Spatial Decision Support System: Controlled Tile Drainage – Calculate Your Benefits

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Abstract. *Climate projection studies suggest that extreme heat waves and floods will become more frequent, affecting future crop yields by 20%-30%, globally. Managing vulnerability and risk begins at the farm level where best management practices can reduce the impacts associated with extreme weather events. A practice that can assist in mitigating the impact of some extreme events is controlled tile drainage (CTD). With CTD, producers use water flow control structures to manage the drainage of water from their fields, which allows producers to maintain soil water on their fields during periods of crop demand or allows free drainage to facilitate field trafficking and earlier spring seeding. The result is a dampening of the negative impact of extreme events on crop yields. In this study, a spatial decision support system was developed that will 1) allow farmers and other stakeholders to explore potential sites for implementation of tile drainage systems; 2) show predicted yield benefits of crops (corn and soybean) from CTD fields compared to crops associated with uncontrolled tile drainage (UCTD) systems, during varying growing season precipitation. A Multi-Criteria Suitability Analysis was performed to determine potential sites for the implementation of tile drainage systems. Crop yield was characterized by ground yield measurements and satellite-derived Normalized Difference Vegetation Index (NDVI). Yield benefits from CTD fields were determined as the difference between ground yield measurements or NDVI values from CTD compared to UCTD fields. Yield benefits were finally related to precipitation data to enable the creation of yield benefit prediction scenarios under varying precipitation. The results of the suitability analysis and yield difference prediction were combined in the tool, along with additional slope, soil drainage and precipitation layers. The tool development is ongoing and functional on https://demo.gatewaygeomatics.com/ctd/.*

Keywords. *Controlled Tile Drainage, Uncontrolled Tile Drainage, Climate change, corn, soybean, yield, remote sensing, NDVI, Multi-Criteria Suitability Analysis, Spatial Decision Support Tool*

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1 Introduction

Climate projection studies suggest that extreme heat waves and floods will become more frequent, affecting agricultural crop production. Climate change is expected to impact the agriculture sector by causing long-term changes in precipitation, shortage of water availability, unfavorable soil conditions, increased plant diseases, crop pest persistence and pest infestations (Reid et al. 2006; Wreford et al. 2010). Many studies have been conducted to study the predicted impacts of climate change on crop production (Schlenker & Lobell 2010; Piao et al. 2010) and some have predicted a 20-30 percent reduction in grain production (Wreford et al. 2010).

Predicting the intensity and frequency of these extreme weather events and the response of cropping systems is difficult, increasing the uncertainty for the entire agriculture sector (OECD 2014). However, the risks associated with the climate variability can be addressed at the farm level (Howden et al. 2007) by adopting best management practices (BMPs) that can assist in reducing the impacts associated with these extreme weather events.

Controlled tile drainage (CTD) is a water and nutrient conservation strategy which regulates the loss of water from the fields through the use of control structures (Wilkes et al. 2014). The outlet in the control structure is crucial in drainage water management practice and its depth is decided according to the season, the type of field operation to be performed (such as sowing, planting, harvesting etc.) (Frankenberger et al. 2004), precipitation conditions and crop growth stage (Ghane et al. 2012). This practice retains nutrients and soil water in the field, providing environmental benefits by reducing the loss of nutrients such as nitrogen and phosphorus in the form of surface run-off (Sunohara et al. 2014; Drury et al. 2009). It also ensures that these nutrients are readily accessible to the crops for growth (during growing season or drought conditions), thus enhancing crop yields (Crabbé et al. 2012; Kross et al. 2015). Research by Agriculture and Agri-Food Canada has documented an average of 4% improvements in corn yield from CTD fields compared to uncontrolled tile drainage (UCTD) systems. During a single season extreme event this best management practice may increase improvements beyond the 4% (Crabbé et al. 2012). Despite these findings, CTD systems are not widely deployed where they could be in Canada. At the local level, farmers can be encouraged to implement CTD by demonstrating the economic benefits obtained in the form of increased crop yields. Spatial decision support systems can support the decision-making process by assessing the effectiveness of BMPs and predicting variations in crop yield (Al-Gaadi et al. 2016) under different weather scenarios. Some of these models are web based and allow the users to make decisions regarding different practices such as application of fertilizers, irrigation, transportation etc., to improve crop production (Kumar & Babu 2016). Decision Support System for Agro-technological Transfer (DSSAT) model is one of the most widely used models for studying the impacts of climate change in crop yields and crop production systems (use of DSSAT to study changes in rice growth and yield, Dias et al. 2016). This model also allows researchers to make decision regarding the different agricultural practices and cropping system in order to obtain better crop yields (Jones et al. 2005).

Within this context, the main objective of this study is to assist farmers and other stake holders in decisions related to the implementation and management of tile drainage systems by the development of a spatial decision support system that will: 1) allow farmers and other stakeholders to explore potential sites for implementation of tile drainage systems (CTD or UCTD); 2) show predicted yield benefits of crops (corn and soybean) from CTD fields compared to crops under UCTD management, during varying growing season precipitation.

2 Methodology

2.1 Study Area

The study was conducted for the province of Ontario, the second largest province in Canada (Fig. 1a). It has the highest number of farms (25.6%) and about 7.7% of Canada's total farm area (Statistics Canada 2017a; Statistics Canada 2017b; Mailvaganam 2017). Corn and soybean are the two most dominant cash crops (Statistics Canada, 2012a; Statistics Canada 2017a). In 2016, Ontario accounted for 59.8% of national corn for grain area and 49.6% of national soybean area.

