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Generation of Site-specific Nitrogen Response Curves for Winter Wheat using Deep Learning

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Abstract.
Nitrogen fertilizer response (N-response) curves are tools used to support farm management decisions. The conventional approach to model an N-response curve is to fit crop yield in response to a range of N fertilizer rates as a quadratic or exponential function. The purpose of the model is to identify the profit maximizing N rate given the costs of nitrogen and the price paid for the crop yield. We show that N-response curves are not only field-specific but also site-specific and, as such, economic optimal (profit maximizing) rates should be calculated for each field each year prompting the use of on-field precision experiments (OFPE) utilizing precision agriculture technologies. We propose a methodology that allows deriving N-response curves automatically instead of using parametric curve fitting approaches. Thus, we obtain a specific non-parametric N-response curve for each 10 m x 10 m cell of a grid virtually draped on the field. First, we train a convolutional neural network called Hyper3DNetReg using remote sensed data collected during the early stage of the winter wheat growing season (March) to predict crop harvest yield values . The neural network models the behavior of the field under different environmental and terrain conditions. Then, we use the trained prediction model to obtain an N-response curve per cell by simulating what would be the yield response given a range of nitrogen rate values between 0 and 150 pounds per acre (lbs/ac). Results show that the shape of the N-response curve depends on the region of the field from which it was calculated. Related work will address the problem of generating prescription maps that merge the site-specific economic optimal rates calculated from our N-response curves while also minimizing the overall fertilizer applied and the number of jumps between consecutive cells' nitrogen rates.

***Keywords**.*
Nitrogen response curves, Site-specific, Deep learning.

Introduction

The economic optimal nitrogen rate (EONR) is defined as the nitrogen rate beyond which there is no actual profit for the farmers. Estimation of the EONR is usually obtained after fitting pre-selected, parametric yield response functions to crop yield data. Some traditional approaches assume plateau-type, quadratic, and exponential functions (Bullock & Bullock, 1994; Watkins, et al., 2010; Kablan, et al., 2017). Other approaches are based on basic agronomic principles, as is the case of the Liebig response functions (Ackello-Ogutu, Paris, & Williams, 1985). It is worth mentioning that different crop yield data models can produce different EONR estimations (Meisinger, Schepers, & Raun, 2008).

Previous works have documented that the EONR is highly dependent on the type of crop, soil, environmental conditions, and other factors (Nyiraneza, et al., 2010; Tremblay, et al., 2012). Some work has tried to account for the field and year variability by introducing stochasticity on crop yield models that used conventional functional forms, obtaining better results than their deterministic counterparts (Tembo, et al., 2008; Tumusiime, et al., 2011; Boyer, et al., 2013). However, the variability of the nitrogen response (N-response) functional form across the fields has not been widely addressed by previous work (Anselin, Bongiovanni, & Lowenberg-DeBoer, 2004; Maxwell, et al., 2018).

We argue that trying to fit a single N-response curve for an entire field implies the strong assumption that the field is homogeneous and behaves similarly everywhere. However, it is reasonable to consider that this assumption does not always hold when there exists variability in the terrain of the field (e.g., terrain slope and soil composition). Thus, in this work, we consider that N-response curves are not only field-specific and year-specific but also site-specific.

In particular, we propose to use a convolutional neural network (CNN) called Hyper3DNetReg (Morales & Sheppard, 2021) that maps the spatial features into predicted yield values. The CNN acts as a complex crop yield data model whose implicit functional form is non-parametric and is learned from the data. We use an early-yield prediction dataset and show how different N-response curves can be generated for different regions of a field using the learned yield prediction model. In addition, we explain that having site-specific N-response curves allows for site-specific N recommendations.

Proposed Methodology

Datasets

In previous work, we presented a curated early-yield prediction dataset of winter wheat (Morales & Sheppard, 2021; Hegedus, 2022). In this case, the early-yield prediction of winter wheat can be viewed as a regression problem where its explanatory variables are determined by the set of features collected during the growing season (March). Below, we report the list of features that were used:

- Nitrogen rate applied.
- Terrain slope.
- Terrain elevation.
- Terrain aspect.
- Topographic position index (TPI).
- Sentinel-1 Vertical Transmit-Vertical Receive Polarization (VV) backscatter coefficients.
- Sentinel-1 Vertical Transmit-Horizontal Receive Polarization (VH) backscatter coefficients.

