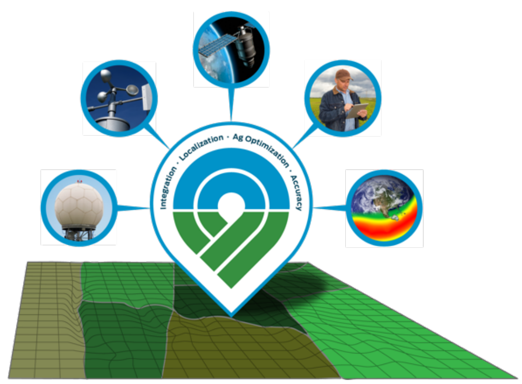
Agricultural Intelligence Begins with Agriculturally Relevant Weather Data

Data can do a lot to help make decisions, but not all data is created equal. Knowing how to select the right inputs, how to interpret it in the right context, and what signals matter and which don't is all key to ensuring the data is actually meaningful for the audience. Weather data may seem basic, but when it comes to agriculture it's crucial:

- Weather variability is increasing and throwing off traditional models and farming practices around the world. A data feed or radar map alone doesn't help a farmer know what to do this season, this week, or today.
- Placing emphasis on the *right* data means deriving more relevant insights, and that means knowing what plants actually need and how farming actually works.
- Understanding the right inputs to use ensures the data is relevant *for agriculture*; a weather station at the nearest airport is irrelevant for a field 50 miles away.
- Context is key—plants have different needs so knowing what's planted in a field means interpreting the data to make better decisions.

aWhere uses multiple sources of weather data for every location



No single source of raw data is reliable enough or sufficient to paint a complete picture of real, on-the-ground conditions.

Ground stations only represent the immediate local area, but cannot identify what happens in the reaches of space between them. Doppler radar becomes much less useful for agricultural purposes beyond 75km. Even satellites, constantly on the move, can have gaps in available data. Any weather data provider who predominantly relies on a single technology cannot paint a picture reliable enough to drive important food production and trading decisions.

Our data center continuously imports and processes multiple high-quality sources of raw meteorological data—never relying on just one source for any location. Our ground station network spans the globe, and only includes agriculturally-relevant weather stations (those in fields or away from cities). Layered on top of that is Doppler radar and both public and aWhere-exclusive satellite data. Our proprietary algorithms select the most appropriate sources and logic for each location, and we do all this with the same approach, quality, and resolution all around the globe.

The Problem with Single-Source Solutions

Many providers rely heavily on a single source of data, but no single source is infallible. For example, Doppler radar is an excellent technology but does not paint a complete picture. Figure 1 shows the supposed coverage of all Doppler radar in the US, about 150km radiuses from each station. But this map ignores the curvature of the Earth, and so as you get farther from a radar station, the beam moves further away from the ground. This is fine for tracking large storm systems, but becomes very unreliable for regular rain that might hit a field. Figure 2 shows the effective range of Doppler for agricultural purposes, or about 75km radiuses, leaving a lot of farm land uncovered by effective radar data.

