

Redesigning Yield Map Plots for Comprehension and Usability

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Abstract

A standard method to display the relationship between two variables is through visualization. However, if these variables occupy the same spatial domain, there is difficulty in perceiving any statistical relationships between the data. Data occupying the same spatial domain is common in the agricultural field, and while visualizations in this area exist, they do not conform to the principles of effective chart design. As a motivating example to illustrate challenges and potential solutions, we examined visualizing the relationship between crop input application and crop yield. Understanding this relationship is crucial as inefficiently applying crop inputs, like nitrogen fertilizer, impacts profit and the environment. The purpose of the Data Intensive Farm Management (DIFM) project is to allow farmers to run experiments that establish the effect of crop application on yield in specific locations. These trials, called On-Farm Precision Experiments (OFPE), leverage the ability to precisely control the application type and rate using GPS-enabled machinery while conducting these experiments. While maps attempting to display this relationship exist, they do not follow the principles of effective chart design. Our objectives are to identify the perceptual issues in current visualizations from our motivating example and to propose plots to mitigate these challenges. By documenting the process of improving graphics to increase comprehension and ease of use, these ideas can be used with similar data in the agricultural field to display it better. Visualizing the data more effectively makes the information presented more attainable for more people and may allow further insight into the data.

Keywords: visualization, spatial correlation

1. Introduction

With a projected increase in future crop demand, researchers are conducting studies on crop input application to increase yield, focusing on sustainability (Tilman et al., 2011). The systematic inefficient application of crop inputs on farm fields is a worldwide issue. Examples of typical crop inputs include nitrogen fertilizer and seeds. For instance, farmers seek to aid crop growth by introducing nitrogen fertilizer to their fields, as under natural conditions, the amount of nitrogen in the soil is small (Gruber and Galloway, 2008). Nitrogen is an essential component of food production as it is a component of amino acids, the building blocks of proteins, and allows plants to photosynthesize efficiently (Maheswari et al., 2017). Unfortunately, nearly half of the nitrogen fertilizer supplied to the field is not used by crops, resulting in excess nitrogen in the ecosystem (Billen et al., 2013). This excess nitrogen can be harmful to the environment (Nikolenko et al., 2018; Menegat et al., 2021). Excess nitrogen use may also impact profits, as farmers purchase more nitrogen than necessary. Current adoption of tools that aid in decision-making is low. So the focus has turned to

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using more data-driven decision making and building tools to aid with this. To collect the data and build the tools, more research needs to be conducted.

The Data Intensive Farm Management (DIFM) Project’s purpose is to develop cyber-infrastructure to easily generate the data necessary for a better understanding of this problem by allowing farmers to run experiments that establish the effect of crop input application on the yield on their fields (Bullock et al., 2019). This data can support more optimal decision-making by finding an optimal application rate that balances profit and sustainability (Kyveryga, 2019; Bullock et al., 2020). These trials, called On-Farm Precision Experiments (OFPE), leverage the ability to conduct an experimental design developed using site-specific information and precisely controlling the input application rate using GPS-enabled agricultural machinery (Bullock et al., 2019). These experiments then help inform optimal management decisions.

To design these experiments, farmers use an open-source web-based trial design tool developed in *R Shiny* (link) that allows for the specification of plot dimension, treatment type (generally nitrogen or seed), treatment rates, and equipment parameters, among other factors. Then, the web-based tool creates an appropriate experimental design (usually latin-square based) using these inputs. Once the user is satisfied with the experimental design, the web-based tool generates shape files that are then entered into their input machine to direct the application of treatments at the specified rates in the designated locations per the experimental design. After planting, the equipment generates a shape file containing the as-applied rates (which differ from the target rates due to sensor error and machine limits) (Trevisan et al., 2021). At the end of the growing season, harvesting equipment generates similar shape files containing yield measurements and their measurement location.

While statistical and machine learning models are beneficial tools to help determine the site-specific optimal rates, it is also valuable to visually explore the collected data on how crop yield responds to different input application rates at various locations on the field. Hopefully, by visually showing this relationship, trust is built in eventual machine learning output on optimal management decisions. A general principle of data visualization is to show the data and to show it clearly (Gordon and Finch, 2015). In this scenario, following this principle is difficult, as the different shape files (planned, as-applied, harvested) occupy the same spatial domain, making it extremely difficult to visualize in a way that allows the viewer to perceive any statistical relationship between the data. While yield maps attempting to display the data exist, they do not conform to the principles of effective chart design. Ineffective visualizations can lead to longer graph comprehension time, decrease readability of a graph, and an inability to discover or the incorrect discovery of patterns (Miller, 1956; Macdonald, 1999; Huang et al., 2009; LYi et al., 2021).