The study fields are located within an experimental micro watershed in Eastern Ontario, Canada (45.26 N, 75.18 W) (Fig. 1b,c). From 2005 to 2016, different field pairs with confirmed water drainage practices were selected and studied. Each pair consisted of one field under CTD and one field under UCTD management (Fig. 2). All other agriculture practices and variables (fertilizers, nutrients, varieties, etc.) were constant within a pair. Slopes are <1% and the fields are dominated by soils that drain poorly or imperfectly (Fig. 3)

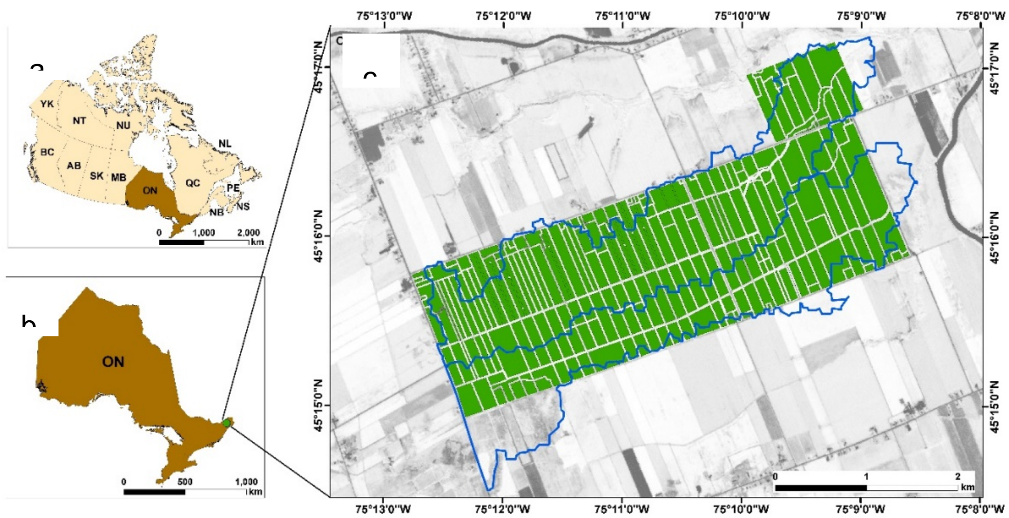

Fig. 1 a. Location of Ontario in Canada; b. Location of study area within Ontario. c. Location of study fields within the experimental watersheds in Eastern Ontario, Canada. Green represents the study fields and watershed boundaries are in blue.

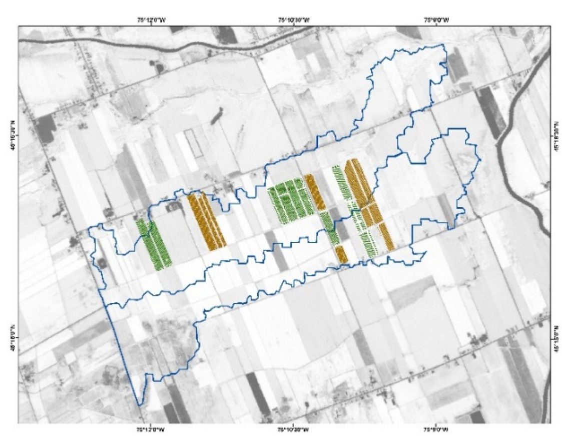

Fig. 2 Map illustrates the field pairs selected for the year 2012 for measured yield data.
Different colors indicate different crop types i.e. corn (brown) and soybean (green). Each field pair consists of one field under CTD and one field under UCTD. Same approach was used for the years 2009 – 2011 and 2016 for the measured yield data and; 2005 – 2007, 2009 – 2016 for Normalised Difference Vegetation Index (NDVI) analysis

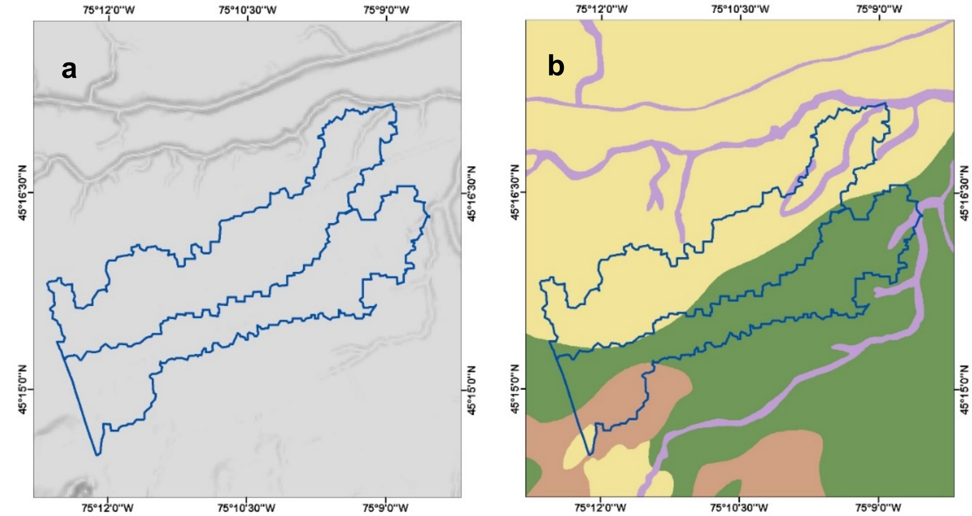

Fig. 3 a. Percent slope less than 1% in the study area; b. The study area is dominated by soils that drain poorly or imperfectly. Color green, yellow, pink and purple represent soils that drain "poorly", "imperfectly", "well" and "rapidly", respectively

2.2 Methods and Analysis

2.2.1. Suitability Analysis

A Multi-Criteria Suitability Analysis was performed in ArcMap 10.3.1 to determine potential sites for the implementation of tile drainage systems. Soil drainage and slope were selected as two main factors.

One of the most important variables that impact plant growth is the soil's drainage capacity which can be determined by its texture. Coarse textured soils such as sandy soils have large pore spaces and are excessively drained, thus reducing their ability to hold enough water. On the other hand, fine textured soils such as clays have small pore spaces and do not drain well. Since they have a higher water storage capacity, they can become saturated, resulting in poor aeration and decreasing the plant's ability to absorb water (O'Green 2013). Soil data were obtained from the Land Information Ontario (LIO) (https://www.javacoeapp.lrc.gov.on.ca/geonetwork/srv/en/main.home) and were reclassified to rank the soils with very poor drainage as "Most Suitable" and the soils that drain rapidly as "Least Suitable" (Table 1).

Table 1. Reclassification of soils and slope where "0" indicates the lowest suitability for implementation of tile drainage, and 6 indicates the highest suitability.

