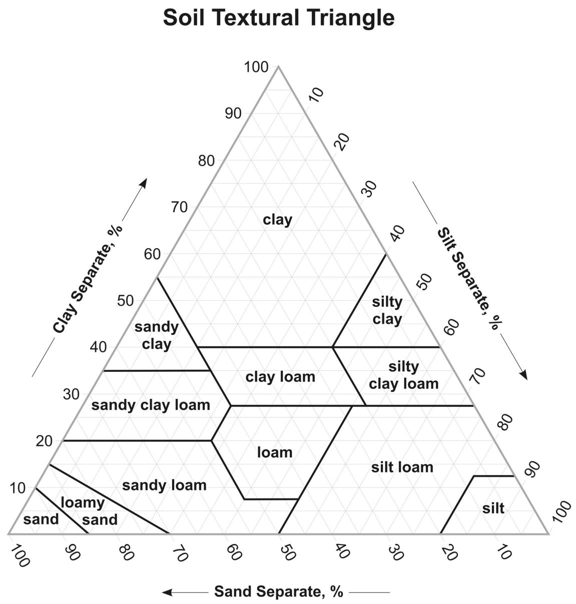

Fig. 2. Soil textural triangle used for determining soil texture. Image Courtesy of USDA-NRCS [8].

The texture of the soil affects physical dynamics such as water-holding capacity, water movement, and root growth [9][10]. The physical properties of the soil also determine how heat propagates spatially through the system.

Soil also affects the chemical and biotic properties of a crop system. For example, one of the key chemical processes in the system is the nitrogen cycle, which describes how nitrogen is transformed into various forms by different processes. Nitrogen is not available to the plant as a nutrient in all of these forms, however, so the chemical and biological dynamics determining how much, and when, nitrogen becomes available for use by the plant become very important to the growth of the plant. In particular, organic matter that is left over in the soil from the previous year's crop becomes an important source of nitrogen for the plant, provided that temperature and moisture conditions favor the action of certain bacteria that break down the organic matter and release the available nitrogen in the form of ammonia in a process called *mineralization*. This process is in direct contrast to a reverse process, called *immobilization*, that makes nitrogen less available to the plant, depending on soil conditions.

CERES-Maize simulates these dynamics for different layers of varying thicknesses, characterizing a cross section of soil to a given depth. Specifying a number of parameters for each layer, as well as specifying the number of layers and thickness of each, characterizes a particular soil type. For example, claypan soil has a hard layer of clay at some layer below the surface that roots cannot penetrate, [11]. Soil scientists have sampled, identified and recorded different soil types for different locations around the world and recorded them in various databases. Sometimes these databases include the CERES parameters needed to simulate each soil [12].

C. *WEATHER*

There are four daily weather inputs required for CERES-Maize: solar radiation, maximum and minimum air temperature, and precipitation, [3]. Weather plays an important part in the crop growth process, with temperature and solar radiation seemingly intertwined, while the effects of precipitation depend on the soil type (especially the water-holding capabilities of the soil) and the availability of irrigation.

Temperature and solar radiation are connected by the fact that, in the absence of nitrogen and water stress, high solar radiation can improve crop yields, but only when combined with moderately low temperatures, which increases crop growth duration allowing the crops to intercept more radiation. High temperatures tend to decrease the duration of growth, which means that crop yields also diminish. Moderately low temperatures, although useful in increasing crop duration, when combined with low solar radiation do not increase yields substantially, [13].

High levels of precipitation tend to increase crop growth unless puddling occurs, which suffocates the crops [14]. Although average precipitation may be high, if the timing does not coincide with important growth periods, and if water retention in the soil is poor, then yields will be adversely affected, [15]. Low precipitation causes water stress, although irrigation can mitigate the effects of poor water-holding capacity in soil and low levels of precipitation if regulated correctly [16].

The fact that plants die or thrive depending on various weather conditions indicates that weather is a input parameter with the potential to be sufficiently exciting for identifying key dynamics in the system. Different soils react differently to different weather patterns, since their hydraulic, thermodynamic, chemical, and biotic characteristics can vary significantly. The ability for a weather pattern to cause very different plant growth in different soil types, then, becomes a key factor in its ability to inform farmers about the kinds of soils on their farms.

III. METHODS

We introduce two measures to help understand the potential of different weather patterns to create informative data for identifying soil type in CERES-Maize simulations. The first, characterizing the *productivity* of the weather pattern across all soils, helps us classify which weather patterns are generally good for growing corn. The second measure, characterizing the *distinguishability* of a weather pattern in terms of causing different soil types to grow corn differently, helps us classify how informative the weather pattern is for identifying soils. This section presents these measures and describes our experiment simulating CERES-Maize with real weather data using documented soil parameterizations characterizing soils across the continental United States.