The yield value in bushels per acre (bu/ac) is considered the response variable of the regression problem. The yield is measured during the harvest season (August) using a combine harvester equipped with a yield monitor that collects georeferenced values from the field. Hence, the data acquired from the winter wheat fields in March is used to predict crop yield values in August of the same year.

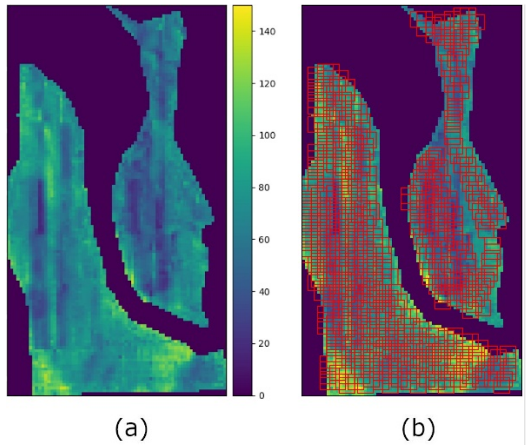

Fig 1. Image rasters corresponding to the G1 field. (a) Yield raster. (b) Automatic extraction of 5×5 m pixel patches.

Each field was divided into a grid where each cell represents a region of 10×10 m. By doing this, all the data was aggregated on a scale of 10 m. Fig 1a shows a yield raster for one of the fields of our dataset from 2018 where each pixel represents an area of 10 m x 10 m.

We chose Hyper3DNetReg as the yield prediction model due to its ability to exploit spatial information from its two-dimensional (2-D) input patches by using 2-D and 3-D convolutional filters. Thus, the collected data rasters need to be pre-processed to create the training datasets used to fit the Hyper3DNetReg models. Specifically, we automatically extract square patches using a 5×5 pixel window allowing a maximum overlap of 0.75, as shown in Fig 1b. This approach differs from traditional methods that rely on models trained on 1-D features regardless of the spatial distribution (Gonzalez-Sanchez, Frausto-Solis, & Ojeda-Bustamante, 2014; Kim & Lee, 2016; Wei, et al., 2020). Table 1 shows the total number of extracted samples and the years of observation for each field used in our experiments. Here, F1 and G1 are two fields of winter wheat from two different farms in Montana.

Table 1. Number of samples and years of observation for each field

Field	# Samples 1st Year	# Samples 2nd Year	# Samples 3rd Year	Observed Years
F1	408	316	317	2016, 2018, 2020
G1	484	497	614	2016, 2018, 2020

Yield Prediction

In this section, we use the collected datasets to train and test the Hyper3DNetReg models. These models are field-specific; that is, they are trained on data of a given field from previous years (2016 and 2018 in this case) and used to predict yield maps using data from the last observed year (2020 in this case) of the same field.

In our previous work (Morales & Sheppard, 2021), we showed that 2-D deep regression models yielded better results than regression models that use a single output. Therefore, in this work, we only use Hyper3DNetReg models with output windows of 5×5 pixels (i.e., the input window size matches the output window size), as shown in Fig 2.

After training the Hyper3DNetReg models using data from 2016 and 2018, they are tested on data from 2020. Here, the predicted yield maps are obtained after averaging the resulting overlapping output patches. We refer the reader to our previous work (Morales & Sheppard, 2021) for further details on how the predicted yield maps are generated. Table 2 shows the metrics obtained after comparing the generated predicted maps and their corresponding ground truth. The metrics that are used for comparison are root mean square error ($RMSE$), root median square error ($RMedSE$), and average structural similarity using a windows size of 3 ($SSIM3$) and 11 ($SSIM11$). Fig 3 illustrates the comparison between the ground-truth maps and the predicted yield maps that results from applying our Hyper3DNetReg network. The performance values shown in Table 2 are slightly better than those shown in the original paper due to more careful hyperparameter tuning.

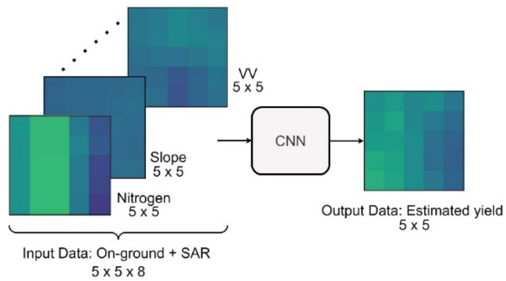

Fig 2. Hyper3DNetReg yield prediction model using an 5×5 – pixel output window.