Reclassification of soils		Reclassification of slope	
Drainage	**Reclassified Values**	**Percent Slope**	**Reclassified Values**
Very Poor	6	0.00 – 0.05	6
Poor	5	0.06 – 1.00	5
Imperfectly	4	1.01 – 2.00	4
Moderately Well	3	2.01 – 3.00	3
Well	2	3.01 – 4.00	2
Rapidly	1	4.01 – 5.00	1
Very Rapidly	1	>5.01	0
Water	0		
Variable	0		
Others	0		

Slope was selected as the second factor. Artificial drainage systems are considered more suitable for flat surfaces as they do not drain easily as compared to steep slopes (Cooke et al. 2008). Provincial Elevation Data were obtained from the Province of Ontario (https://www.javacoeapp.lrc.gov.on.ca/geonetwork/srv/en/main.home) and percent slope was derived from this data. Various studies have described or suggested installation of tile drainage in fields with slopes ranging from 0 to 4% and sometimes from 0 to 6% (AAF, ANR 2017; Franzmeier et al. 2001). Therefore, fields with slope below 5% were considered as “Most Suitable” whereas fields with slope above 5% were ranked as “Least Suitable” (Table 1).Water was taken as a constraint and therefore all the water bodies were classified as zero. The two factors (soil and slope) and constraint (water) were combined, where both slope and soil were given an equal weight of 50%, to obtain final sites ranging from “Not Suitable” to “Highly Suitable”.

2.2.2. Yield Benefit Prediction

Yield benefit was characterized by the difference in yield from CTD fields compared to UCTD fields. The difference in NDVI from CTD fields compared to UCTD fields was used as a proxy for yield differences, as an alternative for ground yield data.

<u>Crop yield from yield monitor data</u>

Crop yield was obtained from farmers (estimated from field yield monitor data) for the years 2009 – 2012 and 2016. The data was in bushels/acre and was converted into kg/ha. For corn, 1 bushel/acre equals 62.77 (63) kilograms/hectare and for soybean, 1 bushel/acre equals 67.25 (67) kilograms/hectare (Johanns 2013). Statistical Analysis was performed on a sub sample of 300 points from each field. To determine statistical significant differences between yields from fields under CTD and UCTD treatments, Welch’s t-test (for two samples with unequal variances) and Cohen’s *d* effect size were used. Cohen’s *d* is the measure of effect size i.e. it is used to determine the magnitude of the effect of a treatment as compared to another (Cohen 1992). It can be calculated using the following formula:

$$Cohen's\ d = \frac{\mathrm{Mean}_{CTD} - \mathrm{Mean}_{UCTD}}{\mathrm{S}_{Pooled}} \quad (1)$$

where, Mean_{CTD} is the mean of yield under CTD, Mean_{UCTD} is the mean of yield under UCTD and S_{Pooled} is the pooled standard deviation of the samples. It can be calculated as:

$$\mathrm{S}_{Pooled} = \sqrt{\frac{(\mathrm{S}_{CTD})^2+(\mathrm{S}_{UCTD})^2}{2}} \quad (2)$$

where, S_{CTD} is the standard deviation of the yield under CTD and S_{UCTD} is the standard deviation of the yield under UCTD.

Effect size can be interpreted as small (0.20), medium (0.50) and large (0.80) (Cohen 1992). In this study, a positive value would indicate that the effect of the CTD treatment on crop yield is higher than the effect of the UCTD treatment. Finally, the percentage difference between the average yields from CTD vs UCTD fields was calculated using the following formula:

$$\text{Percentage Difference} = \frac{(\mathrm{Mean}_{CTD} - \mathrm{Mean}_{UCTD})}{\mathrm{Mean}_{UCTD}} * 100 \quad (3)$$

where, Mean_{CTD} is the mean yield from the CTD field and Mean_{UCTD} is the mean yield from the UCTD field. A positive value indicates that the yield is higher for crops under CTD management whereas a negative value indicates that the yield is higher for crops under UCTD management.

Satellite Derived Normalized Difference Vegetation Index (NDVI)

Satellite-derived NDVI was used as a crop health indicator (Rouse et al. 1974). The NDVI was derived from Landsat satellite images (for the years 2005, 2008, 2009, 2010 and 2015), SPOT satellite images (for the years 2006 and 2007) and RapidEye satellite images (for the years 2011, 2012, 2013, 2014 and 2016).

For each of the years, satellite images were orthorectified and atmospherically corrected in PCI Geomatica 2017. The NDVI was calculated from the corrected satellite images using the following formula:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}} \tag{4}$$

Statistical analysis was performed on a sub sample of 100 points from each field. For Landsat satellite images most of the fields already had less than 100 sample points, so all the sample points were used for statistical analysis.

To study if there were any statistical significant differences between NDVI from fields under CTD and UCTD treatments, Welch's t-test (for two samples with unequal variances) and Cohen's *d* effect size were determined.

Finally, the percentage difference between the mean NDVI value for crops under CTD and UCTD management was also calculated. The pairs with percentage difference values greater than 25% were eliminated. From the analysis of our data, a difference of 25% or larger indicated fields with different planting dates.

Relationship between Crop Yield/Crop Vegetative Health and Precipitation

The yield and NDVI percentage differences were summarized for each year. While agriculture practices were matched within each field pair, the practices were not necessarily matched between pairs and could potentially use different agricultural practices such as crop variety, fertilizers, and crop spacing.

Precipitation can be considered an important indicator of crop yield differences between CTD and UCTD, especially when all the parameters are constant for the field pairs and water being the variable parameter (as being managed through CTD).

Local precipitation data (for the study fields) for the years 2005 to 2017 were obtained from site measurements and Environment Canada (http://climate.weather.gc.ca/prods_servs/cdn_climate_summary_e.html) and were summarized into monthly, growing season (May-August) and annual totals.

The relationships between yield or NDVI percentage difference and precipitation were characterized for corn and soybean using Ordinary Least Square (OLS) Regression. A small dataset was available for this analysis, thus interpretation of the results should be done with caution. The research on the relationship between these variables is still ongoing and the interpretation should be done with caution. The main objective of this study is to demonstrate the use of the methodology presented here, in the development of an online spatial decision support tool.

2.2.3. Online Spatial Decision Support Tool

All the results were summarized from the suitability analysis and the yield difference prediction for use/implementation in the online spatial decision support system. Additionally, precipitation, yield prediction maps, slope and soil drainage layers were also prepared and added to the online tool. The tool development is ongoing and functional on https://demo.gatewaygeomatics.com/ctd/.

Precipitation data

Provincial monthly long term climate normals were obtained from Environment Canada (http://climate.weather.gc.ca/prods_servs/cdn_climate_summary_e.html). The weather station points with precipitation values were used to create a continuous dataset across Ontario, using the Inverse Distance Weighting (IDW) interpolation method (with a power coefficient of 2) The climate normals (precipitation) for 1981-2010 were interpolated across Ontario.

