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| --- | --- | --- | --- |
| **Origin of link** | **Landing page** | **Subpage** | **Target audience** |
| Website or Email attachment | Weather and products | Agrochemical performance in the field | Prospective clients |
|  | Weather and products | Cloud cover data engineering | LinkedIn skill bragging |
|  | Weather and products | How to binomial glm | Current clients |
|  |  |  |  |
| Private link only | Diversified ag simulation | Importance of crop diversification | Prospective clients |
|  | Diversified ag simulation | databasing and forecasting | Current clients |
|  | Diversified ag simulation | tableau/dashboards for agroecology | LinkedIn skill bragging |
|  |  |  |  |
| Website or Email attachment | Image processing for ag | Drone image data problems | Prospective clients |
|  | Image processing for ag | The importance of front-ends/tools coming from AI projects | Current clients |
|  | Image processing for ag | Potential deliverables or service | Prospective clients |

The content here should match the 9 cells above.

**Weather and products**

**Agrochemical performance in the field**

Agrochemical products deal with all the environmental extremes that occurs in the field. High temperatures, cold winds, and record droughts prevent products from working as intended.

[image of frost damage]

Products either succeed or fail in the field, and end-users can report those successes. But how can we use that information? For example, a client suspects that extremely high daytime temperatures in spring prevents an herbicide from working. Is that actually occurring in the field? If so, at what temperatures? A survey can get us halfway there, but we want some hard numbers.

[Image of salesperson taking survey data from a farmer or pesticide control operator]

Imagine we have a survey of 49 growers using a product gave us reports of the product succeeding. They reported “yes” or “no” to a salesperson who tabulated the data and entered it into an Excel file that was shared securely.

[flow chart of data being emailed or shipped]

Surprisingly, that’s all the data we need to start answering this question. The rest of the information can be generated by our environmental data scientists. Daily temperatures, rainfall, even cumulative degree days, all of these can be leveraged against the surveys. We can use this information to pinpoint thresholds at which products fail and rule out time periods that aren’t of concern because products succeed without issue.

[picture of someone working on a computer giving answers back to the salesperson. Lame but it gets the point across]

Click here to learn more about the data engineering side – how do we get climate data?

Click here to learn more about the models that can be used by product development teams.

**Cloud cover data engineering**

Cloudiness is easy to define but hard to measure with remote sensing. Dense cloud cover blocks UV rays, but also starves fast-growing plants of light for photosynthesis. Both factors impact agrochemical products.

[stock image of sun shining through clouds onto a farm]

In one or our recent projects, we needed to estimate the cloud cover on farms for the entire week prior to product application date. Our client provided location information and end-user survey and we did the rest.

[Landsate image]

LandSat 8 is a satellite photography program that hosts images taken of earths surface. We can’t just download the photos – these are many millions of high-resolution images. Instead we write a script which asks that database to only provide information from specific places and times.

[image of farm maps in R]

Using GIS tools we wrote a small program which maps the locations farms and draws a 5km circle around the property. If a farm used a product on May 7th, we then downloaded all the images from May 1 to May 7th. This process was automated and repeated for every single farm they had as customers.

[Image of a cloud cover photo with a grid on it and a number]

We then wrote a script to calculate which proportion of the photograph was covered with thick clouds (% cover). We took the average values for the week prior and *viola*, weekly % cloud cover specific to each and every farm that used this product!

[a short table showing % cover and product survey results]

Click here to learn more about how models using this data can help the development teams.

**How to interpret product success and failure models**

We value the time of our clients and believe in providing the “highlights” as well as the nitty gritty details. Good product teams want to get into specifics and the specifics are our strong suite.

[Picture of something techy like R code or reporting]

When providing reports to clients, we often show the models used to draw conclusions. Some model outputs are easy to interpret – like bar graphs or time series.

[pic of bar graph and trends]

Here we show important and critical modeling tool, but one that is not always easy to visualize. We then explain how such a model can be used to gather the real critical insights – the take-home message to bring stakeholders.

A client has provided us with 49 growers reporting success or failure of a product. EcoData provides environmental data and completes the modeling (statistical analysis). It looks like very cold temperatures negatively impact products, but how can we know for sure. And when is it too cold and when is it ok to use the product?

[bar graph of how many yeses and how many nos]

We can just count the number of yes and nos, but that doesn’t really tell us how confident we can be or what the temp cutoffs are.

This is a model with “fake” data used for illustration.

[Image of a binomial glm ggplot output with perfect data that would give a p-value of 0.0001]

On the left side are product failures, on the right are product successes.

[Show a ggplot figure highlighting the curve]

This area is where we figure out what the thresholds are. The product starts to fail at 35F (1.6 C), and by 32F the product no longer succeeded.

Sometimes its good to rule out hunches. In this second case, we considered it wasn’t temp, but the age of the plant the product was applied to.

[ggplot figure with a null result]

Old plants or young plants, we see that there is no clear point at which the products succeeded or failed across the board. It’s all over the place. That’s ok – this is critical to know and rules out wasteful action like telling end-users the wrong thing to do.

In the real world, things are more complex.

[ggplot figure with mixed answers and a lame p value]

Here we would suggest our client collect more data and do more surveys. There are some trials that failed at low temps, but not many. There’s some trend that might be wroth looking at. We wouldn’t want to bet the farm on it (no pun intended). A result like this justifies a closer look for the product team or maybe warning salespeople that there is a small risk of high temperatures messing up the product.