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Measuring Ground Truth:

Benefits of Infield Weather Data for Agriculture

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EXECUTIVE SUMMARY

The agriculture industry has broadly deployed gridded data systems to monitor weather and climate remotely across a wide variety of field conditions. Data accuracy is vital to the intent of these deployments. Satellite-enhanced gridded data systems, such as IBM's The Weather Company (IBM-TWC), generally measure weather conditions at widescale resolution, often spanning up to 30km per data point. This methodology can result in data gaps which fail to capture variations in microclimates, requiring data averaging and extrapolation brought on by a lack of ground-level data granularity. As an enhancement, localized ground-truth data, such as Arable's, provides an accurate snapshot of actual field conditions to fill in the gaps, leading to superior decision-making at the field level.

Using contextual discussions and charts, this paper examines the differences between IBM-TWC's weather data and measured ground-truth data from the Arable Mark 2—a portable, highly accurate in-situ weather and climate sensing system. The studies encompass a range of common weather measurements and important crop health indicators to provide a comprehensive argument in favor of using groud-truth data for agricultural desicion-making.

KEY FINDINGS

In individual comparison studies performed at locations around the world, the gridded data system showed a wide range of deviation from ground-truth, including:

- **Rainfall:** overestimated by as much as 361%
- **Air temperature:** average errors were over 3°C
- **Relative humidity:** errors as high as 25%
- **Evapotranspiration:** underestimated by as much as 91%
- **Phenology:** growth stages as much as 9 days premature
- **Ideal spray conditions:** missed as much as 54% of the time
- **Northern corn leaf blight (NCLB) risk conditions:** missed 25% of the time

Localized ground-truth agriculture data, as exemplified by that provided by Arable, provide a critical augmentation to widely adopted gridded data systems.

1. INTRODUCTION

This white paper examines differences across a suite of meteorological and agronomic observations by comparing values between two different types of sources: (1) gridded data products and (2) localized measurements from in-situ Arable Mark 2 devices. We define "gridded data products" as services that map a predicted set of weather variables to a particular grid cell based on latitude and longitude; together, these cells cover the entire Earth's surface. The grid cell size or the resolution of these products can vary, but all represent a modeled average of weather conditions across some predefined area. Gridded data products are derived from a fusion of many different data sources, including ground observations from multiple point locations, satellite and radar observations, and various National Oceanic and Atmospheric Administration (NOAA) databases, such as Climate Forecast System Reanalysis (CFSR). Gridded data are the source for many widely used weather products that provide global coverage estimates for historical, current, and forecasted (i.e., future) weather conditions.

One well-known example of a gridded data product is IBM's The Weather Company (IBM-TWC). According to IBM-TWC documentation, their services "synthesize multiple historical observational data sets to create a worldwide, high-resolution, gridded representation of past weather conditions" (The Weather Company, IBM-TWC). Their observations are derived from a fusion of many ground sources and other data products and are also gap-filled with remote sensing satellite data. Remote sensing techniques allow for the measurement and mapping of physical, chemical, and biological properties of Earth's surface based on the amount of electromagnetic radiation reflected, emitted, or scattered from objects. There are three aspects to the resolution of remote sensing products: spatial (the area covered by the corresponding pixel), spectral (the part of the electromagnetic spectrum measured), and temporal (the sampling frequency of the same region of interest) (Longley, 2005). The IBM-TWC datasets represent a gridded data product where each grid cell represents a modeled average of weather conditions based on a given area defined by the pixel resolution (Chen et al., 2018).

Gridded data products, such as IBM-TWC, are among the most widely used datasets in weather and climate. These products can provide a comprehensive snapshot of conditions. However, ground truth reference data from local weather stations are not always available, and so the associated uncertainty with gridded data products is generally unknown. The observations used to generate gridded data products are coarse —up to 30km—often with significant data gaps infilled using remote sensing satellite data. Recent advances in characterizing the Earth's surface via orbiting satellites have been a growing interest in various domains, including agriculture. However, the use of remote sensing satellite data alone warrants caution, as they have limited reliable ground truth validation at the required scale (Wang et al., 2016). The major limitation of gridded datasets, like IBM-TWC, is the poor representation of local conditions due to coarse grid cell resolution, data gaps, and compounded uncertainties from a fusion of many different data sources. Decisions based solely on the interpretation of unknown- or low-accuracy data may have economic repercussions as these uncertainties and errors propagate over time.

The preferred spatial scale of crop-related measurements ranges from microscale (less than 0.1km), provided by localized weather stations, to toposcale (0.1km-3km), measured by remote sensing systems (WMO, 2006). Monitoring agriculture through gridded data products at coarser resolutions may be suitable for some broad applications. Still, better resolution is required to capture the full extent of individual microclimates and plant responses to management operations at the field scale. Consistent examination of the wide range of meteorological conditions and other factors that impact plant growth is required to adequately assess growing season conditions (Lobell, D. B., 2009; Hoogenboom, 2000). Therefore, the ability to measure highly accurate real-time weather data that reflect local field conditions is crucial in agricultural data-driven decision-making. Gridded data products with large spatial resolution often do not reflect these local field conditions and often posess lower levels of the accuracy and timeliness needed to provide consistent and actionable data for agronomic applications. Thus, these products on their own present challenges to growers who require better information for practical, informed decision-making.

On the other hand, real-time, localized measurements from in-situ device deployments have proven highly accurate and appropriate for agricultural decision-making. Localized measurements uncover spatial heterogeneity and temporal dynamics that improve management recommendations at the field scale (Pattey, E. et al., 2001). Crop growth analytics based on these in-situ measurements are thus more robust, helping growers make more intelligent decisions that directly translate into higher yields at lower costs.

This white paper examines the differences between localized measurements from the Arable Mark 2 and gridded data products from IBM-TWC. Section 2 describes the methods used in this analysis; Section 3 outlines the study results; Section 4 summarizes the findings.

2. METHODS

This paper provides an accuracy assessment showing how IBM-TWC datasets perform against Arable. The IBM-TWC datasets draw from gridded data products based on either 4km or 30km gridded systems, depending on the variable of interest. The paper focuses on geographically diverse global locations, including Argentina, Australia, Brazil, Chile, India, Mexico, Ukraine, and different parts of the United States, including California and the Midwest.