The organization of this paper is as follows:

- In Section 2, we analyze the shortcoming of such yield maps and document the map design process to maintain the spatial context of the data while allowing viewers to perceive relationships between variables. Maintaining spatial context is crucial as yield can vary spatially due to variables like soil variability.
- Section 3 presents our process to produce useful and visually engaging charts for a wide variety of users (farmers, researchers, crop consultants) while adhering to the principles of good chart design.
- The last section summarizes the main criticisms of current yield maps and discusses our proposed improvements.

2. Yield Maps and Graphical Perception

Figure 1 is an example of a map given to farmers and consultants. On this field, a seed and nitrogen trial were conducted simultaneously, with each input trial represented on a separate map. This figure superimposes the yield map (same for both Figure 1a and Figure 1b) on top of the trial design map provided by the trial design tool. The colored rectangles (green scale for seeds and grayscale for nitrogen) represent the underlying trial design, with the different color hues representing the planned treatments. The overlaid yield plot is made of circles representing the yield measurement location, as recorded by the harvesting

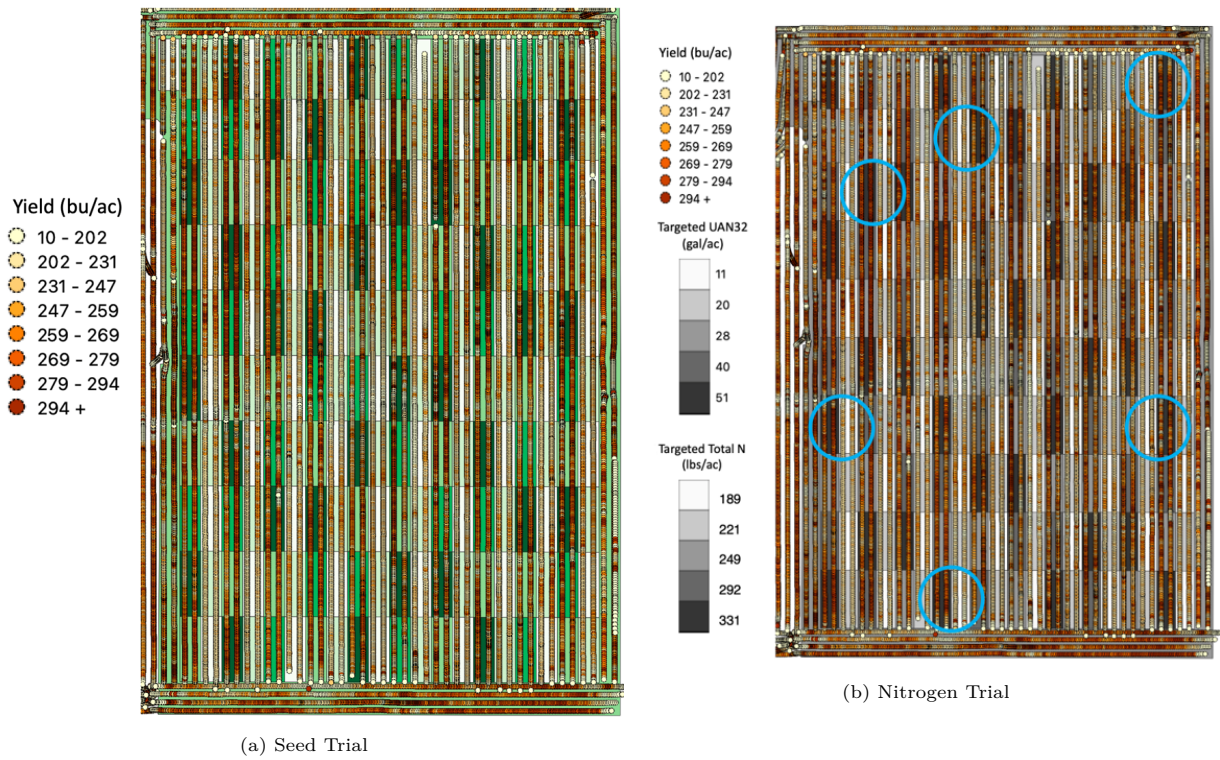


Figure 1: Example of a current map produced by DIFM for farmers that superimposes the trial design and yield information. These figures represent a seed and nitrogen trial conducted simultaneously. The blue circles in (b) were manually added to denote areas where the lowest target nitrogen group and highest nitrogen group are side-by-side. They generally show that low yield is associated with the lowest target and high yield with the highest target rate. These plots violate several principles of effective chart design, like failing to show the data clearly.

equipment. The circle color represents the crop yield amount in bu/acre, which in this example represents corn yield. The plot was developed using QGIS.