For 2011 to 2017, cumulative monthly precipitation data were obtained for each year (from Environment Canada) and spatial interpolation was performed using the IDW method. Interpolation was performed using 80% training sites and the method was validated using 20% test sites. Finally, Mean Absolute Error (MAE) and Relative MAE (RMAE) were calculated using the following formulas:

$$\text{MAE} = \text{Abs}\ (\text{Predicted Precipitation} - \text{Measured Precipitation})/\text{n} \tag{5}$$

And:

$$\text{RMAE} = \left(\frac{\text{MAE}}{\text{Mean of Measured Annual Total Precipitation}}\right) * 100 \tag{6}$$

where, n is the number of weather stations.

Table 3 summarizes the results from the error assessment of the interpolated precipitation dataset.

Table 3. Summary of the Mean absolute error, mean of measured precipitation and relative mean absolute error for precipitation in the years 2011 - 2017

Year	Mean Absolute Error (mm)	Mean of Measured Annual Total Precipitation (mm)	Relative Mean Absolute Error (%)
2011	151.24	881.19	17.16
2012	115.15	791.23	14.55
2013	190.27	1044.75	18.21
2014	152.19	823.67	18.48
2015	159.96	759.13	21.07
2016	92.34	814.06	11.34
2017	128.52	858.56	14.97

Yield Prediction Maps

Yield prediction maps were prepared to demonstrate different scenarios of percentage yield difference under different precipitation conditions (dry vs. wet). For this, cumulative growing season precipitation (May to August) was calculated from the spatially interpolated precipitation data.

The yield percentage difference was calculated using the following functions:

$$\text{Corn Yield Percentage Difference} = -0.0224x + 8.3514 \tag{7}$$

$$Soybean\ \text{Yield Percentage Difference} = 0.0101x - 0.5865 \tag{8}$$

where, x is the total growing season precipitation.

Optimized Hot Spot Analysis (OHSA) was then performed using ArcGIS 10.3.1 OHSA tool to evaluate spatial clusters of yield difference percentage for corn and soybean in wet, dry and average precipitation years.

3 Results and Discussion

3.1 Suitability Analysis

The final map with potential areas for implementation of tile drainage in Ontario had 7 classes ranging from 0 to 6. Classes 0, 1 and 2 were combined to represent areas “Not Suitable” for implementation of Tile Drainage systems. Class 3 represents areas with “Low Suitability”, Class 4 represents areas with “Medium Suitability”. Classes 5 and 6 were combined to represent areas with “High Suitability” (Fig. 4). The grey area in the map shows the areas for which the data were not available.

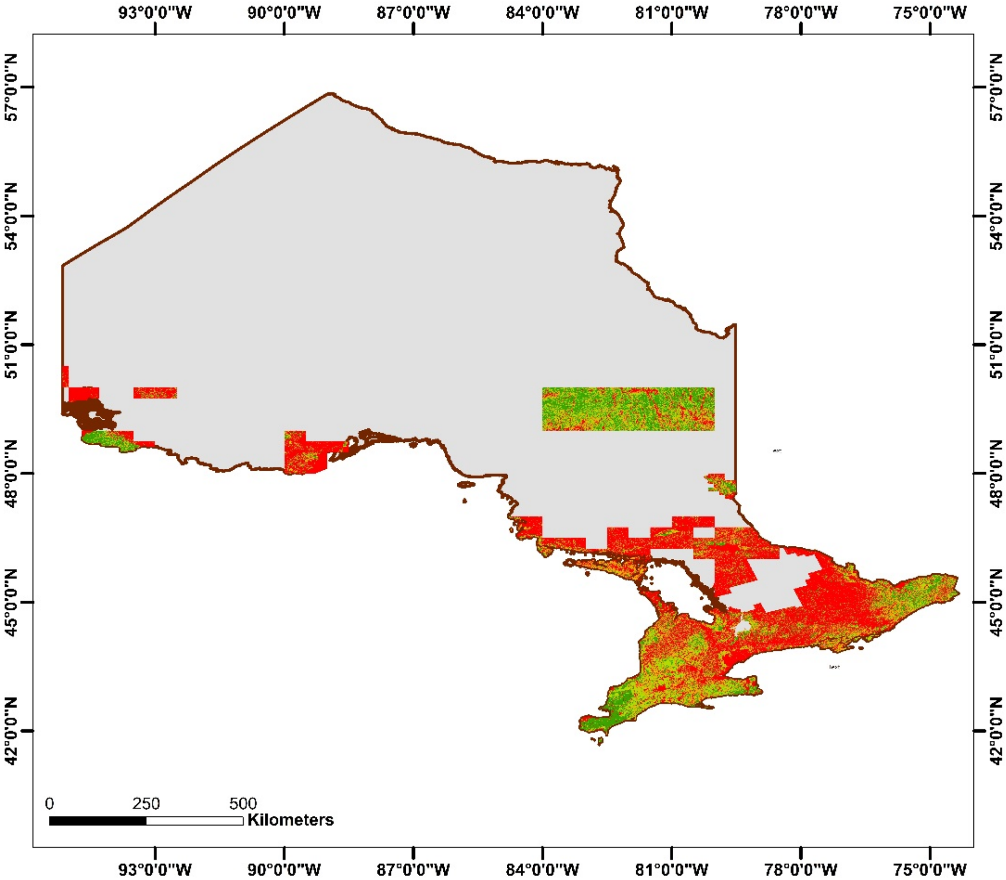

Fig. 4 Map representing areas with varying levels of suitability for the installation of tile drainage systems. Grey represents areas with no information of potential sites. Red represents areas that are ``Not Suitable`` for the installation of tile drainage systems, orange represents areas with ``Low Suitability``, light green represents areas with ``Medium Suitability`` and dark green is for areas ``Highly Suitable`` for the implantation of tile drainage systems.

In this study, both slope and soil drainage were given equal weight. However, weight assigned to these factors can be changed to study how it impacts the overall result. In a study carried out at North Dakota State University, researchers studied the saline, sodic and saline sodic soil types to determine their suitability for tile drainage performance. They concluded that the soils that have a sodium adsorption ratio of less than 6 do not hamper the performance of the installed tile drainage system. Their rationale for this study was the reduced performance of installed tile drainage system with time resulting from change in soil composition due to salt and water drainage (Cihacek et al. 2012).