A. *CERES-MAIZE SIMULATION STUDY*

In this paper, we use a set of soils from [12], which is a DSSAT converted version of the ISRIC-WISE 1.1 database of soils [17]. This data set contains 3404 soils from around the world, exhibiting a wide variety of soil textures. We restrict our attention to the subset of soils that are contained within the continental United States. See [18] for a description of how the soil parameters vary across this data set.

CERES-Maize also requires us to specify a set of genetic parameters representing the growth properties of a particular hybrid of maize, a planting date, and various initial conditions. These parameters should be chosen to be consistent with a particular weather pattern. For instance, if we are driving the simulation with weather measured from Des Moines, Iowa, then the simulation should also simulate a cultivar (genetic parameters) that farmers near Des Moines would typically use, along with a planting date and initial conditions typical for farmers in Des Moines. Matching these parameter values to the weather location is important because farmers choose different cultivars, with different genetic properties, precisely in response to the climate at their farm's location; the seed one would plant in Minnesota is different than the seed one would plant in Texas.

Wanting to keep these "extra" parameters constant across the study, we therefore chose weather data sources that were geographically close, for which it would make sense to use the same cultivar (genetic parameters), planting date, etc. Choosing Missouri as a central location among our soil sample sites, we used a subset of the weather data reported by the University of Missouri for weather stations in Missouri[19] from 2001 to 2012 (see Figure 3). These sites were: Albany, Auxvasse, Brunswick, Cardwell, Charleston, Clarkton, and Portageville Delta. These weather data included daily precipitation, solar radiation, and max and min temperature.

One common corn hybrid grown in these Missouri locations is Pioneer P3162, for which the genetic coefficients for CERES-Maize simulation were reported [20]. We also chose April 1st as a planting date, which again is common for Missouri. We then assume typical initial conditions (soil water content, nitrate, and ammonia by soil layer) and a nominal management practices of applying 200lbs of anhydrous ammonia as fertilizer on March 15th. All of our simulations thus use these same parameters as defaults, allowing us to focus on the relationship between different years' weather patterns and soil type.

B. MODEL-BASED WEATHER MEASURES

Let $s_i \in S$, $i = 1, 2, ..., N$ be a soil type out of the set of N available soils. Let $w^l[k] \in W$ be a year of daily weather data, from October 15th of year $k-1$ to October 15th of year k, $k = 1, 2, ..., T$, measured at location l, $l = 1, 2, ..., L$. Each $w^l[k]$ contains all weather-related information required for CERES-Maize to function, meaning it has a value for precipitation, solar radiation, maximum temperature, and minimum temperature for each day of the year. Moreover, in this study $N = 93$, representing distinct soil types sampled across the continental United States, $T = 12$, representing years 2001 through 2012, and $L = 7$, representing seven weather stations in Missouri.

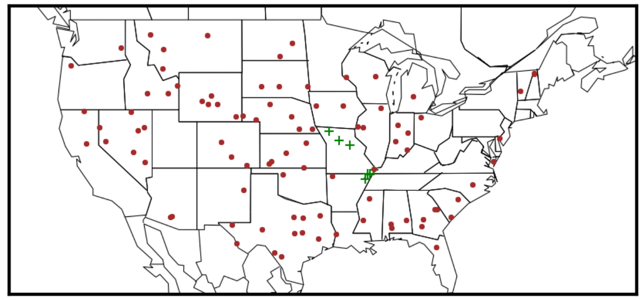

Fig. 3. Map of soil samples and weather stations. The soil samples (across the continental United States) are represented by small circles, and the weather stations (only in Missouri) are represented by plus symbols.

Let $f : (S, W) \to \mathbb{R}$ be the operator representing a CERES-Maize simulation of a farm. This simulation only takes a soil type and a weather-year as input, because all other CERES parameters, such as planting date, cultivar genetic coefficients, etc., have been set to the default values described above. The resulting value, $y \triangleq f(s_i, w^l[k])$ is called the *yield* for that simulation, and the matrix of yields across all soil types, i, and weather years, k, for each weather station l, is denoted $Y^l_{i,k} \triangleq f(s_i, w^l[k])$. Note that $Y^l \in \mathbb{R}^{N\times T}$ for each value of $l = 1, 2, ..., L$.

CERES-Maize also has the ability to conduct an *unstressed* simulation. This means that the software runs the simulation, but provides as much water or nitrogen available to the plant as needed, regardless of the soil type or weather pattern. We let $g : (S, W) \to \mathbb{R}$ be the operator representing the unstressed simulation of CERES-Maize, and define $U^l_{i,k} \triangleq g(s_i, w^l[k])$ with $U^l \in \mathbb{R}^{N\times T}$ for each value of $l = 1, 2, ..., L$. Note that $U^l_{i,k} \geq Y^l_{i,k}$ for all i, k, and l, since the unstressed simulation can do no worse than the stressed simulation.