Table 2. Yield prediction results

Field	$RMSE$	$RMedSE$	$SSIM3$	$SSIM11$
F1	10.74	6.93	41.63	61.71
G1	14.88	8.94	20.51	42.27

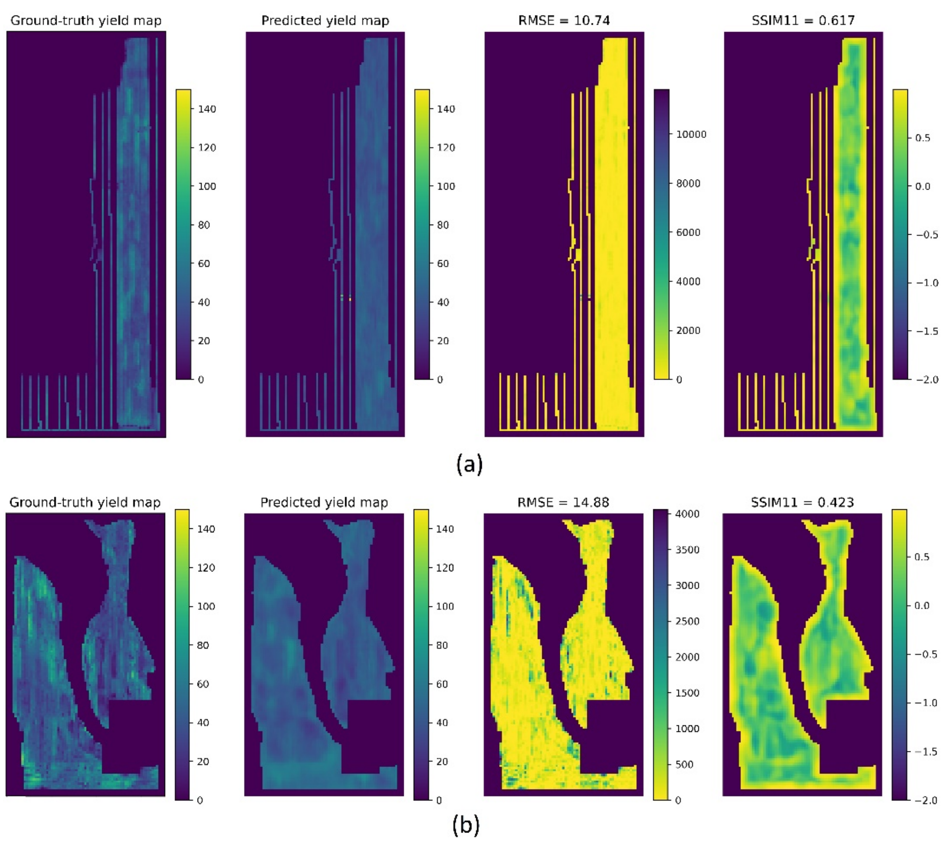

Fig 3. Yield prediction, square error map, and structural similarity map of the (a) F1 field and (b) G1 field.

N-response Curves

A site-specific Hyper3DNetReg model is a mapping from the feature space to the yield value space. In our previous work, we demonstrated that the Hyper3DNetReg models trained for different fields performed better than other traditional and more recent machine learning methods (e.g., linear regression, stacked autoencoders, and 3-D CNNs). This implies that our Hyper3DNetReg network models the mapping from the feature space to the yield value space better than other approaches. Therefore, here we propose a method to generate N-response curves that are specific to each location of the field using Hyper3DNetReg models. To do so, we apply the learned Hyper3DNetReg model at each location of the field with varying nitrogen rate values between 0 and 150 pounds per acre (lbs/ac) with a step size of 3 lbs/ac.

For example, Fig 4a depicts the original nitrogen rate map applied on F1 in 2020 and the corresponding yield prediction. In contrast, Fig 4b, Fig 4c, and Fig 4d show the results of applying constant nitrogen rates of 50, 75, and 100 lbs/ac, respectively.