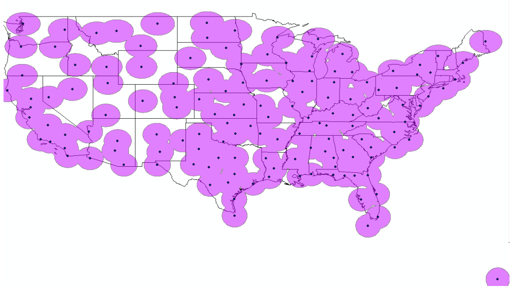


Figure 1

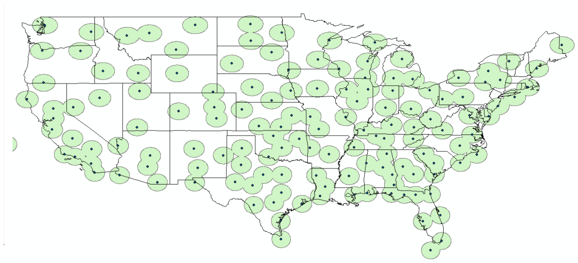
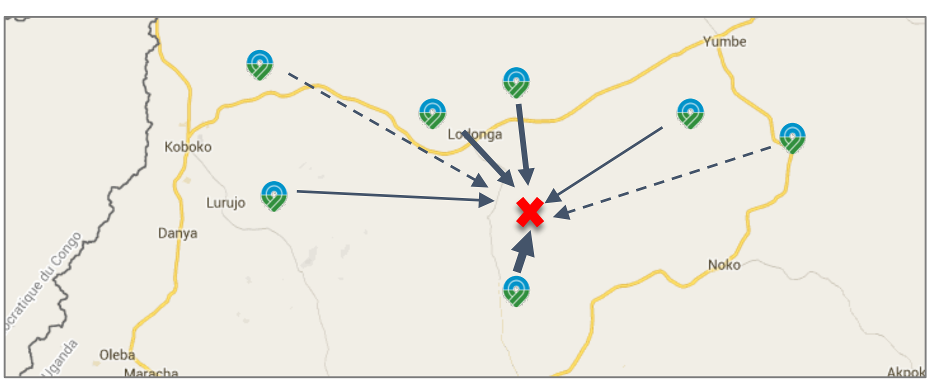


Figure 2

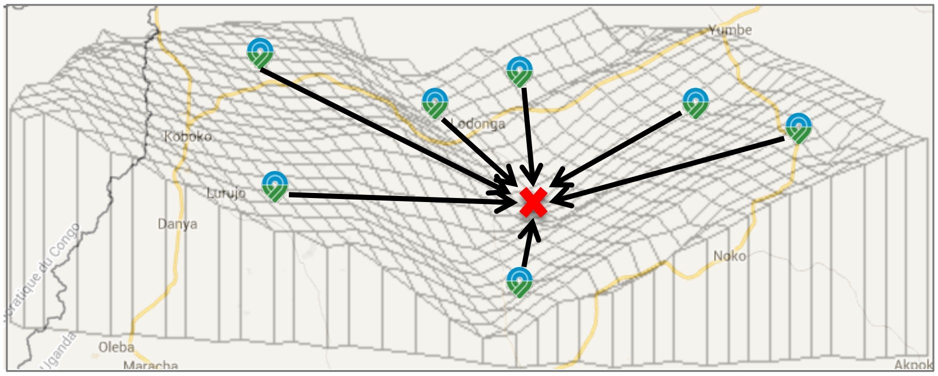
aWhere uses advanced interpolation mechanisms to provide hyperlocal and highly accurate weather, regardless of station density

Weather stations are only useful in the area immediately surrounding them, and the challenge facing weather data providers is how to calculate the weather in between.

One of the more common approaches is to use a rough Inverse Distance Weighted algorithm to calculate the different in temperatures between two points. As an example, consider the next graphic, which shows a smattering of stations and the desire for the weather at a central point. Basic IDW—used by many data providers—would assume an average of the surrounding stations should be a good guess at the weather in the middle.

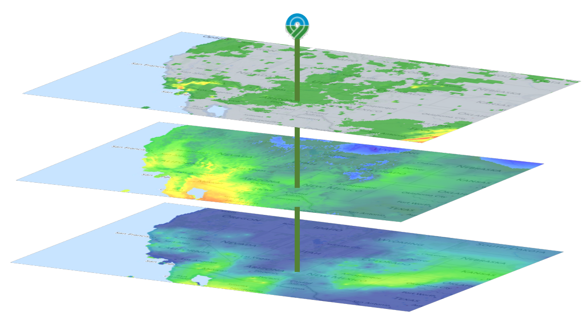


However, this technique ignores topography and some essential meteorological principles: that *adiabatic* attributes change predictably with elevation. In order to accurately calculate the temperature at the center point, one *must* take into account the topography and elevation of the source stations.



For all temperature based data (daily minimum and maximum temperature and humidity) aWhere utilizes 3D curvilinear algorithms that interpolate and compare many observations for each reported location value. Our approach is also *non-exact.* Many models attempt to force the interpolation to all available station data. If a station is broken, or is positioned in a microclimate, a large of amount of error will ripple throughout the region's interpolation. Our non-exact model catches errant stations or out-of-norm readings to represent a highly accurate picture for the whole region. The 3D curvilinear function also enables every elevation in between stations to have the best estimate of temperature variable for any given latitude, longitude, and elevation.

