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Article

Evaluation of Crop Water Status Using Sensor Integration

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ABSTRACT

About a decade ago, active optical crop canopy sensors are being used to manage in-season variable nitrogen (N) fertilization in cornfields to match the plant demand that occurs mid season, increasing the efficiency compared to broadcast N applications. There were also initiatives of using ultrasonic sensors to measure plant height on-the-go for N application and crop water demand estimation, but no studies have integrated the optical, ultrasonic and canopy temperature for crop water stress assessment. The objective of this chapter is to evaluate the crop water status using infrared thermometry integrated with optical and ultrasonic sensors. Specifics objectives are: (i) evaluate the corn canopy temperature under different previous crop, N rates and irrigation levels; (ii) test a procedure for water stress assessment in commercial cornfields using the integration of sensors, (iii) correlate plant based sensor measurements (N status, plant height and canopy temperature) with grain yield, soil attributes and detailed topographical features, and (iv) study the spatial dependence of canopy temperature. This study was conducted in one small plot study area and on three producer's fields in 2010. The small plot experiment consisted of two irrigation levels (70 and 100% of evapotranspiration – ET), two previous crop schemes (corn after corn – CC and corn after soybeans – CS), and four N rates (0, 75, 150, 225 kg N ha^{-1}). Canopy temperature, optical reflectance and plant height was measured from R2 until R6 in the small plots. At the producer's fields, three long strips across center pivots were used to have a non-limited N and water crop and then continuous georeferenced sensors measurements were taken during side-dress (V11 growth stage) in about 10 hectares in each field. In the small plot study the crop canopy temperature was influenced by the irrigation levels and N rates. The procedure proposed could be used to identify zones in the producer's field where water stress can be a yield limiting factor other than N derived. Inside the zones considered that water stress played a major whole, there were low correlations between plant height, plant N status and canopy temperature, indicating that the canopy temperature had more influence from water stress than vegetation cover. Concave and lower elevation areas had higher yields compared to convex and high elevation, showing that the detailed elevation mapping can be beneficial to delineate stables zones that possibly could be used in variable irrigation systems. The spatial dependence of canopy temperature was over 65 meters across producers' sites, showing that the commercial high clearance applicator's swath width was adequate to obtain accurate maps. The integration of plant N status, plant height and canopy temperature was beneficial to detect water stressed zones in the field. Opportunities can be foresee also for on-the-go N fertilization using integration of these sensors because is likely that water stress can be confounded with different N supply during the growing season and in different zones in the field.

Keywords: active crop canopy sensor; plant height; canopy temperature; sensor integration

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Abbreviations: IRT, infrared thermometers; NSI, nitrogen sufficiency index; HSI: Plant Height Sufficiency Index; CC, corn after corn; CS, corn after soybean; Tc-Ta, canopy temperature minus ambient temperature; Tc-Tr, canopy temperature minus canopy temperature of a well watered plot; CWSI, Crop Water Stress Index; MTCI, Meris Terrestrial Chlorophyll Index.