This analysis considers both core measurements and derived agronomic features, as outlined later in this section. A similar analysis was published in another white paper, Arable Mark 2 Core Measurements: An Accuracy Comparison (Arable, 2020), which focused on the accuracy of the Arable Mark 2 and other commercial-grade weather stations compared to co-located, gold-standard instrumentation. The study found that the Mark 2 is a competitive alternative to traditional weather stations regarding data accuracy and reliability across variables like air temperature, rainfall, and other critical agricultural inputs. These findings show that Arable's dynamic machine learning platform and novel approach to sensor measurements avoid some of the typical sources of error and generate highly accurate outputs that can be a trusted source of ground truth. In this paper, we characterize the deviations of IBM-TWC datasets from Arable as a reference ground truth representing the local field conditions.

The climate and crop variables considered fall under three broad categories:

I. Core measurements:

a) Rainfall

b) Air temperature

c) Relative humidity

II. Derived features based on core measurements:

a) Reference evapotranspiration (ETo). We calculate ETo using Arable's unique machine learning model based on localized environmental variables measured by the Mark 2. IBM-TWC provides ETo directly as part of their feature offerings.

b) Growing degree day (GDD) accumulation and its effects on plant development (phenology). We calculate a horizontal cutoff GDD using the maximum (upper) and minimum (lower) temperature thresholds specific to each crop and variety. GDD captures the heat that induces plant development through the following equation:

$$GDD = \frac{Tmax + Tmin}{2} - Tmin$$

III. Crop disease risk models:

a) Delta T. This model identifies ideal weather conditions for spraying by calculating the difference between wet and dry bulb temperatures (Australian Government Bureau of Meteorology, 2004). The recommendations suggest avoiding spraying pesticides when Delta T is too high or too low—and ideally should only be applied when the values are between 2°C and 8°C. Delta T values greater than 10°C are considered unsuitable spraying conditions.

b) Northern Corn Leaf Blight (NCLB). This model identifies NCLB risk based on air temperature (risky between 13°C and 28°C) and leaf wetness detection. If the number of consecutive Wet Degree Minutes (WDM) reaches 5400 while in the risky temperature range, NCLB becomes a crop risk (IPM, U. of Illinois, 2002). We identify leaf wetness using Arable's unique algorithm based on localized environmental variables measured by the Mark 2. On the other hand, IBM-TWC leaf wetness is defined as periods when relative humidity is greater than or equal to 90% (Sentelhas et al., 2008).

In the next section, we compare localized Arable data to gridded data from IBM-TWC at various global locations. We characterize the differences between each source, providing performance metrics such as mean difference, overall percentage difference, confusion matrix results, etc. As mentioned above, the Mark 2 device's accuracy against co-located, gold-standard instrumentation has been previously established (Arable, 2020) and thus can be considered ground-truth for the comparisons made in this analysis. In this context, IBM-TWC's divergence from Arable's infield measurements represent the deviation of gridded data from actual field conditions, which are more accurately represented by Arable. We also use the core measurements as inputs into various physical models to generate different biological responses relevant to crop management, including evapotranspiration and GDD estimates, as well as crop disease predictions for Delta T and NCLB risk.

3. RESULTS

3.1 Core Measurements

This section shows two types of visualizations: time series plots that show measurement accumulations over specified periods, and scatter plots that show Arable Mark 2 data (x-axis) versus IBM-TWC gridded data (y-axis). Both types of visualizations were generated using hourly datasets. In the scatter plots, the black identity line represents where measurements from each source are equal. Points falling above or below that line correspond to instances of over-and under-estimation, respectively, noting that the farther the value falls from the line, the larger the deviation. In contrast, a tight scatter centered about the line represents minimal difference and a close match to Arable's data.

3.1.1 Rainfall

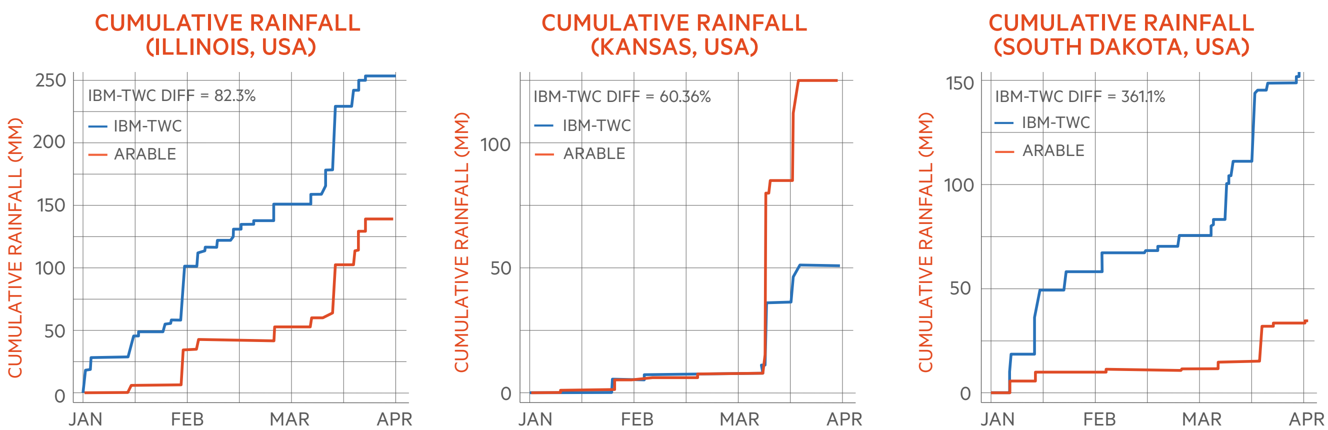

Figure 1. Cumulative liquid precipitation at different locations in the Midwest (USA).

Figure 1 shows the cumulative liquid precipitation measured over three months from January 2021 to April 2021 in three Midwestern US states: Illinois, Kansas, and South Dakota. Kansas has the smallest difference with an underestimation of 60%, or about 75mm over the three-month time frame. Illinois and South Dakota show more significant deviations, overestimating by 82% and 361%, respectively.