Design choices made in both plots make them perceptually sub-optimal. First, the circles representing the harvested crop yield overlap, obstructing the visual cue of color, thereby reducing the search efficiency (Bravo and Farid, 2004a,b). Due to the overlap, distinguishing the circle color requires more effort, made even more difficult by its black outline. As a consequence of the color obstruction, errors may occur when searching for a pattern between yield and treatment, the goal of the map, as the density of the overlapping measurement burdens the human perception (Huang et al., 2009). Clutter issues are common among superimposed graphics, as these graphs attempt to display multiple variables in the same space (Gleicher et al., 2011). A second perceptual concern with Figure 1 is related to the number of categories used to group the yield measurements (eight). Due to working memory limits, the recommendation for categorical scales is five to seven (Miller, 1956; Silva et al., 2011). As the number of categories increases, it becomes harder for the user to distinguish between colors, and remember the meaning of each color (Macdonald, 1999). Hence, with more than the recommended number of categories, it is more difficult to associate a color with the correct yield category. The additional load on the user’s cognitive system increases the comprehension time of the graph (Huang et al., 2009). Additionally, Figure 1a omits the legend for the trial design, so the user does not know what the target applications are and would have to look elsewhere for this information. Transfer errors are a drawback of making a chart in a different application (QGIS) than the rest of the report (Word).

Finally, the chosen color scheme is another significant perceptual concern related to the map. The use of a green gradient for the seed trial with a red-orange gradient for yield is of particular concern. Red-green color blindness is experienced by approximately 8% of men and 0.5% of women of Northern European ancestry. It is difficult for those affected individuals to discriminate between these colors, including colors that contain a component of those colors (Wong, 2011). Thus, separating the target application rate and yield measurement would be difficult for those users. The inability to discriminate colors negatively impacts performance in decoding information from the plot (Silva et al., 2011). Choosing the colors representing the different variables in Figure 1a more strategically may make the graph more accessible to this population of users.

Figure 2 is another variation of this map used in DIFM reports produced with *R*. This figure only presents a nitrogen trial. It uses juxtaposed maps, meaning the yield and trial design maps are laid-out side by side. The trial design map is on the left side and is identical to the underlying map in Figure 1b. On the right side is the yield plot, where the yield point measurements were transformed into polygons based on the distance between points, swath width (repetitively cut strips), and headings (harvester direction). This graph also has perceptual issues, including, once again, the choice of the color scheme of the green and red-orange gradient. Additionally, the color scheme for nitrogen between Figure 1a and Figure 2 is inconsistent and should be represented uniformly in DIFM reports to lessen confusion.

Due to the juxtaposition of the two maps, Figure 2 does not have issues with visual clutter or overlapping information. Particularly as non-overlapping polygons now represent the yield measurements. Additionally, juxtaposed plots tend to be easier to create than superimposed graphs. On the other hand, a juxtaposed layout places most of the comparative burden on the users’ memory (Gleicher et al., 2011). A mental image is relied on for comparison in these scenarios, as the user moves their eyes between images (shifting focus). The plot contents may not be accurately formed in working memory, leading to potential errors when deriving patterns (Vanderplas et al., 2020; LYi et al., 2021). For example, the user would have to identify the corresponding regions of each plot and then visually derive some correlation assessment. This is a demanding set of visual and cognitive operations, made even more difficult by the lack of visual cues for locations.

The presentation of other plots found in journals and extension publications, likewise displaying the relationship between target application and yield, also have perceptually sub-optimal design choices. These examples show the widespread problem of perceptually optimal plots in the agricultural domain. For example, a juxtaposed layout, comprised of a target map and the distribution of yield measurement locations,