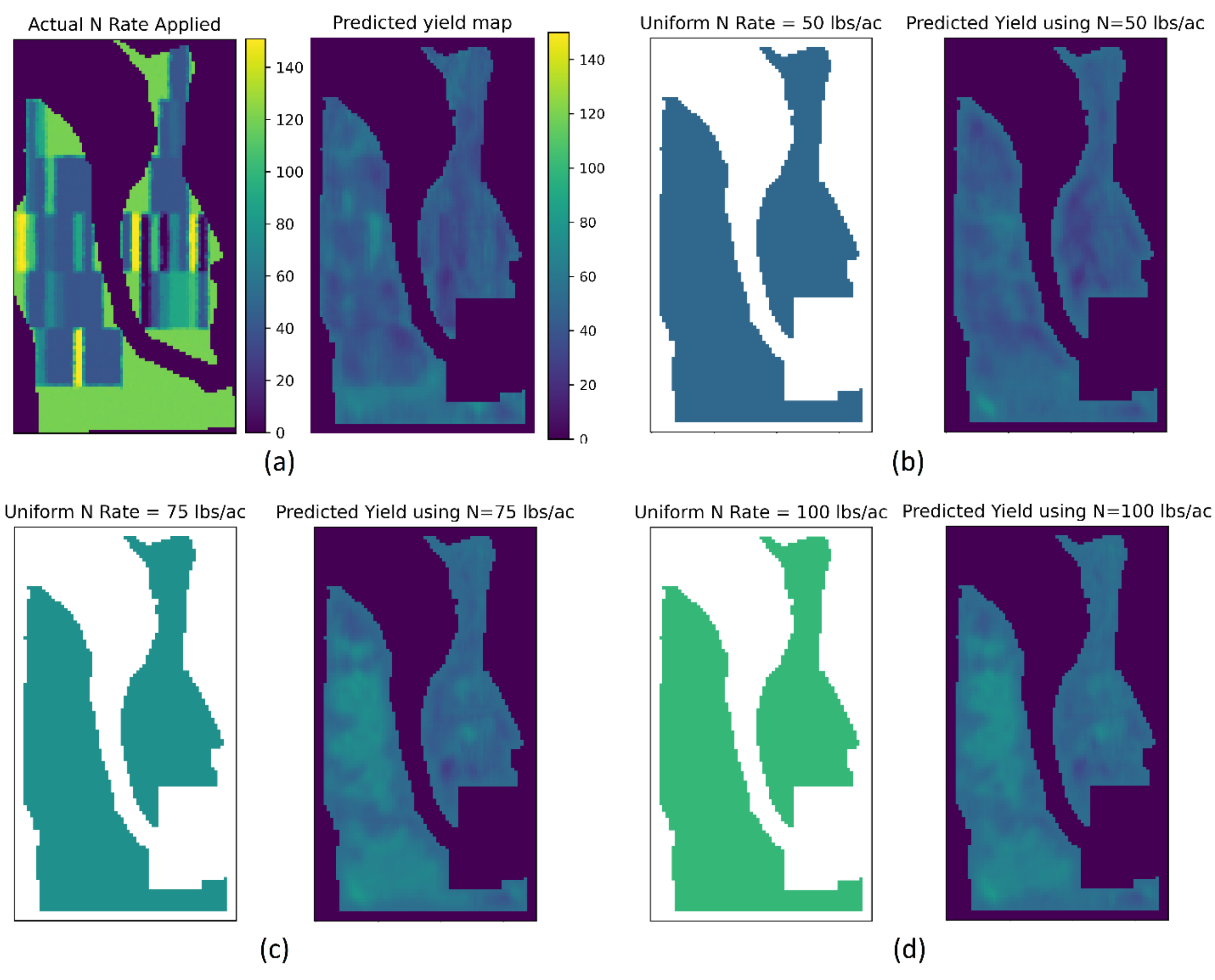

Fig 4. Yield prediction for the G1 field using different N rates. (a) N rate values applied on the field during the growing season (March 2020). (b) Uniform N rate of 50 lbs/ac. (c) Uniform N rate of 75 lbs./ac. (d) Uniform N rate of 100 lbs./ac.

From the yield maps generated after simulating using a wide range of N rates for the entire field, we obtain an N-response curve for each 10×10 m cell of the field. Fig 5 and Fig 6 show six different N-response curves generated from the F1 and G1 fields, respectively. Note that, in both cases, different regions of the field react differently to the nitrogen rate applied. Specifically, some regions of the fields reach a plateau for high N rates while others experience a rapid decline.