To evaluate the results of the suitability analysis, a map of existing tiles was obtained from the Province of Ontario (https://www.javacoeapp.lrc.gov.on.ca/geonetwork/srv/en/main.home). For example, in Fig. 5, the map in the centre shows areas that already have installed tile drainage systems. By comparing Fig. 4 and 5, it is evident that the areas that show medium and high suitability already have tile drainage system installed but no information is available about the type of tile drainage system (i.e. CTD vs UCTD). Zooming in on certain suitable areas reveals that there are gaps in the already existing tile drainage systems, i.e. many crop fields do not have any installed tile drainage systems and can be further explored (Fig. 5: b1 and b2; c1 and c2). Moreover, as can be seen in a1 and a2 (Fig. 5), many areas may seem suitable in the map due to appropriate slope and soil drainage but zooming in on these areas reveal that these areas are covered by forests and not crop fields. Hence, such areas can also be eliminated from further processing.

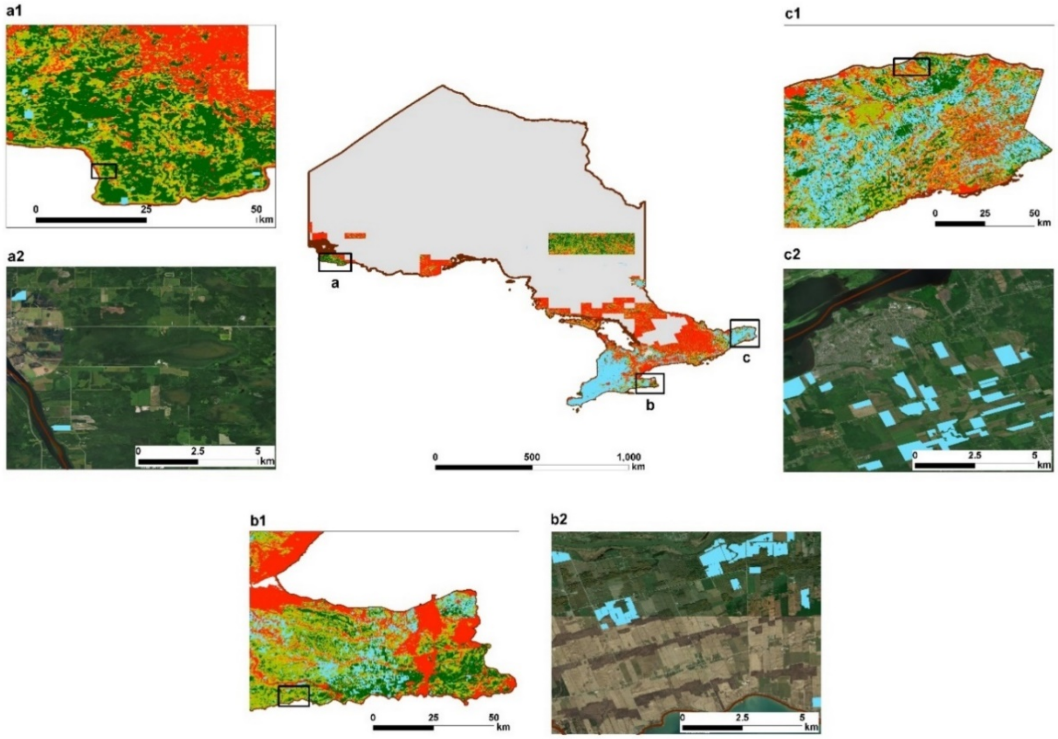

Fig. 5 Map in the centre represents areas that already have tile drainage systems. Areas with already existing tile drainage systems are represented in blue. On comparison, areas that show medium or high suitability already have tile drainage systems installed. Though, the rectangular strip in the centre of the map shows suitable areas but on closer inspection, it was revealed that the area is mostly forested.

3.2. Relationship between percentage difference yield or NDVI and Precipitation

Table 4 provides a summary of total precipitation and the results of the statistical analysis for corn and soybean yields

Table 4. Summary of the total precipitation, average crop yields for both CTD and UCTD, Cohen's *d*, *p*-value, and crop yield percentage differences

Variable	Year	No. of Field Pairs	Total Precipitation: May-August (mm)	Cohen's *d*	*p*-value	% Difference	Average Crop Yield (kg/ha)		Standard Deviation	
							CTD	**UCTD**	**CTD**	**UCTD**
	2009	1	254.6	0.14	0.09	1.35	13176.83	13001.23	1152.20	1403.06
	2010	3	235.2	0.20	0.16	1.83	15352.51	15043.07	1561.38	1640.58
$Yield_{Corn}$	2011	3	319.8	0.10	0.29	0.74	13690.35	13513.61	1892.86	1687.17
	2012	3	205.4	0.50	0.00	4.83	11840.65	11604.78	1264.71	1152.02
	2016	1	284.8	0.35	0.00	3.87	12174.02	11720.11	1377.87	1170.99
	2010	2	235.2	0.11	0.15	2.69	4087.64	3980.67	756.33	1111.87
	2011	5	319.8	0.17	0.28	4.90	4694.25	4588.69	1328.30	1474.95
$Yield_{Soybean}$	2012	3	105.4	0.14	0.09	1.91	4535.66	4450.58	458.51	745.25
	2016	3	248.8	-0.09	0.27	-1.33	3507.99	3555.15	456.63	575.35

Fig. 6a represents average corn yields for the years 2009, 2010, 2011, 2012 and 2016. For corn, the percentage difference between the CTD and UCTD management was always positive, which indicates higher yields for corn fields under CTD management. The differences were also statistically significant for 2009, 2012 and 2016 ($p<0.1$). Fig. 6b represents average soybean yield values were obtained for the years 2010, 2011, 2012 and 2016. The percentage difference was found to be positive for the years 2010-2012 and negative for 2016.