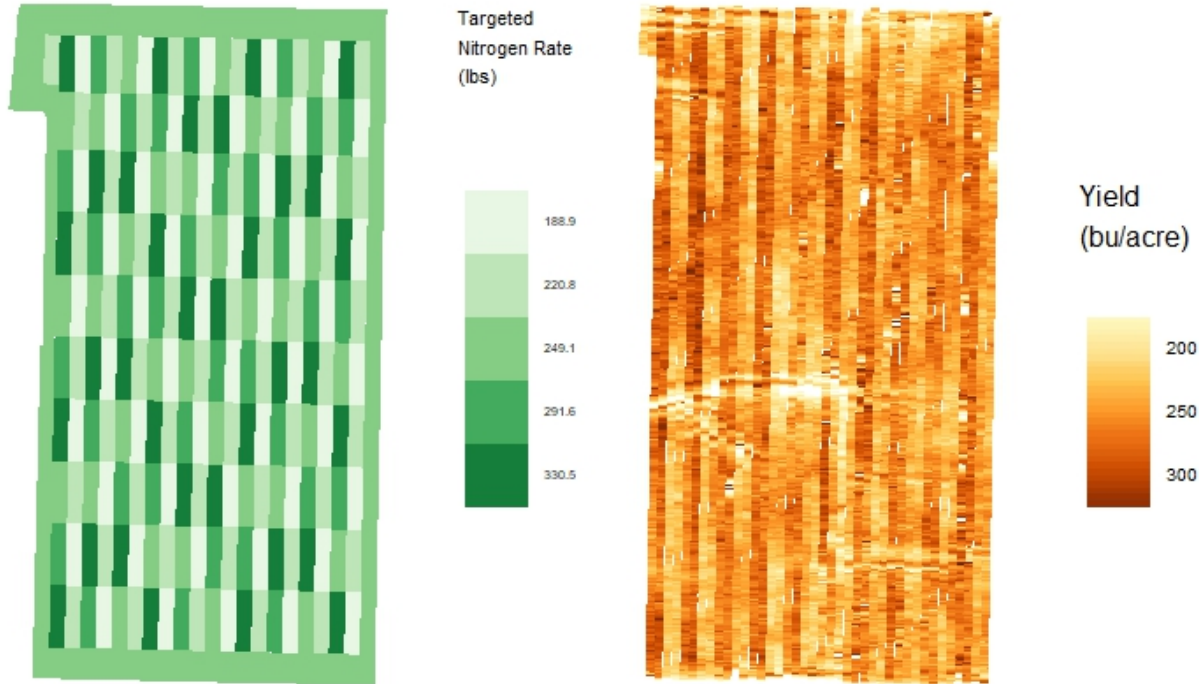


Figure 2: Another example of a DIFM plot, where now the information about input application and yield for a nitrogen trial is juxtaposed. This map poses issues as the comparative burden relies solely on the user.

can be found in Figure 4 of [Peerlinck et al. \(2018\)](#). The yield map is similar to Figure 1, due to overlapping points with a black outline. The true number of points is then obscured, concealing information about the yield point distribution. Users with red-green color blindness will have difficulty accurately reading the target values on the prescription map due to the chosen red-green color scheme. Also, the author used a similar color scheme to represent a target value and yield points. The overlap in color schemes is an issue as it may interfere with each when trying to derive information. A similar situation arises in Figure 1 and Figure 2 by [Poursina and Brorsen \(2021\)](#), with the same color scheme applied to the target and yield map.

The right-hand side of Figure 4 in [Gardner et al. \(2021\)](#) is another example, where a slight overlap in the color scheme for the nitrogen treatment map and yield map occurs. In addition, due to the juxtaposition of three different plots for this field (seed rate, nitrogen rate, yield), simultaneously comparing the maps is difficult since high mental effort is required. The minimal spatial cues to aid in comparing the variables across plots add to the difficulty. Figure 3 of [Trevisan et al. \(2021\)](#) has similar problems. The right-hand side of Figure 2 in [Maxwell et al. \(2018\)](#) does use a different color scheme for the treatment and yield map. However, the treatment variable uses the popular but problematic rainbow color scheme. Firstly, the rainbow color scheme is sub-optimal due to no inherent ordering of magnitude when the input application it represents has an ordering of magnitude ([Light and Bartlein, 2004](#)). Secondly, the extremes are visually close (red and violet), confusing users to differentiate values on both ends of the scale ([Silva et al., 2011](#)).

Even if only displaying a yield map, the yield maps tend to have sub-optimal design choices. Most of these choices are related to color schemes. For example, Figure 1 in [Tao and Bullock \(2019\)](#) uses a stop-light color scheme. However, for diverging color schemes, the transition between the two extreme colors should go through a neutral color, like white ([Midway, 2020](#)). Yellow is sub-optimal as a transition color as it tends to have a highlighting effect ([Silva et al., 2011](#)). More importantly, since the map only displays the magnitude of yield, a univariate color scheme would be more effective ([Vanderplas et al., 2020](#)). The stop-light color

scheme also would make it difficult for those who are red-green color blind to differentiate yield values.

Another example can be found in Figure 1 from Leroux (2020). In this figure, the yield measurements are obscured, concealing their true value. Additionally, in Figure 7 in Searcy (1997), a plot is used to display corn yield on a farm field in Texas. This plot first has more than the recommended number of categories (ten in total). The squares representing each yield measurement also overlap, obstructing the visual cue of color. Finally, a better color scheme should be chosen, as the current color scheme does not necessarily imply an ordering among the categories. Hence, a sequential scale of one color from light to dark would be more appropriate and color-blind friendly (Midway, 2020). Thus, prescription and yield maps tend to have some commonalities among their sub-optimal design choices. These include visual clutter, the number of scale categories for yield, and color scheme choice. We want to develop a new map that presents the same information while also addressing the weaknesses of the previous maps.