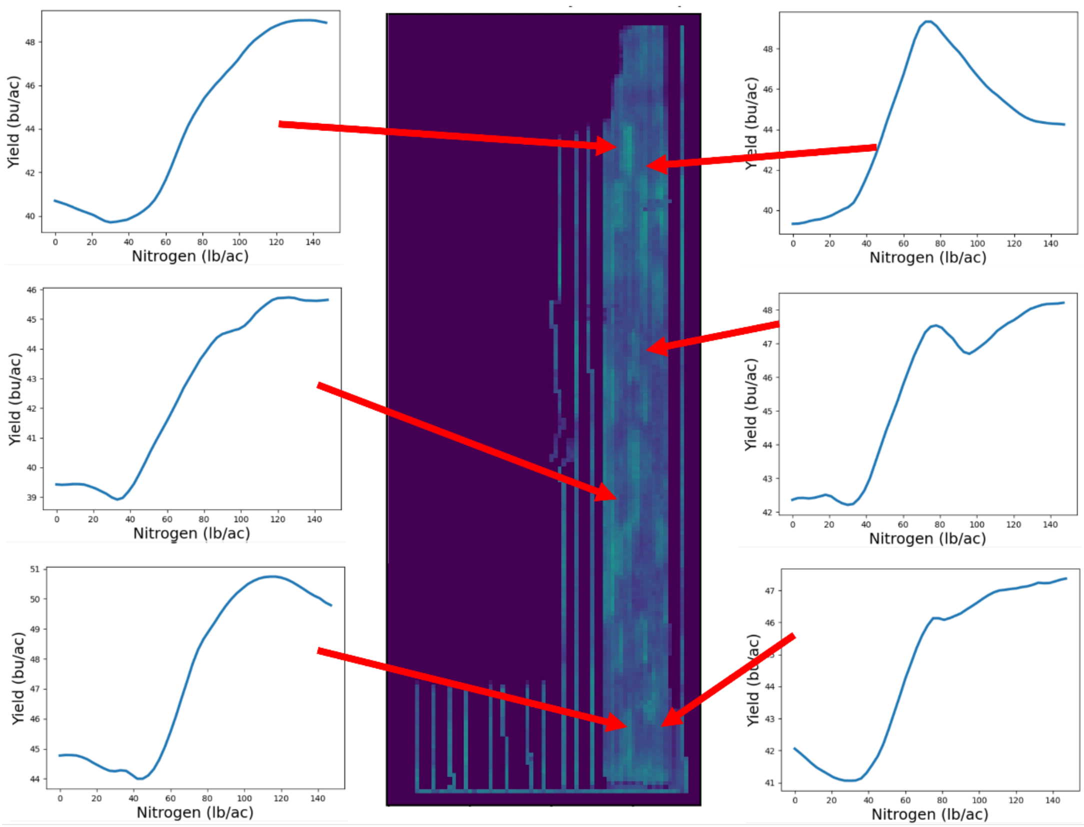

Fig 5. N-response curves generated for different regions of the F1 field.