INTRODUCTION

Infrared thermometers (IRT) were introduced into agriculture more than 40 years ago as a hand-held tool to remotely measure the surface radiometric temperature of crops to characterize water stress in plants, predict yields and manage irrigations. Using optics and specialized detectors, these sensors were engineered to filter thermal radiation in the mid to far-infrared region (8 to 14 µm) converting to a digital temperature without direct physical contact between the leaf and the thermometer (Hatfield et al., 2008, O'Shaughnessy et al., 2011). Advances in IRTs have increased the options available for irrigation and light sensors self-powered are available in the market at reasonable price. The main goal of these IRT is to obtain crop canopy temperature measurement to assess crop water status (Aston and Van Bavel, 1972; Idso et al., 1978; Idso et al., 1982). Several studies indicated that foliage temperature can be correlated with soil moisture content, plant water stress and plant transpiration rate (Idso et al., 1978, Howell et al., 1984, Jackson et al., 1981, González-Dugo et al., 2006). It was suggested that vapor pressure deficit (VPD), net radiation and wind speed could influence the canopy temperature (Sepulcre-Canto et al., 2006). Further studies demonstrated a linear relationship between vapor pressure deficit and foliage temperature, obtained one of the most important contributions for proper use of IRT called crop water stress index (CWSI) developed at the USDA-ARS US Water Conservation Laboratory, Phoenix, Arizona (Jackson et al. 1981). They also showed that canopy temperature (Tc) minus air temperature (Ta) is essential to study the water status of a crop, relating Tc-Ta to productivity and crop water requirements. Other studies compared the measured canopy temperature to that of a well-watered reference plot (Tr) as an indicator of water stress (Fuchs and Tanner, 1966), representing by Tc-Tr (Sepulcre-Canto et al., 2006). Moran et al., (1994) found that vegetation cover assessed by vegetation indices can be negatively correlated with canopy temperature, because the soil background

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can influence the canopy temperature measurements. It was also found that evapotranspiration and field water deficit can be estimated using remotely sensed measurements of surface temperature (crop + soil) and reflectance (red and near infrared spectrum) with limited on-site meteorological data (net radiation, vapor pressure deficit, wind speed and air temperature). Challenging also is to separate the plant water requirement from N stress (Zhu et al., 2011, Clay et al., 2006) and also separate the soil spatial variability like texture and others nutrients from N deficiency (Zillmann et al., 2006). Even knowing that several factors can influence the assessment of crop water status using canopy temperature measured by IRTs, due to interferences and calibration of the equipments, there were initiatives for complex variable rate irrigation systems that rely on canopy temperature to manage water in center pivots with success (Sadler et al., 2002, O'Shaughnessy et al., 2010). About a decade ago, active optical crop canopy sensors are being used to manage in-season variable N fertilization to match the plant demand that occurs mid season, increasing the efficiency compared to broadcast N applications (Stone et al., 1996; Raun et al, 2005; Tubana et al., 2008, Schmidt et al., 2009). There were also initiatives of using ultrasonic sensors to measure plant height on-the-go for N application (Sui et al., 2006) and plant height measurement along the season to estimate evapotranspiration and crop water demand (Sammis et al., 1988), but no studies have integrated the optical, ultrasonic and canopy temperature for on-the-go crop water stress assessment. The objective of this chapter is to evaluate the crop water status using infrared thermometry integrated with optical and ultrasonic sensors. Specifics objectives are: (i) evaluate the corn canopy temperature under different previous crop, N rates and irrigation levels; (ii) test a procedure for water stress measurements in cornfields using the integration of sensors, (iii) correlate plant based sensor measurements (N status, plant height and canopy temperature) with grain yield, soil attributes and detailed topographical features, and (iv) study the spatial dependence of canopy temperature.

MATERIAL AND METHODS

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Research Fields

This study was conducted on small plots at the South Central Agriculture Laboratory (MS10), near Clay Center, Nebraska and on three producer's fields in 2010 (BR10, HU10 and BL10). The BL10 field was near Brule, Nebraska, and the other (BR10 and HU10) near Aurora, Nebraska. All fields were sprinkler irrigated to provide enough water for high yielding corn production. The hybrids, starter fertilization and water management were selected by each farmer and similar hybrids were selected for the small plots in SCAL. Soil characteristics and other management practices and related information can be obtained in chapter 2.

Sensor Platform

One optical sensor, two ultrasonic and one infrared temperature sensor (IRT) were mounted in an aluminum apparatus designed to keep enough distance between sensors to avoid interference and close enough to measure the same target. The aluminum piece was painted with a back color ink around the infrared thermometer to avoid interferences of the aluminum surface. For the small plots field, the sensors were installed in a bicycle and integrated with a differential global navigation satellite system (DGPS) to gather data in the same location. For the producer's fields the sensors were installed in the boom of a high clearance machine. All sensors were adjusted to make measurements in the corn rows, trying to have the minimum bare soil interference in the readings.