3. Redesign

The primary purpose of this project is to document the development process of improved alternatives to spatial correlation displays used in agricultural applications. There are many papers on statistical graphics, but relatively few document the improvement process to increase comprehension, ease of use, and perceptual accuracy. First, we considered each comparative graphic layout: superposition, juxtaposition, and explicit encoding (Gleicher et al., 2011). We decided to start with superposition (spatial overlay) shown in Figure 1, as juxtaposed maps require a higher cognitive load to compare across plots, and explicitly encoded maps do not directly show the data (LYi et al., 2021). On the other hand, superimposed graphs show the data while allowing the user to use their perceptual system instead of their memory (Gleicher et al., 2011). When spatial location is a key component of the comparison, the superimposed layout is beneficial, as the individual maps occupy the same axes (Wood et al., 2007; Wang et al., 2018). In this section, we plan to address the perceptual issues one at a time. We begin by addressing one of the major issues with the original map (Figure 1a): the overplotted circles, which make it impossible to see the yield information, as the circle boundaries (which are not colored) are more prominent than the shaded interior and tend to overlap.

The first redesign iteration (Figure 3) superimposes the yield and trial design maps. Note that yield measurements in the headland (the region around the trial design) are omitted, as this data is less reliable due to differences in sun exposure and changes in driving speed, among others. Instead of a single point for yield, we used yield polygons to represent the area where the measurement was taken to reduce the amount of information obscured. The yield polygons are created in the same fashion as the yield map (right) in Figure 2. During this first design iteration, we maintained the (problematic) color scheme of the original to provide continuity and obtain buy-in from domain experts who associate specific colors with specific variables. The top layer (yield map) introduces transparency to discern both design elements, and the relationship between the variables is determined through blending colors (Midway, 2020). Finally, a continuous scale was used for yield measurements instead of a discrete.

We introduced a different color scheme in the second design iteration (Figure 4) to address the color-blindness issues from the first iteration. We continued to use red for the response variable (yield). In this iteration, we utilized a continuous scale for the yield measurement. However, we chose to use a sequential blue color palette to represent the target treatments. We chose a sequential blue scale as Wong (2011) listed it as a color that can be differentiated by those with red-green colorblindness. Once again, we introduced transparency for the yield variable in an attempt to blend the colors. This map allows the user to see that higher nitrogen rates are associated with a higher yield.

A bivariate color map is an alternative to color blending in displaying the relationship between the target and yield variables. These maps can be helpful if the relationship between the variables is more important than the individual values (Elmer, 2013). In bivariate color maps, two univariate color scales combine into a sequential color scheme. A 3x3 map (3 categories for each variable) is the recommendation, as more categories hinder interpretation (Leonowicz, 2003). We chose quantiles to split the data into low, medium,

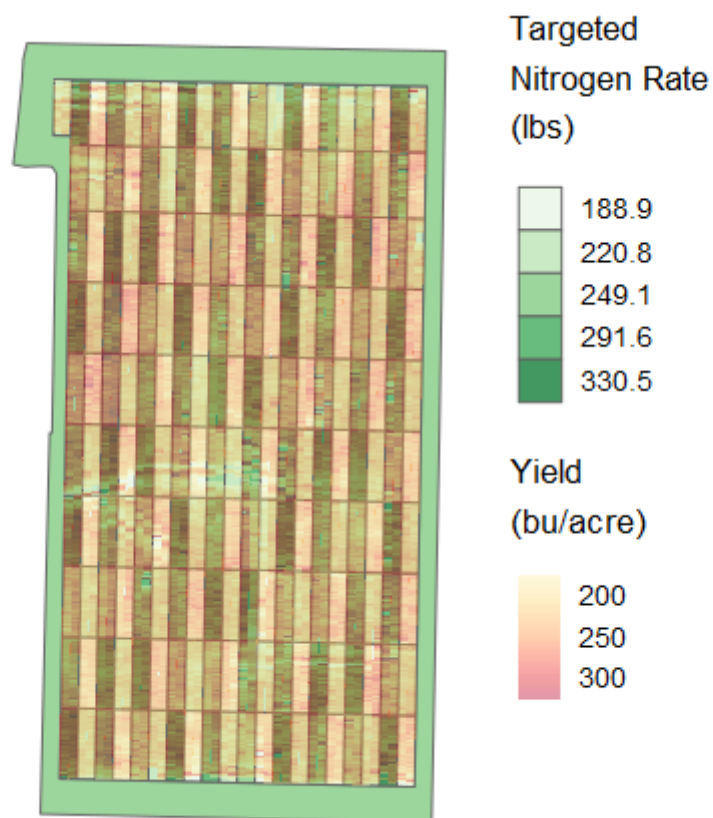


Figure 3: The first step in the redesign process, maintains the initial color scheme, but transparency was introduced to allow both layers to be shown simultaneously. This potentially allows the user to derive a correlation between these variables through implicit color blending.