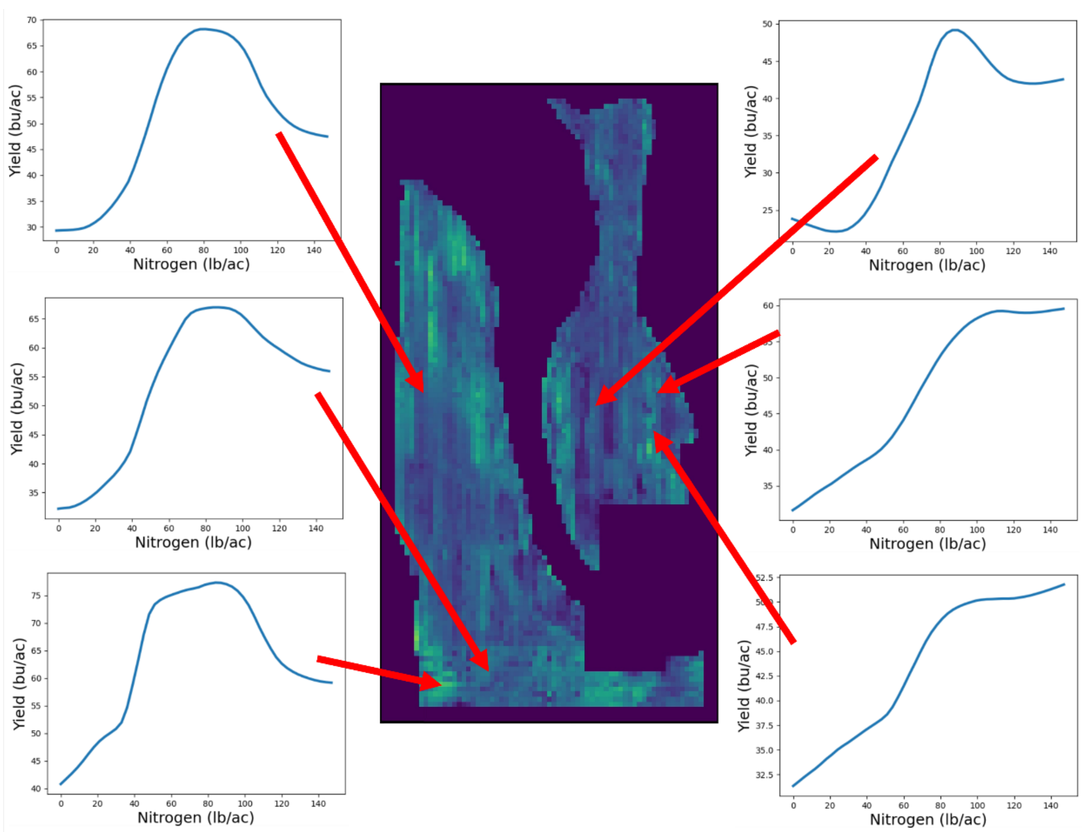

Fig 6. N-response curves generated for different regions of the G1 field.

From Fig 5 and Fig 6, it is observed that the slope and the position of the local maximum of the generated N-response curves vary depending on the field location. This is important because traditional methods suggest that the EONR point can be found as the N rate at which the first derivative of the N-response curve – which depends directly on the slope – is equal to a common yield-nitrogen price ratio (Bullock & Bullock, 1994). Thus, considering that the EONR point is estimated from a single N-response curve and that we are obtaining different N-response curves for different regions of the field, we would be able to find different EONR points for different regions of the field

It is worth mentioning that traditionally the EONR calculation assumes concave functional forms with a single local optimum (e.g., quadratic and exponential functions). On the other hand, the N-response curves generated by our non-parametric approach may have more than one local optimum. This can be seen in two of the N-response curves shown in Fig 5 that have at least two local maxima. Therefore, the traditional EONR calculation is not sufficient for these cases.

Furthermore, we argue that uncertainty plays a crucial role in yield prediction and EONR estimation. Uncertainty may arise due to representational bias, training data variance, and parameter uncertainty (Pearce, Brintrup, Zaki, & Neely, 2018). It can be quantified using prediction intervals (PIs) that consist of an estimate of the upper and the lower bounds within which a prediction will fall with a certain probability. For future work, we will present an N-response curve generation method coupled with non-parametric PIs generated by the modified Hyper3DNetReg models automatically.

Finally, we should consider that the EONR values obtained from our site-specific N-response curves may differ significantly between neighboring cells. We refer to this phenomenon as "jumps." Hence, jumps put a strain on the farmer's equipment, so it becomes necessary to minimize the jumps when determining the prescription maps (Peerlinck, Sheppard, Pastorino, & Maxwell, 2019). Therefore, future work will focus on generating prescription maps that merge the site-specific economic optimum points calculated from our N-response curves while also minimizing the overall fertilizer applied and the number of jumps between consecutive cells' nitrogen rates.

Conclusion

Traditionally, EONR estimation is carried out assuming parametric N-response curves for an entire field. In this work, we have proposed that N-response curves should be site-specific, and their functional form can be learned from data.

In our experiments, we have used the Hyper3DNetReg convolutional neural network, which is an accurate yield prediction model that can be used to generate N-response curves. Thus, our initial results using two different winter wheat fields showed that different regions of the field have different responses to the N fertilizer. Moreover, the N-response curves generated by our method may have more than a single local optimum. Therefore, conventional EONR calculation methods cannot be applied directly.

Future work will address the need of incorporating uncertainty quantification into the N-response curve generation by using automatically generated prediction intervals. Furthermore, these curves will be used to generate fertilizer prescription maps based on multi-objective optimization while considering other factors such as the minimization of jumps.

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