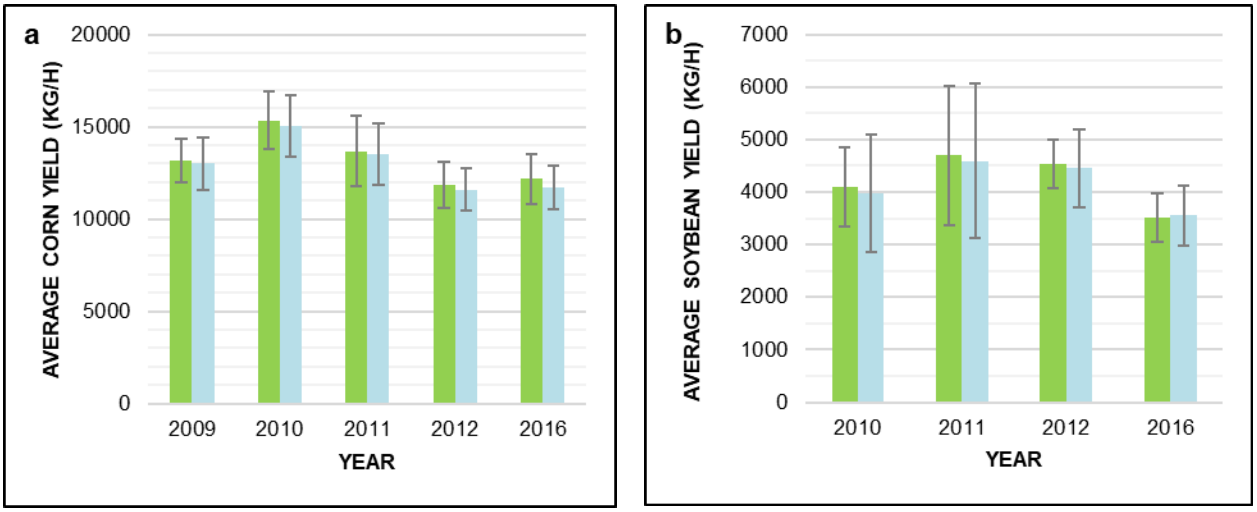

Fig. 6a. Average corn yields for the years 2009 - 2012 and 2016.
Green bars represent average yields for crops under CTD systems and blue bars represent average yields for crops under UCTD system. The error bars represent standard deviation for each year. The Welch's t-test was used to compare mean corn yield from CTD and UCTD fields and *p*- value were found to be 0.09, 0.16, 0.29, 0.00 and 0.00. Percentage Differences were 1.35, 1.83, 0.74, 4.83 and 3.87, respectively. b. Average soybean yields for the years 2010 - 2012 and 2016. Green bars represent average yields for crops under CTD systems and blue bars represent average yields for crops under UCTD system. The error bars represent standard deviation for each year. The Welch's t-test was used to compare mean crop yield from CTD and UCTD fields and *p*-value were found to be 0.15, 0.28, 0.09 and 0.27. Percentage Difference were 2.69, 4.90, 1.91 and -1.33, respectively.

Table 5 provides a summary of total growing season precipitation and the results of the statistical analysis for NDVI obtained for corn and soybean.

Table 5. Summary of total precipitation (May-August), Cohen's *d*, *p*-value, percentage difference for NDVI

Variable	Year	No. of Field Pairs	Total Precipitation: May-August (mm)	Cohen's *d*	*p*-value	% Difference
$NDVI_{Corn}$	2006	3	379.0	-0.14	0.50	-0.52
	2007	5	211.0	0.21	0.05	0.05
	2009	7	254.6	-0.18	0.53	-0.34
	2010	7	235.2	-0.16	0.32	-0.14
	2011	6	319.8	-0.36	0.15	0.66
	2012	9	205.4	0.30	0.36	0.51
	2016	4	284.8	0.11	0.25	0.14
$NDVI_{Soybean}$	2005	2	346.0	-0.35	0.39	-1.00
	2006	1	379.0	0.25	0.08	0.15
	2011	6	319.8	-0.43	0.18	-0.74
	2012	3	205.4	-0.87	0.00	-1.28
	2013	3	411.0	0.59	0.08	0.52
	2014	3	345.6	0.27	0.12	0.50
	2015	4	375.6	-0.5	0.17	-0.60
	2016	1	284.8	-0.19	0.17	-0.25

The following graphs (Fig. 7) represent the relationship between total growing season precipitation and percentage difference yield or NDVI.