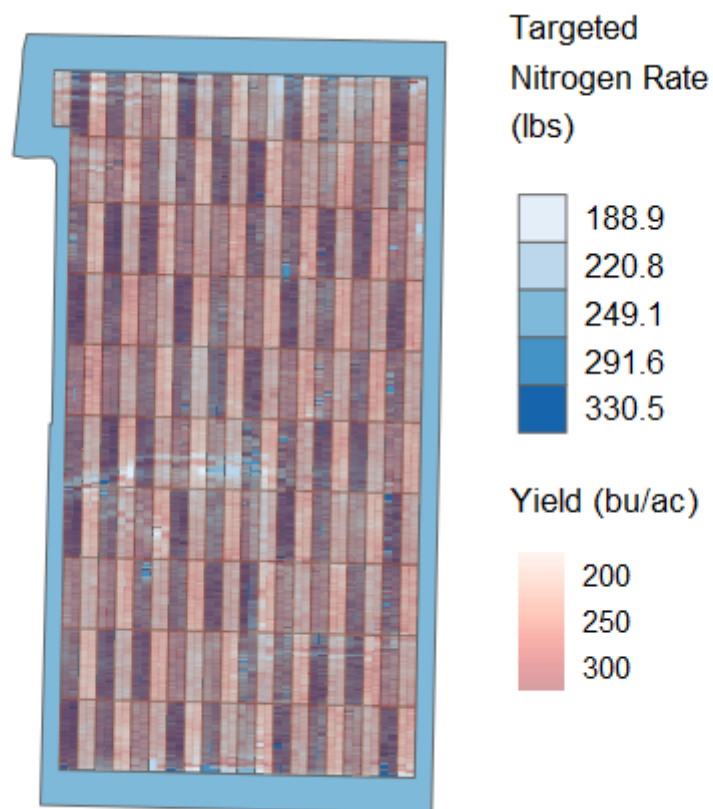
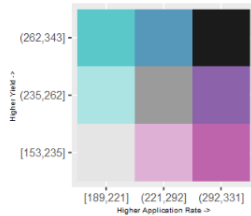
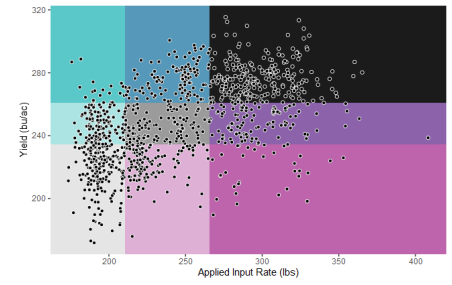
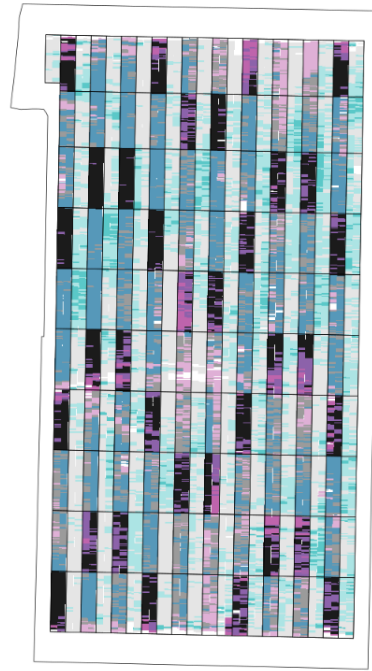


Figure 4: The second step in the redesign process focuses on color choice. Here, instead of the problematic red-green color scheme, a blue sequential palette is introduced for the treatment variables, so the two variables are distinguishable to those who are red-green color blind.



(a) Bivariate Color Map



(b) Scatterplot of data using the same colors

Figure 5: The bivariate color map has been suggested as an alternative to blending colors for bivariate data. In this map, each of the variables are made into three categories. Extra attention is focused on the diagonal of the color scheme to show the relationship between the variables. For example, the black representing high input application and high yield sticks out. A scatterplot is added to give more specific information about the value of the different data points.

and high categories (Biesecker et al., 2020). Since we are interested in the direct relationship between our variables, the focus is on the diagonal, so the diagonal values used a grayscale color scheme. Then the colors in the upper left and lower right have a complementary color scheme to show their separation (Strode et al., 2020). Figure 5a is an example of our proposed bivariate color map. It is then easy to juxtapose this plot with a scatterplot (Figure 5b). In this plot, the points represent the as-applied versus the yield, colored by the category from the bivariate color map.