Precipitation can vary widely from one point to another in the same region, and capturing an accurate measurement requires blending ground station data, Doppler radar (where available and close by) and infrared and microwave satellite scans. aWhere blends all these data together using a daily calibrated moving filter - calibrating the satellite based observation with multiple 'nearby' ground stations for every location.



Over the years aWhere has tuned this integration to account for the varying season sun-angles, movement of the inter-tropical convergent zone and the monsoon—so that the result corrects dynamically for known shortcomings in the satellite alone observations. For example, NOAA's rainfall satellite system grossly underestimates rainfall during the Bangladesh monsoon yet overestimates the rainfall in Tanzania during the rainy season. aWhere's system corrects for this utilizing more data and all ground stations—not just the 100 'best' stations as do the passive satellite algorithms. The moving filter assures that the calibration is "what is best for that day" for that agro-ecozone.

aWhere's approach is consistently and highly accurate globally

We are often asked about our "weather data accuracy" which is very important to us since our observation and forecast accuracy underpins the results of our many agronomic models.

When evaluating weather data accuracy, it's important to consider the purpose of the data and the decisions being supported. For consumer-grade data providers, being 25% off in a forecast may be sufficient when planning a picnic. For industries such as energy, accuracy of storm and lightening activity is most important to protect lives. In agriculture, the question is what matters for plant growth and health during the whole length of a growing season. The measurements on any single day are not as important as the accumulated values over weeks.

> aWhere is the only weather and agronomic data provider exclusively designed to drive agricultural decision making.

aWhere breaks the world into 22 agronomic zones and statistically cross validates our estimates against each ground observation station with that station removed.

Around the world, the temperature we report for any arbitrary geolocation differs from ground observations by a mean of less than 0.67°C and 75% of the time we are within 1°C. When measuring precipitation accuracy, the most important value to track is the accumulated measurement. Barring sudden large events, the risk to a plant's health and region's yield comes from whether there is a steady and sufficient amount of water over the whole season. Over the course of a growing season, aWhere's accumulated precipitation accuracy typically improves, as shown in the chart below.

	Global	US Corn Belt	Southeast Asia
Temperature			
Difference on any given day	+/- 0.67°C	+/- 0.58°C	+/- 0.56°C
Accumulated GDUs at 90 days	+/- 24.36 (≈1 calendar day)	+/- 23.26 (≈1 calendar day)	+/- 22.39 (≈1 calendar day)
Precipitation			
Difference on any given day	+/- 4mm	+/- 6.17mm	+/- 6.89mm
Average Difference when accumulated over 90 days	+/- 2.03mm	+/- 1.39mm	+/- 1.56mm

aWhere goes beyond weather data

aWhere's view of agriculture intelligence places a heavy emphasis on making weather data meaningful. We provide more than basic figures; we offer out-of-the-box metrics that interpret that weather data specifically for agricultural decisions—from food production to commodities trading.

For example, equally important to tracking the presence of precipitation is tracking its frequency or even absence. A metric may show a region received 100mm of rain in the last month, but that can be terribly misleading if that rain all came on a single day. Other metrics, such as potential evapotranspiration and the P/PET ratio would quickly identify that the region is in trouble and yields are likely to suffer.

Likewise, increasing weather variability continues to invalidate 30-year climatological norms as a comparison metric. We've built our platform with an approach to long-term averages that allows for a dynamic and highly flexible calculation of any of the weather or agronomic values over any range of years. This empowers fast and readily available 3, 5, 10, or 20 year averages that deliver much more insight than climatology can provide.

Layered on top of this is specialized knowledge of how weather directly drives other risks to fields and regional yields. Our agronomic models can help predict pest and disease risk, measure likely harvest dates, guide day-to-day operations, identify global supply chain risk, and monitor agro-meteorological risks to a crop, region by region.

And all of our insights are delivered on an enterprise-grade API platform that can integrate with any application or workflow. For more on our data and technology, or to start experimenting with a trial of our data, visit http://developer.awhere.com.