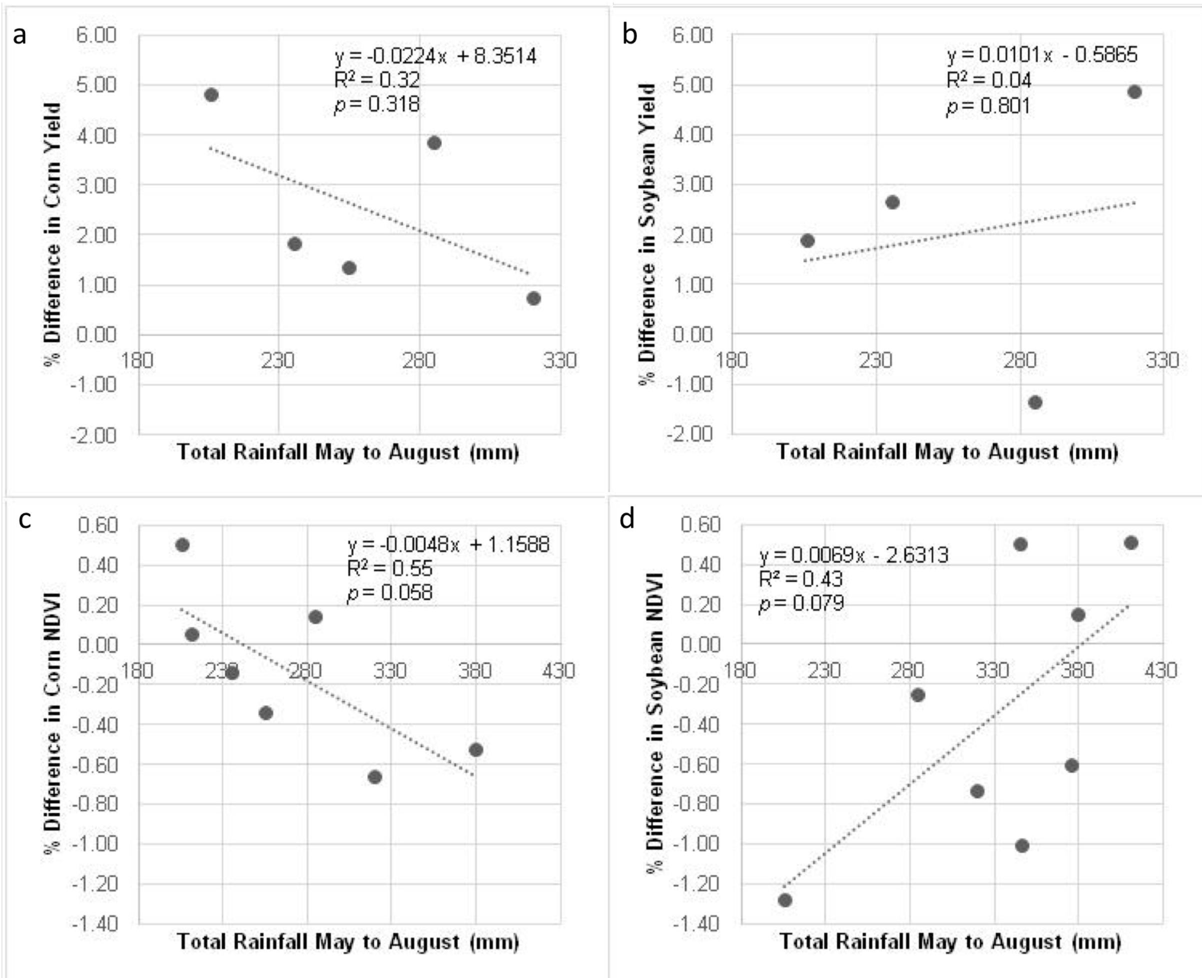

Fig. 7 Graphs representing a, b. relationship between Total precipitation and Percentage Difference in Crop Yield (for corn and soybean); c, d. relationship between Total Precipitation and Percentage Difference in crop NDVI (for corn and soybean)

NDVI is an indicator of crop vegetative health and provides relative magnitude and direction of crop yield differences but is not an exact indicator of crop yield. For example, in 2009, the percentage difference for corn NDVI was -0.34%, i.e. the corn vegetative health under UCTD was better in comparison to CTD management. However, for the same year, the percentage difference for corn yield was 1.35% which means that the corn yield under CTD management was higher in comparison to UCTD management. This suggests that crop vegetative health is not an indicator of absolute crop yield, but it does provide relative information about changes in crop yield, as shown in Fig. 7.

The plot between percentage corn yield difference and percentage NDVI difference (Fig. 8) shows a linear relationship and strong correlation. This suggests that in the absence of yield data, satellite-derived NDVI can be used to provide information about yield differences between CTD and UCTD fields.

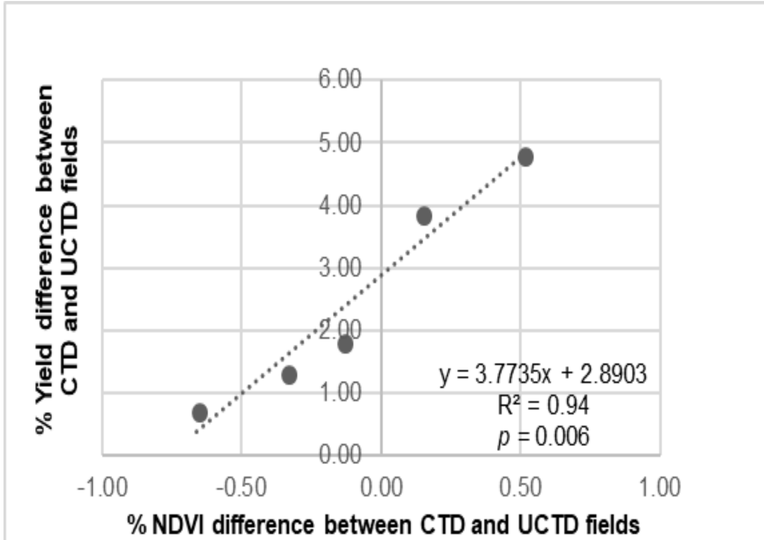

Fig. 8 Relationship between Percentage Corn Yield Difference and Percentage NDVI Difference

3.3. Online Spatial Decision Support Tool

The online tool represents the summarized results of the suitability analysis and the yield benefit characterization. The tool was developed using Open Source software that follows the common Open Geospatial Consortium (OGC) technology standards. The tool is functional on https://demo.gatewaygeomatics.com/ctd/. Using this tool, farmers, extension personnel and other users will be able to determine locations suitable for the implementation of tile drainage (Fig. 9) and explore different scenarios of crop yield benefits from CTD as compared to UCTD under varying crop and precipitation scenarios.

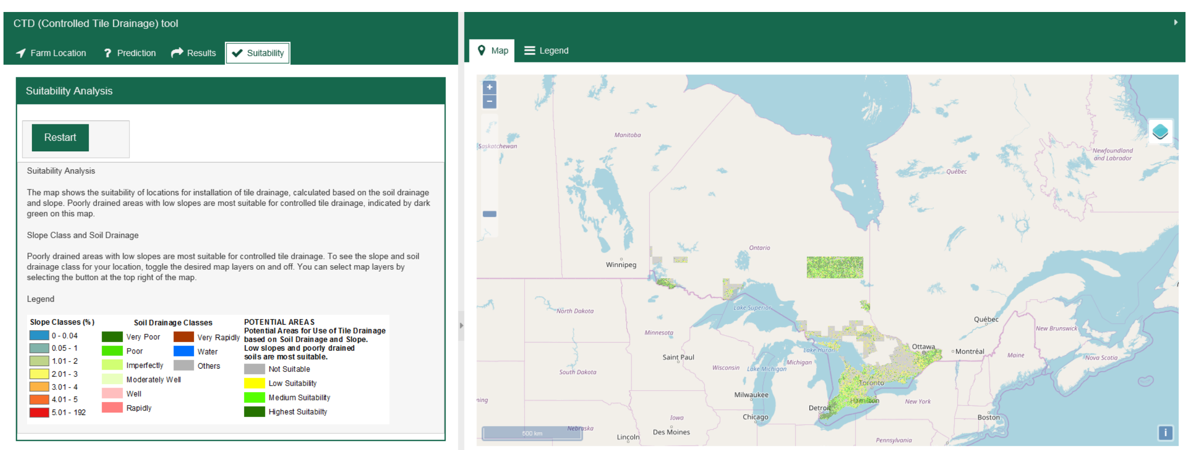

Fig. 9 Screenshot of the tool for determining suitable areas for tile drainage installation

On the first page, users can find the location of their farm by either manually entering the Latitude and Longitude coordinates, by selecting the closest weather station or by right-clicking on the map to add a farm location (Fig. 10).