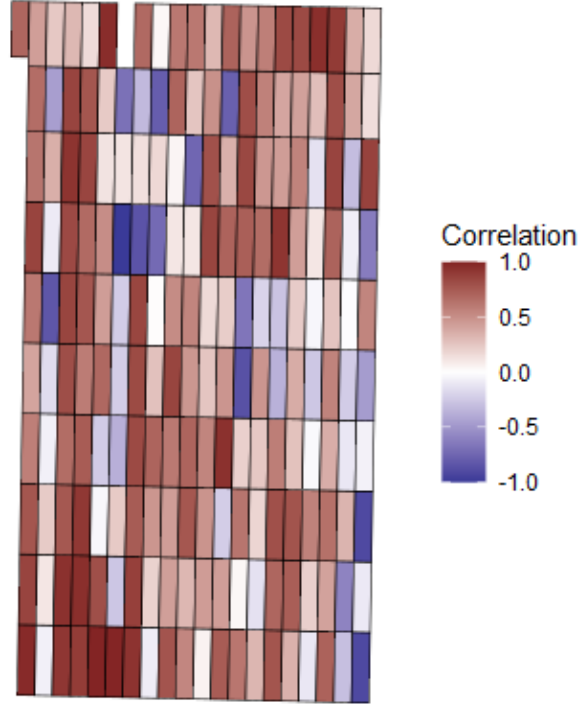


Figure 6: This plot directly states the relationship (correlation) between the as-applied treatment information and crop yield.

Next, we wanted to provide a more direct statement of the correlation between input application rates and yield (Figure 6), as determination of this relationship through color blending may be difficult and time-consuming for some users. Directing stagn the correlation uses another comparative layout: explicit encoding. Explicit encoding is helpful as it displays the encoding of the relationship, which spares the viewer of the effort to find it (Gleicher et al., 2011). We wanted to maintain some spatial information when presenting the correlation, as field location may also play a role in this relationship through variables like soil type. First, we used the as-applied treatments as this is the true treatment amount applied to the field. Second, to maintain spatial awareness, the correlation between the as-applied and yield measurement **was calculated** within each trial plot (outlined by black boxes). A diverging color palette was used, as correlation values have both magnitude and sign, using blue for negatively correlated values and red for positively correlated values, with a neutral color of white representing no correlation (Macdonald, 1999). This is due to the common cultural association of blues for negative numbers and red for positive numbers when used in conjunction. The viewer now directly sees the relationship between the variables while maintaining some spatial orientation through the trial plots.

Unfortunately, while the relationship between the variables was directly encoded, it can be complicated to connect the displayed relationship back to the data (Gleicher et al., 2011). Meaning, while the plot states

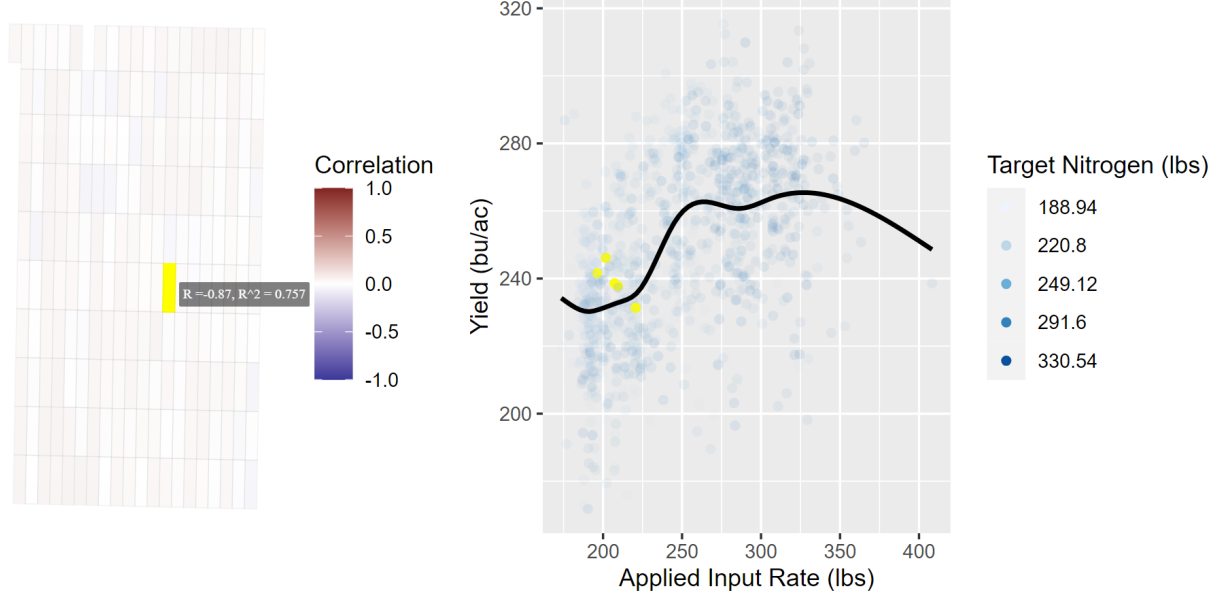


Figure 7: This figure overcomes the decontextualization weakness of Figure 5 by juxtaposing the correlation plot with a scatterplot of the values used in the correlation calculations. They are connected using interactivity.