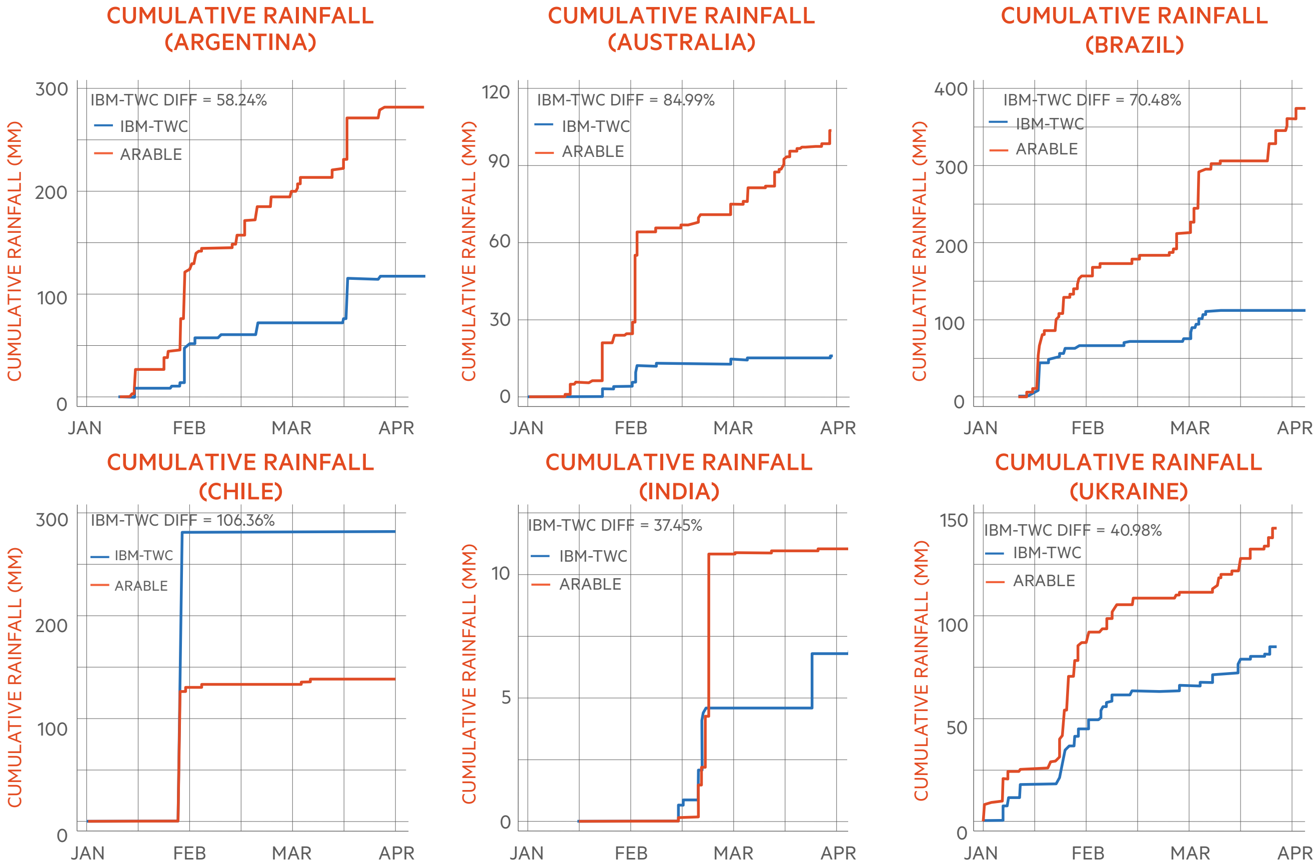

Figure 2. Cumulative liquid precipitation in Argentina, Australia, Brazil, Chile, India, and Ukraine.

Figure 2 shows a similar comparison from the same period extended to other countries: Argentina, Australia, Brazil, Chile, India, and Ukraine. India has the smallest difference with an underestimation of 37%, while Chile has the most significant deviation with an overestimation of 106%. In most cases, the IBM-TWC gridded data predicted too little rainfall, with differences as small as 5mm (India) and as large as 320mm (Brazil).