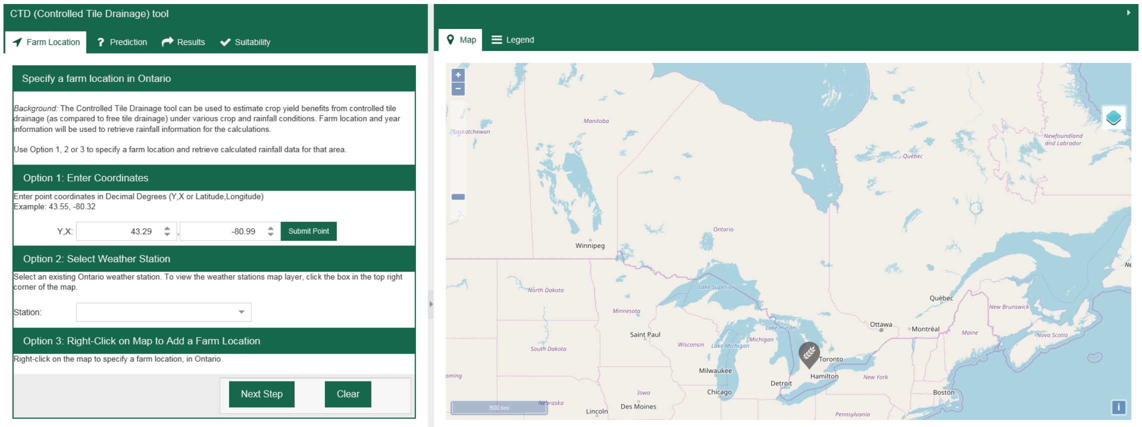

Fig. 10 Estimating crop yield benefits from CTD as compared to UCTD: Determining farm location using different options

On the second page, the crop type (corn, soybean and forage) and year of interest should be selected. Precipitation values are based on the year selected and the farm location as determined in the previous step.

Finally, on the third page, results are displayed in the form of number values and graphs that show the percentage difference (positive or negative) of CTD fields as compared to UCTD fields. Note that for forage, only NDVI data was avaiable.

The tool allows users to explore suitable areas for the installation of tile drainage and can be used to subsequently explore the performance of CTD systems under varying growing season precipitation and crop types.

The tool includes additional map layers (precipitation, slope, and soil drainage) which can be selected for visualization in the map. It will enable farmers and other stakeholders to see the slope and soil drainage properties for their farm locations or area of interested.

Yield prediction scenario maps are also available and depict different percentage yield across the province under varying weather scenarios (e.g. representative dry, wet and average years) Fig. 11 shows the percentage yield differences for corn and soybean under dry conditions.

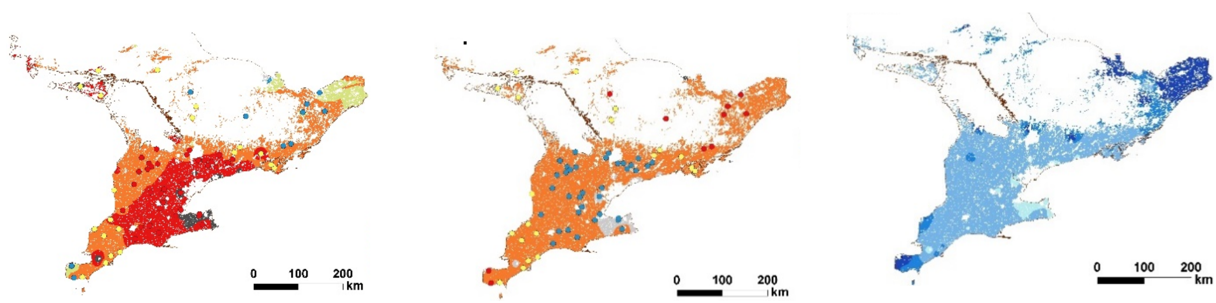

Fig. 11 Maps depicting spatial clusters of yield difference percentage for corn and soybean in dry year, Southern Ontario. The dots represent yield difference spatial clusters for corn and soybean (a & b). Blue represents cold spots, which are clusters of significantly low values of percentage yield diffeences with 90 – 95% confidence. Red presents hot spots, which are clusters of significantly high values of percentage yield differences with 90 – 95% confidence. Yellow dots represent not significant values. The continuous color map indicates the different yield percentage ranges. a. For corn, light grey represents areas with less than 5% yield difference. Blue represents a range of -0.49 – 0.00%. Green represents 0.01 – 0.95%. Orange represents a range of 0.96 – 3.50%. Red represents yield difference range of 3.51 – 5.00%. Finally, dark grey represents areas that have a corn yield percentage difference greater than 5.00%. b. For soybean, light grey represents areas with less than 0.95% soybean yield difference. Orange represents a range of 0.96 – 3.50%. Dark grey represents areas that have a soybean yield percentage difference greater than 5.00%. c. Precipitation map depicts the cumulative precipitation for the growing season (May to August). The color range is from light blue to dark blue and depicts the following ranges <150 mm (light blue), 150 – 260 mm, 260- 310 mm, 310 – 400 mm and > 400 mm (dark blue).

4 Conclusion

The online tool was built as a pilot project for Ontario. The relationship between crop yield and precipitation was established from ground and satellite-derived crop yield indicators and growing season precipitation measurements. Though NDVI is primarily an indicator of crop vegetative health, it can be used as an indirect indicator of crop yield.

Farmers can use the tool to determine suitable areas for the installation of tile drainage systems as well to obtain information on crop yield differences under CTD and UCTD management which would help them in choosing an appropriate drainage system for their fields.

Limitations and Recommendations

- The crop yield and crop vegetative health differences presented in the tool are based on a small number of sample points. The research on these relationships is still ongoing, and the interpretation should be done with caution. It would be beneficial to include longer time series precipitation and more sample points/study areas to provide more robust relationships between the variables.
- Moreover, the regression functions in this study were developed for a small study area (in Eastern Ontario) with slopes of approximately <1% and soils that drain poorly or imperfectly. The results obtained for this study area were then extrapolated to the entire province of Ontario. Therefore, it is recommended to include more sites that cover different slopes and soil drainage types into the analysis if additional research data becomes available.
- Crop yield and NDVI differences were summarized for each year. This included multiple paired fields maintained by different farmers, having potentially different agricultural practices such as use of different varieties of crop, fertilizer types and application etc. This increases the variability of crop response to CTD, which may explain the weak correlation (R^2) between precipitation and yield difference.
- The CTD systems in the study area are managed conservatively, where they are opened during winters and closed during summers. However, more intensive management of these systems could results in higher yields.

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