the correlation, it gives no additional information on the application rate or yield. Hence we do not know what application rates are leading to the higher yield values or how large the yield values are. A standard practice to overcome this weakness is utilizing a hybrid comparative layout (LYi et al., 2021). A scatterplot was juxtaposed to the correlation plot (combining the layouts of juxtaposition and explicit encoding) to add some context back. Interactivity connects the juxtaposed plots, where hovering over a trial plot in the correlation map highlights the corresponding data in the scatterplot used to perform the calculation (Figure 7). Hovering over a trial plot also inform the user of the exact correlation (R) and also the coefficient of determination (R^2). On the other side, if the user hovers over a point on the scatterplot, the plot will display the point's target input application, as applied input, and yield amount. It will then highlight the corresponding trial plot and all other points on the scatterplot in the same trial plot. Additionally, a trend line was added to the scatterplot to display the overall trend of the data. While not beneficial in static pdf reports, interactivity will be advantageous in a future application designed to help farmers explore their data and facilitate improved management decisions. In the scatterplot, the same blue color palette, to represent the target rates, was used as in Figure 4 to help users to connect those plots.

4. Discussion

While reviewing DIFM reports and journal articles produced through this project, we found the regular use of sub-optimal plots to display the relationship between crop target input application and crop yield. Running themes found in these plots include data points overlapping and the choice of an inappropriate color scheme. In redesigning these plots, we used a superimposed comparative layout to limit the extent of the comparative burden placed on the users. Figure 4 shows our first proposed plot. This plot is an improvement due to the nonoverlapping polygons made from the overlapping yield measurements, so individual measurements are no longer obscured. Additionally, we suggested a better color scheme (red-blue), as these colors do not overlap and are more color-blind friendly. Blending the red and blue color scales represents the relationship between the variables, where, for example, the dark regions represent high target input application and high yield. A drawback of this map is that areas of low target input application/high yield and high target input application/low yield may be hard to differentiate easily. Further, this design

has difficulty displaying the individual values of the variables. However, in viewing the plot on a web page, we can use the *leaflet* package in *R* to allow the user to display the maps individually or superimposed.

Figure 5a introduces a bivariate color map to improve on the drawback of the color-blended map. In this map, quantiles divided each of the variables into three categories, where the crossing of the categories resulted in nine groups, each assigned a unique color (lower left). A benefit of the bivariate color map is its ability to easily denote the values along the diagonal of the color legend or those that display a positive linear relationship. Moreover, the low target input application/high yield and high target input application/low yield categories are easily recognized. However, a drawback of this method is that individual values are not distinguishable due to the categories. Further, individual information about each variable can not be separated, like in the color-blended map. In addition, due to trying to work within memory limits, the categories of each variable may cover a wide range of values and do not give detailed information (Roth, 2017). Technically, the number of colors used is more than the recommendation of seven, but only five are of real interest (diagonal and the other two corners). A scatterplot of the applied input data versus the crop yield was juxtaposed with the color scheme as the background (Figure 5b) to gain additional information. The scatterplot was to add some context on what the data looks like within each category.

Finally, we developed a plot that directly states the relationship between input application and crop yield using the explicit encoding comparative layout. This plot (Figure 6) displays the calculated correlation within each trial plot, as spatial location plays a vital role in this relationship. Spatial location is significant due to spatially varying variables like soil type and precipitation on a field. Now the users no longer have to infer the correlation themselves. To counteract the negative qualities of explicitly encoded graphs (not displaying the data), a scatterplot of the actual data used in the calculations was added to the right-hand side. In Figure 7, the two plots are linked, so the data used to calculate the correlation in a trial plot on the left is highlighted in the scatterplot on the right. Hence, this plot directly states the relationship while also linking to the data. Unfortunately, this version is not compatible with static pdf reports.

The suggested improvements of the original plots follow what is currently known about effective data visualization to help users understand the desired information by avoiding overlapping data points and choosing more effective colors. The next step in this process is to obtain feedback from those using these plots (farmers, researchers, crop consultants) to see which of the suggested plots is preferred and to tweak any of the designs if necessary. In the future, these specific plots will be used in DIFM reports and publications, while the suggestions made during the creation of these plots can be used in other applications for displaying two variables in a spatial domain in the agricultural domain.

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