With the matrices Y^l and U^l thus defined, the measures we develop characterizing each weather-year are functions $m : \mathbb{R}^N \to \mathbb{R}$ that operate on any column of Y^l or U^l. That is to say, any particular weather year will generate a vector $y \in \mathbb{R}^N$, associated with some column of Y^l for some l, for which $m(y)$ becomes an appropriate score for that weather-year. The following subsections define each measure precisely.

1) Productivity Measure: The first measure we consider quantifies the general productivity of a particular weather-year as characterized by CERES-Maize simulations over all N soils in S. To accomplish this, we construct the normalized matrix $W^l \in \mathbb{R}^{N\times T}$, where $W^l_{i,k} \triangleq Y^l_{i,k}/U^l_{i,k}$ for all admissible i, k, l. We then define the productivity of a particular weather year k for location l as

$$m_p[k,l] \triangleq \frac{1}{N} \sum_i W^l_{i,k} \tag{1}$$

which is simply the average normalized yield for that weather-year over all soil types.

2) Distinguishability Measure: The second measure we consider quantifies how differently a particular weather-year causes corn to grow in different soils, according to CERES-Maize. Such a measure is, in some sense, attempting to describe the variability of the column of Y^l corresponding to the weather-year of interest.

Although there are a number of measures one could use to describe the variability of a vector, we consider the following. Let $d[k,l] \in \mathbb{R}^N$ be a normalized distribution given by

$$d_i[k,l] \triangleq \frac{W^l_{i,k}}{\sum_i W^l_{i,k}} \qquad (2)$$

We then consider the Kullback-Liebler divergence [21], or relative entropy, from the uniform distribution to $d[k,l]$. This distinguishability measure is then given by

$$\begin{aligned} m_d[k,l] &\triangleq \textstyle\sum_i d_i[k,l] \log\left(\frac{d_i[k,l]}{\frac{1}{N}}\right) \\ &= \textstyle\sum_i d_i[k,l] \log\left(N d_i[k,l]\right) \\ &= \textstyle\sum_i d_i[k,l] \left(\log N + \log d_i[k,l]\right) \\ &= \log N \left(\textstyle\sum_i d_i[k,l]\right) + \textstyle\sum_i d_i[k,l] \log d_i[k,l] \\ &= \log N + \textstyle\sum_i d_i[k,l] \log d_i[k,l] \\ &= \log N - \text{entropy}(d[k,l]) \end{aligned} \qquad (3)$$

This measure describes how different the distribution of yields, resulting from a particular weather-year over all soils and normalized by their unstressed values, is from the uniform distribution. Clearly if a particular weather pattern resulted in a uniform normalized yield distribution, it offers no information distinguishing one soil from another. This could happen, for example, when weather is extremely corn-friendly, resulting in every soil type producing its maximum yield. By measuring the information distance, in bits, from the uniform distribution, this measure is, in a very concrete sense, capturing the information content about soils contained in a particular weather pattern, as least as far as CERES-Maize is concerned.

IV. RESULTS AND DISCUSSION

Figure 4 illustrates the yields, across all soil types, that result from CERES-Maize simulations driven by the weather recorded at Portageville Delta, MO, in 2001. This figure illustrates the kind of variation in yields one can observe from different soil types.

Figure 5 shows the yields from the same weather station, Portageville Delta, over all 12 years from 2001 to 2012. We discovered in running these simulations that the unstressed yield was the same across all soil types for any given weather-year, and this value is indicated by the triangle capping each year's collection of yields.

The question motivating this study, however, is whether one can characterize weather-years that result in yields that are informative about soil type. Figure 6 and Figure 7 reveal that unproductive weather-years are significantly more distinguishable than productive weather-years, sometimes as much as five times more distinguishable.

This very strong negative correlation between productivity and distinguishability appears to be intrinsic to CERES-Maize, regardless of weather pattern or soil type. Note that different colors in Figure 6 and Figure 7 illustrate different weather station locations, and no matter which color one selects, the trend across weather years has the same general negative slope.

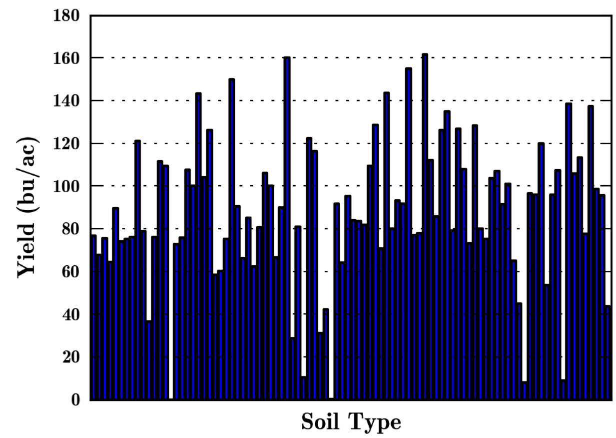

Fig. 4. Simulated yields, from all 93 soil types sampled across the continental United States, driven by weather recorded at Portageville Delta, MO, in 2001.