3.1.2 Air Temperature

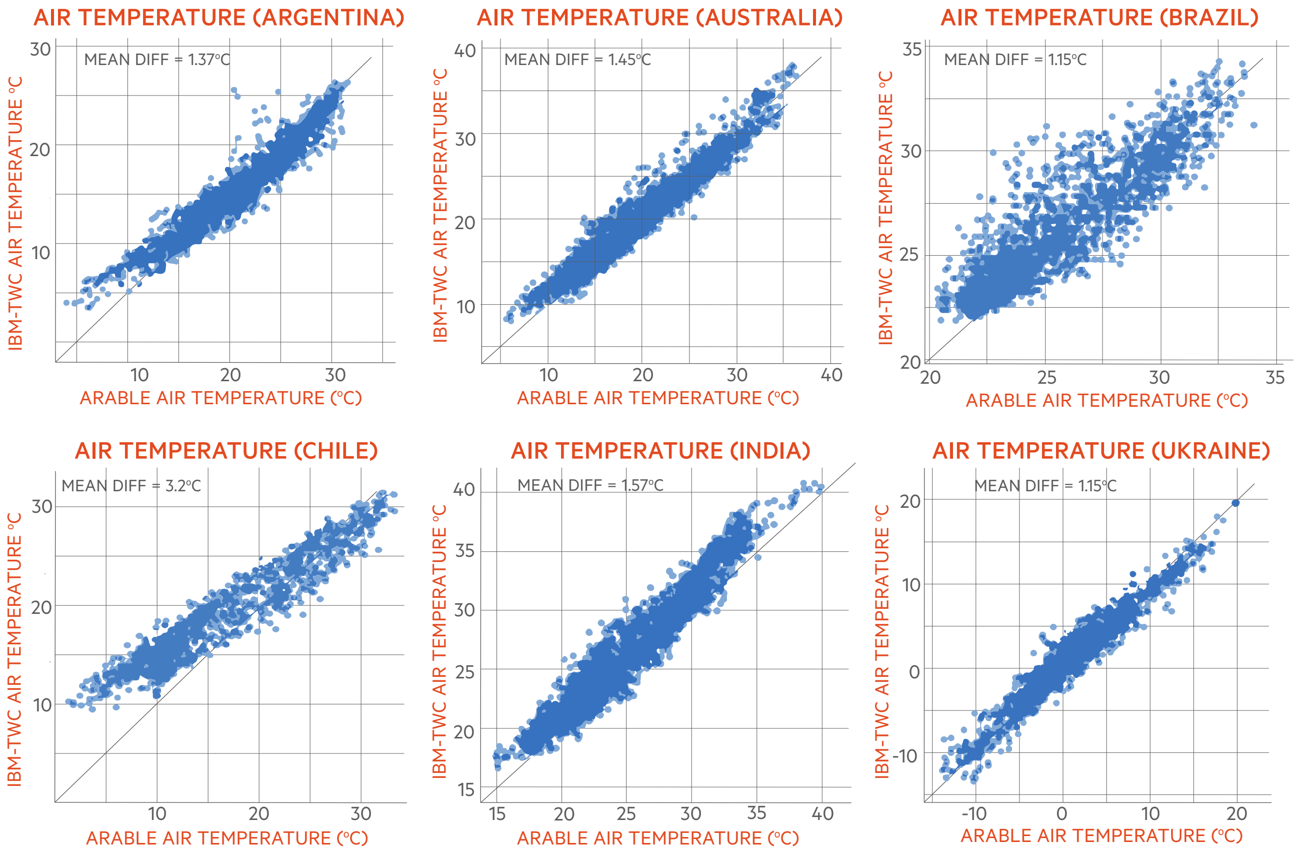

Figure 3. Air temperature in Argentina, Australia, Brazil, Chile, India, and Ukraine.

Figure 3 shows the air temperature measured over three months from January 2021 to April 2021 in six countries: Argentina, Australia, Brazil, Chile, India, and Ukraine. Overall, the IBM-TWC gridded data shows significant deviation from Arable Mark 2 ground truth, with all average deviations greater than 1°C.

Argentina, Brazil, and Chile show a particularly large scatter from the identity line, likely due to a combination of scarce ground data sampling and high cloud cover. Ukraine has the smallest difference of 1.15°C, while Chile has the largest, of 3.2°C.

3.1.3 Relative Humidity

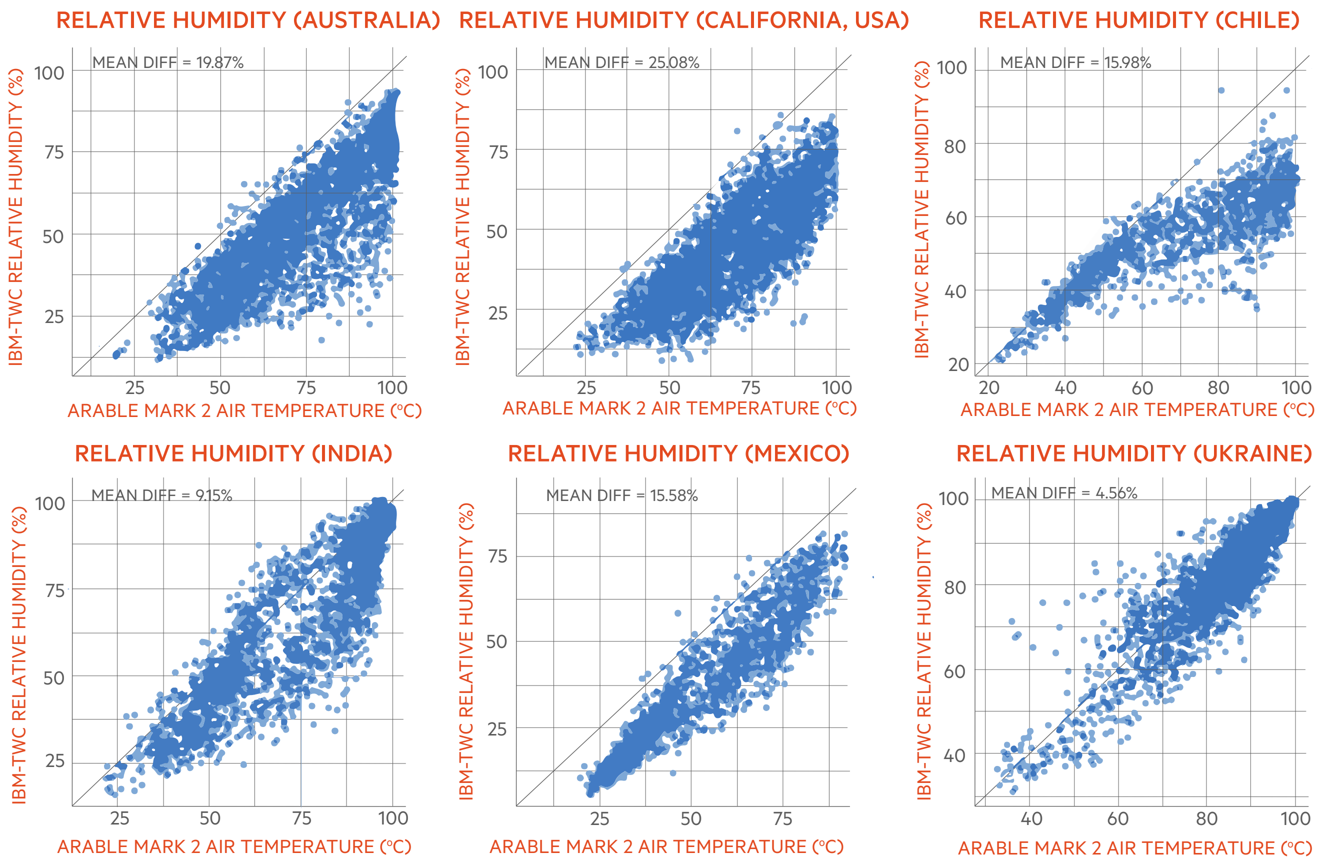

Figure 4. Relative humidity in Australia, California (USA), Chile, India, Mexico, and Ukraine.

Figure 4 shows the relative humidity measured over three months from January 2021 to April 2021 in six countries: Australia, California (USA), Chile, India, Mexico, and Ukraine. Similar to above, IBM-TWC gridded data shows a significant deviation from Mark 2 ground truth, with all average deviations greater than 4%. Ukraine has the smallest deviation of 4.6%, while the largest of 25.1% occurred at a rice field in California. The IBM-TWC gridded data shows a consistent low bias at this site, indicating that the increased humidity caused by flooding the rice fields did not reflect in the gridded data. This case exemplifies a unique situation where the gridded output did not capture the microclimate generated by the particular growing conditions of rice.

3.2 DERIVED MEASUREMENTS

3.2.1 Evapotranspiration

Estimating water loss from cropping systems through biophysical processes such as evapotranspiration requires a suite of precisely measured weather variables representing the field of interest. Many systems aim to provide relevant estimates of reference evapotranspiration, including gridded data products like IBM-TWC as well as dense weather station networks like the California Irrigation Management Information System (CIMIS). However, they often fall short of providing accurate field-level estimates, especially in areas that give rise to different microclimates.

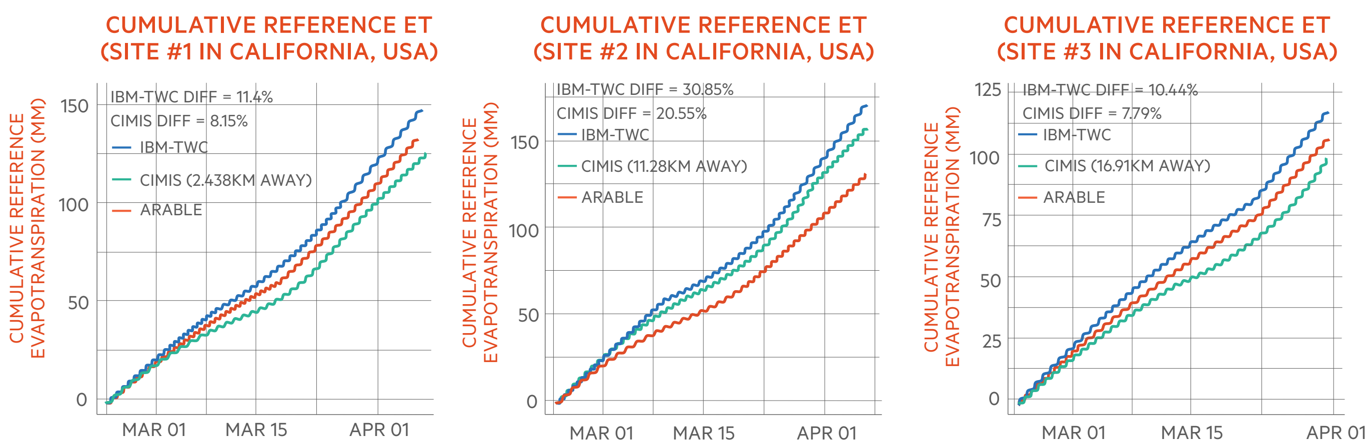

Figure 5. Cumulative evapotranspiration at different locations in California (USA).

Figure 5 shows three different locations in California comparing reference evapotranspiration estimates from the Arable Mark 2, IBM-TWC, and the nearest CIMIS station. Unlike IBM-TWC gridded data, the CIMIS data map to a single point location where a CIMIS station is set up over a reference surface (either grass or alfalfa); its distance from the Mark 2 is indicated in the legend of each plot. At two of the three locations, the Mark 2 estimates fall between those of IBM-TWC and CIMIS, while both IBM-TWC and CIMIS overestimate at the third location. Over the one-month time frame, the smallest deviation observed is 7.8% (CIMIS station), while the largest observed is 30.9% (IBM-TWC). This shows how the lower accuracy in core measurements from IBM-TWC gridded datasets can propagate to derived features like evapotranspiration and demonstrate how CIMIS stations can fail to provide accurate field-level estimates when they are located significant distances away from the field of interest. The latter is an important point since many California growers rely on CIMIS data to make irrigation management decisions. Still, this analysis suggests that these data do not meet the necessary accuracy requirements.

In addition to reduced accuracy, these systems typically only provide reference evapotranspiration (or require the user to input additional variables). For growers, this is not as useful as crop evapotranspiration, which provides water loss specific to the crop type and maturity stage. Arable estimates crop evapotranspiration by generating a dynamic crop coefficient based on NDVI.

Crop evapotranspiration will more accurately reflect the water losses occurring at the field-level and allow growers to make more informed decisions around irrigation management. However, for this analysis, we limit our examination to reference evapotranspiration since we are restricted to feature offerings from IBM-TWC gridded data products and CIMIS.