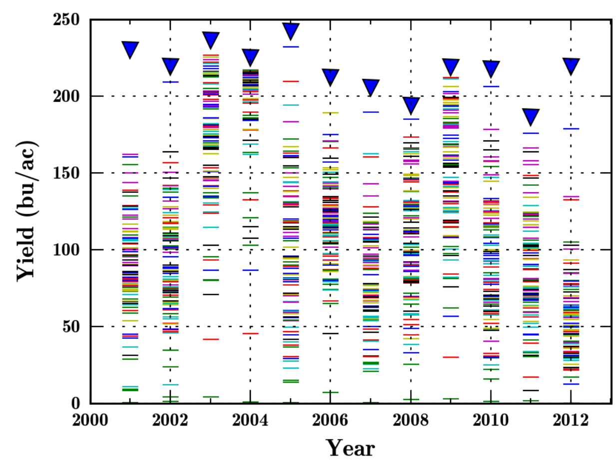

Fig. 5. Simulated yields for each of the 93 soil types sampled across the continental United States, driven by weather recorded at Portageville Delta, MO, each year from 2001 to 2012. The triangle capping each year's yields describes the yield obtained that year from the unstressed simulation, giving an upper bound to the achievable production that year.

V. CONCLUSION

In this paper, we investigate the ability of weather to sufficiently excite crop systems, represented by the CERES-Maize simulation model, in order to identify key parameters in the system. We argue that parameters characterizing soil are often unknown, or only partially known at best, yet farmers, compelled economically to exploit the crop system, have little opportunity to experiment and learn these parameters. As a result, weather is critically important for the identification of crop systems.

Without defining a particular learning algorithm or a specific identification procedure, this work attempts to character-

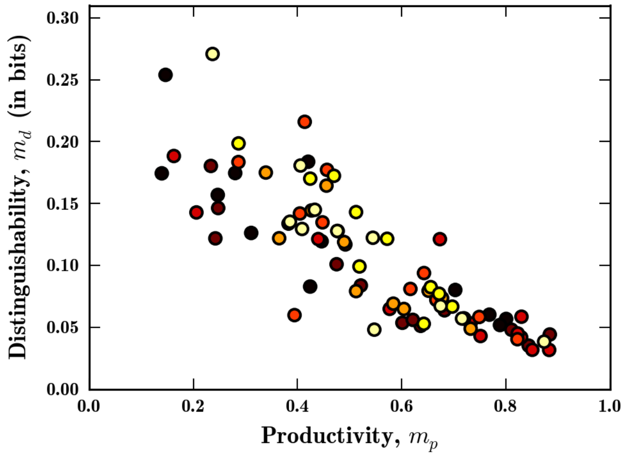

Fig. 6. Distinguishability vs. Productivity for each weather-year, from 2001 to 2012, at each of the seven weather station locations; different colors indicate different weather station locations. The general negative slope indicates that unproductive, or bad weather, is, in fact, the most distinguishable, or informative, in a very well-defined sense, at least as far as corn is concerned.

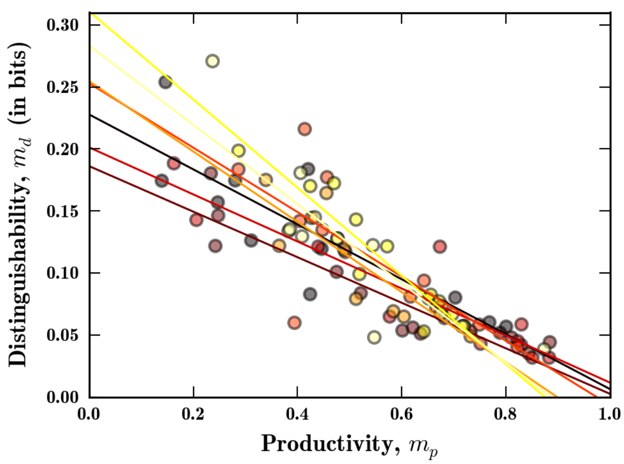

Fig. 7. This figure is equivalent to Figure 6, but includes simple linear regression lines against each weather station. Each color represents a different weather station and matches the color of the data it fits.

ize different weather patterns simply based on their ability to generate informative data for the identification of crop systems in general, and corn, represented by CERES-Maize, in particular. To accomplish this, two model-based measures were introduced, Productivity and Distinguishability, and the weather over multiple years at any single location was shown to result in a strong negative correlation between these two measures. This fact, illustrated in Figure 6 and Figure 7, demonstrates that, from the perspective of corn, it is bad weather that is very good at distinguishing soil type.

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