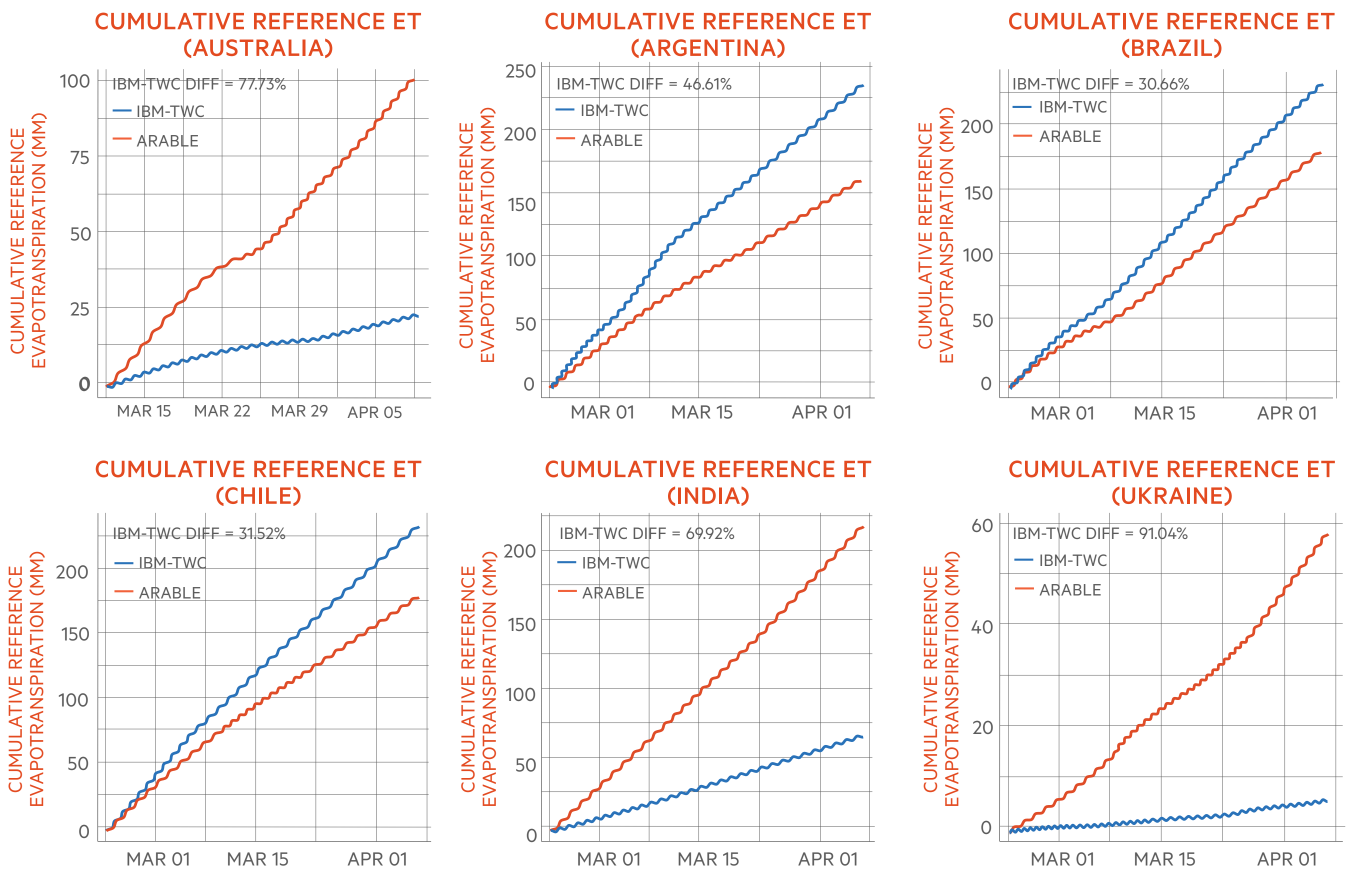

Figure 6. Cumulative evapotranspiration in Australia, Argentina, Brazil, Chile, India, and Ukraine.

Figure 6 shows the cumulative evapotranspiration measured in March 2021 in six countries: Australia, Argentina, Brazil, Chile, India, and Ukraine. There is significant over- and under-estimation of IBM-TWC gridded data as compared to Arable Mark 2 ground truth. Across all countries, there is either a consistent low or high bias, with discrepancies compounding over time, leading to excessive percentage differences. In Australia, India, and Ukraine, a low bias yields percentage deviations ranging from 70 to 91%, while in Argentina, Brazil, and Chile, a high bias yields percentage deviations ranging from 31 to 47%. Decisions made by growers based on these data could lead to poor water resources management and a reduction in crop yield.

3.2.2 Growing Degree Days & Phenology

One of the primary uses of air temperature in agriculture is calculating the rate of metabolic growth based on crop-specific growing degree days (GDD). Calculating GDD from inaccurate data can dramatically increase the chances of missing critical phenological events for pest and quality management of the crop.

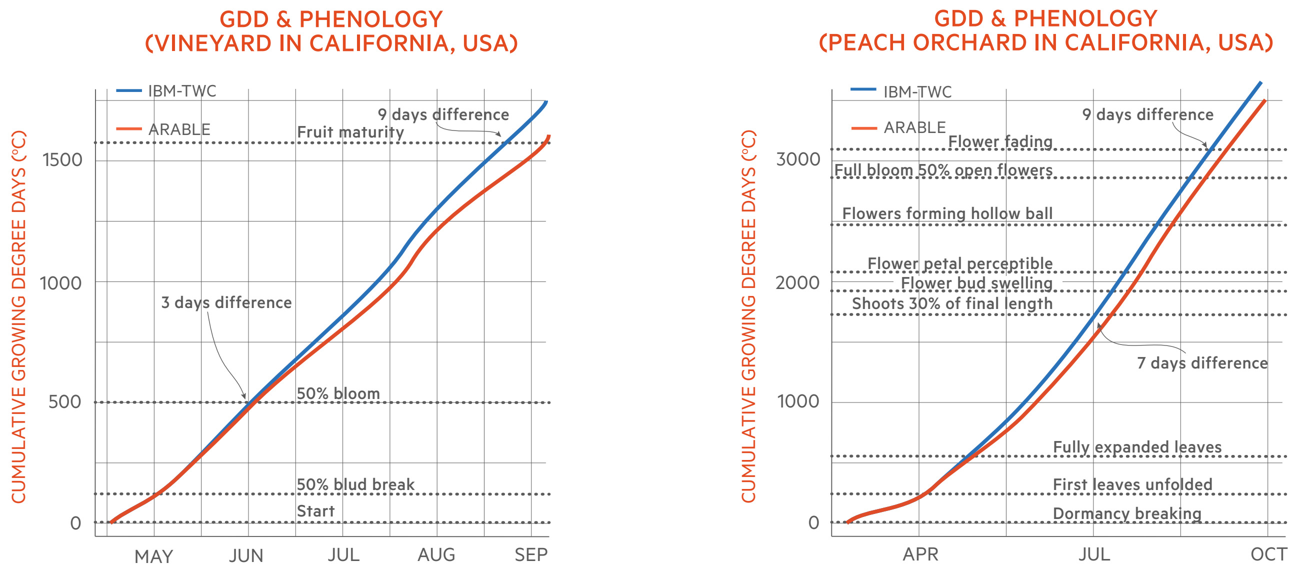

Figure 7. Cumulative GDD and the corresponding phenology of wine grapes and peaches at different locations in California (USA).

The left plot in **Figure 7** shows the GDD accumulation for California grapes using a base temperature of 10ºC. The expected growth stages are identified according to the sum of GDD since the beginning of the growing season. This example shows that calculating GDD based on air temperature from IBM-TWC gridded datasets would have predicted two premature events: 50% of bloom and fruit maturity at 3 and 9 days before the actual developmental stage, respectively.

The right plot in **Figure 7** shows another example of prematurely predicted events for a peach orchard in the California Central Valley. In this case, the stage when “shoots reach 30% of their final length” would have been prematurely predicted by seven days, while the stage when “flowers fade” would have been off by nine days.

3.3 CROP DISEASE RISK MODELING

3.3.1 Delta T

Delta T, also known as "wet-bulb depression," is an indicator of acceptable spray conditions in agriculture. The recommendations are based on droplet drift and pesticide uptake efficiency. High Delta T values indicate a fast water evaporation rate, such that droplets are at risk of drifting away from the targeted crop and may dry more quickly, reducing pesticide performance. Meanwhile, low Delta T values indicate a slow water evaporation rate, allowing droplets that are already prone to drifting to become more potent and a potential risk during temperature inversion at night.

Weather variables such as relative humidity, air temperature, and dew point temperature are crucial inputs to this calculation. Hence, errors in the estimation of these variables increase the risk of spraying at the wrong time. As demonstrated in Section 3.1 above, IBM-TWC gridded datasets often have significant inaccuracies associated with these core measurements—these errors can directly translate into false predictions for ideal and non-ideal spray timing.

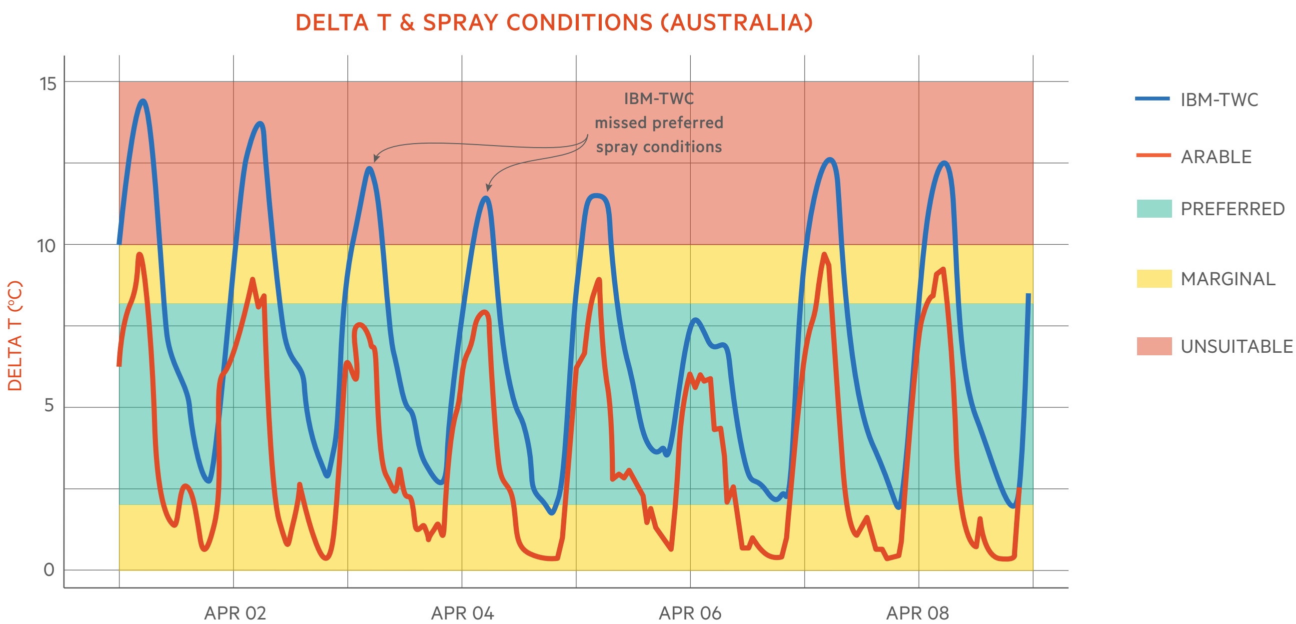

Figure 8. Delta T spray conditions in Australia.

Figure 8 illustrates the separation between Delta T ideal and non-ideal spray conditions at a site in Australia. The green zone corresponds to ideal conditions, while yellow and red represent marginal and unsuitable conditions, respectively. Over this short week-long time frame, we can see that there are two days when IBM-TWC gridded data incorrectly predicted unsuitable conditions for spraying, when in fact, the conditions were actually preferable. This represents two lost opportunities for spraying that could have provided better crop protection. Below, we present the confusion matrix results for Delta T spray conditions computed from much more data (longer time frames, at three different locations).

	IBM-TWC: Preferred Conditions			IBM-TWC: Unsuitable Conditions		
	Australia	California, USA	Kansas, USA	Australia	California, USA	Kansas, USA
Arable: Preferred Conditions	42.8%	26.4%	80.8%	36.7%	54.0%	2.3%
Arable: Unsuitable Conditions	0%	0%	0.2%	99.1%	99.5%	98.7%

Table 1. Confusion matrix results for Delta T spray conditions at three different sites. The Australian dataset covers July 2020 through March 2021, the California dataset covers May 2020 through September 2020, and the Kansas dataset covers July 2020 through April 2021. Note that the "marginal spray" condition was removed for simplicity, so the percentages do not add up to 100%. The green cells indicate agreement between the two sources, while the red cells indicate disagreement.

Table 1 summarizes the confusion matrix results for the Delta T spray conditions (preferred and unsuitable only) across three locations. Looking at the green cells, in California, IBM-TWC correctly identified unsuitable conditions 99.5% of the time but only identified preferred conditions 26.4% of the time. Looking at the red cells, in California, IBM-TWC did not mistakenly identify any unsuitable conditions as preferred (0% of the time). However, they did mistakenly identify many preferred conditions as unsuitable (54% of the time). In other words, a grower that was relying on IBM-TWC gridded data would have missed a majority of the opportunities to spray.

Out of the three locations, only Kansas yielded a false positive rate of 0.2%, meaning that there were only a handful of events where IBM-TWC gridded data incorrectly categorized conditions as suitable for spraying. Even though this percentage might be small, choosing to spray during unsuitable conditions could cause application drift and result in economic losses. On the other hand, there were many missed spraying opportunities, with IBM-TWC gridded data incorrectly classifying preferred conditions as unsuitable 2.3%, 36.7%, and 54% of the time for Kansas, Australia, and California, respectively.

3.3.2 Northern Corn Leaf Blight

Northern Corn Leaf Blight (NCLB) occurs commonly in the Midwestern United States, where a majority of corn is grown. NCLB thrives in high humidity and heavy dew environments when temperatures are in the 13°C to 28°C range. It can be devastating; with early infections, yield losses can be as high as 50% (Salgado, J.D. et al., 2016). Some avenues to battle NCLB include selecting resistant hybrids, crop rotation, and foliar fungicides application. The ability to detect NCLB allows growers to choose a resistant hybrid and determines whether they need to apply fungicide or rotate to a non-host crop to reduce the amount of disease in subsequent seasons.

As described in Section 2, Arable estimates leaf wetness based on a unique algorithm and uses this as an input—along with air temperature and rainfall—to monitor NCLB risk. The IBM-TWC gridded datasets do not provide leaf wetness directly; however, we defined a leaf wetness proxy based on a published algorithm (Sentelhas et al., 2008) and input the corresponding set of measurements into the same disease model to predict NCLB risk. Similar to the above, calculating this risk based on inaccurate data will inevitably lead to ineffective crop disease monitoring strategies.

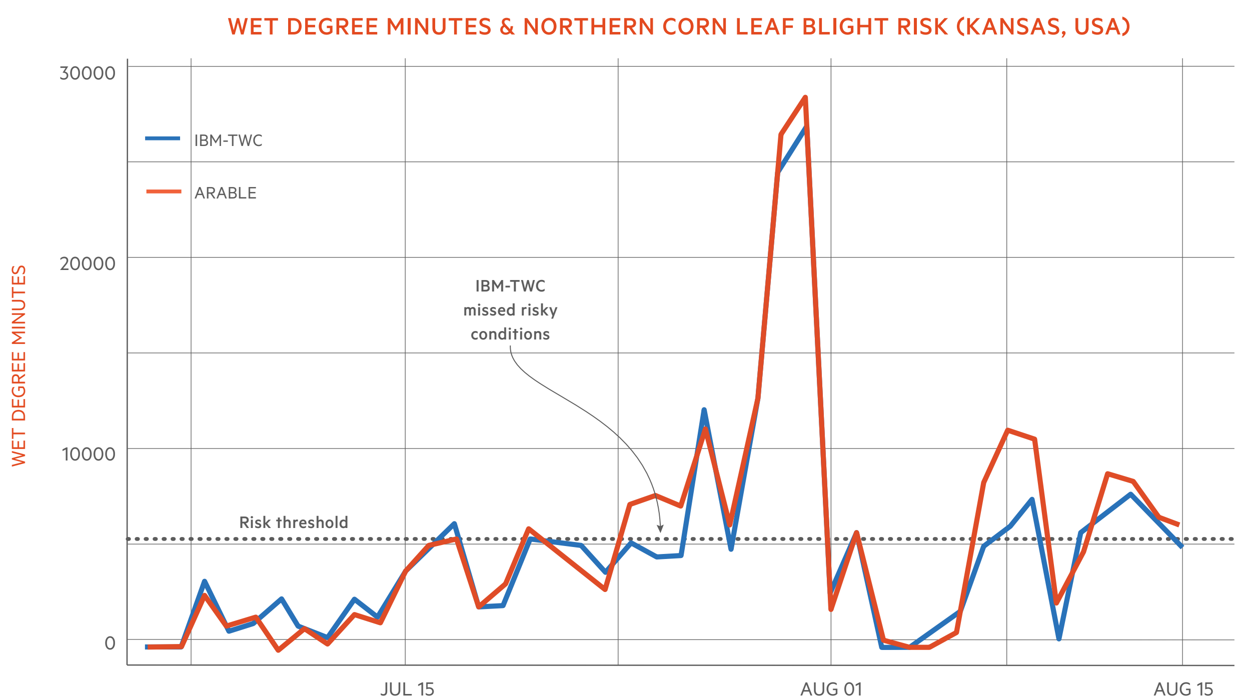

Figure 9. NCLB risk detection in Kansas.

Figure 9 illustrates conditions that present a high risk of NCLB occurrence at a cornfield in Kansas. Wet degree minutes (WDM) above the risk threshold line represent conditions where NCLB is considered high-risk. We can see that there are several instances with considerable discrepancy between the WDM estimates generated by IBM-TWC and the Mark 2. There was one case of separation during late July where high-risk conditions went completely undetected by IBM-TWC. The event represents an instance when growers could have failed to take the appropriate actions to protect their crops. Below, we present the confusion matrix results for NCLB risk at the same site but using more data based on a longer time frame.

	IBM-TWC: High Risk	IBM-TWC: Low Risk
Arable: High Risk	75.0%	25.0%
Arable: Low Risk	0.9%	99.1%

Table 2. Confusion matrix results for NCLB risk at a site in Kansas. The dataset covers July 2020 through March 2021. The green cells indicate agreement between the two sources, while the red cells indicate disagreement.

Table 2 summarizes the confusion matrix results for NCLB risk at a site in Kansas. Looking at the green cells, IBM-TWC correctly identified low-risk conditions 99.1% of the time but only identified high-risk conditions 75% of the time. In other words, a grower relying on IBM-TWC data would have missed 25% of the high-risk events and could have potentially lost crop to the disease. Looking at the red cells, we note that IBM-TWC falsely predicted high-risk conditions—when they were, in fact, low-risk—0.9% of the time. These types of false alerts, although rare, may have undesirable consequences based on any actions taken by the grower.

CONCLUSIONS

This paper assessed the accuracy of IBM-TWC gridded data products using the Arable Mark 2 as a local source of ground truth. Across the core climate variables of rainfall, air temperature, and relative humidity, the study found significant discrepancies in the IBM-TWC gridded data, showing some cases where rainfall was overestimated by more than 360% and the average deviations for air temperature and relative humidity were over 3°C and 25%, respectively. These inconsistencies can be attributed to gridded data products' lower accuracy representing local field conditions due to coarse grid cell resolution (covering up to 30km), data gaps, and compounded uncertainties from a fusion of many different data sources.

Not only is the data incompleteness inherent in gridded products operationally inefficient for growers basing decisions on core measurements, but the observed deviations from ground truth propagate throughout their system, also impacting derived high-value agronomic features. The study showed that reference evapotranspiration could be underestimated by over 90%, as well as significant discrepancies in degree-day accumulations, leading to prematurely predicted phenological events up to nine days off. The study also showed that gridded data products are unreliable when modeling spray conditions and disease risk for crop management. Ideal spray conditions based on Delta T were missed over 50% of the time, and up to 25% of high risk NCLB events went undetected. Relying purely on gridded data for agricultural monitoring is risky and may result in poor crop management, reducing yield, and incurring economic losses.

All of the above suggests that there is no true alternative to in-situ sensor deployments that provide real-time measurements that accurately capture field conditions. Arable is one cost-effective solution that provides highly accurate measurements based on robust sensor technology and a novel machine learning-enabled platform. The core measurements offered by the Mark 2 have been extensively field-tested and are used as trusted inputs for irrigation management, phenology monitoring, spray timing, and disease modeling. As an all-in-one localized weather station and crop monitor, Arable provides high-quality data for more informed decision-making and better agricultural management.

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