Sensors Descriptions

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The optical sensor used was an active light reflectance sensor that emits and receive the canopy reflectance in the near infrared (NIR) and visible spectrum regions. The Crop Circle 470 (CC470) (Holland Scientific, Lincoln, NE) was used. The CC470 is a three band active sensor that measures the NIR at 760nm and the red and red-edge bands at 670 and 720nm, respectively. These spectral bands were used to calculate a vegetation index. From the results obtained in the chapter 1 where was found low variance due to water for some indices, the MTCI was chosen for NSI calculation.

For plant height measurements it was used an ultrasonic distance sensor that measures the sound pulse and scattering from the canopy back to the sensor. The model used was a TSPC-30S1 (Senix, Bristol, VT) that has a maximum range of 4.3 meters and optimum range of 0.10 to 3 meters, with a field of view lower than 5 cm at 1 meter height from the target. It is waterproof and temperature compensated. The output data was calibrated in laboratory and converted to distance in centimeters. The plant height was determined by the difference of the sensor height and the distance from the top of the canopy to the sensor.

Canopy temperature was measured using an non contact infrared temperature sensor (IRT) model PSC SSS – LT02H (Process Sensors Corp., Milford, MA), that has a lower limit temperature of 0 ºC and a Upper limit of 500 ºC, with a 2:1 field of view, and accuracy of 0.5 ºC at objects temperatures > 20ºC for the target temperature. The IRT also measures the temperature of the instrument box and the tip of the sensor. The selection of this sensor was envisioning the use of the tip or box temperature as the ambient temperature (Ta) that is required in most of canopy temperature studies for calculation of the difference of canopy temperature (Tc) minus the ambient temperature (Ta) that is related to water status of the crop. Details about the (Tc-Ta) theory can be found in (Jackson et al., 1981 and Idso et.al., 1978). To calculate the Tc-Ta it was used the ambient temperature measured in site with automated weather stations due to variations of the temperature recorded by either box or tip temperature. For on-the-go purposes it is required to measure

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the Ta in real time to calculate the Tc-Ta, so attempts were done to calculate a similar approach using the tip temperature (Tc-Tt), where Tt was the tip temperature measured in the same time with the target temperature or canopy temperature (Tc).

Experimental Design and Data Analysis

Small Plots

The small plot experiment consisted of two irrigation levels (70 and 100% of evapotranspiration – ET), two previous crop schemes (corn after corn – CC and corn after soybeans – CS), and four N rates (0, 75, 150, 225 kg N ha^{-1}) with 3 replications. Canopy temperature was measured from R2 until R6 growth stages. Soil moisture sensor probes were installed to monitor hourly the soil available water during the growing season. The experimental design was a randomized complete block split-split plot, with irrigation levels as main plot, previous crop as subplot, and fertilizer N rate as sub-sub plots. Analysis of variance was done to evaluate treatment effects on canopy temperature (Tc-Ta) and means separation using the Duncan Multiple Range Test ($p<0.05$). Irrigation levels, previous crop and replications were considered random effects. It was used time-repeated measures analysis with PROC MIXED to evaluate the Tc-Ta at different growth stages (R2, R3, R4 and R6).

On-farm research sites

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At the producer's fields, three long strips across center pivots were used to have a non-limited N, where was applied 250 kg N ha^{-1}. These strips were used to calculate the nitrogen sufficiency index (NSI) for the optical and plant height sufficiency index for the ultrasonic sensors (HSI) and also to have a reference canopy temperature where N and water were not limiting. To evaluate the plant water availability in the time of sensing, it was used data from two sets of soil moisture probes measuring at 30, 60, 92 and 121 cm soil depth installed in two locations inside the reference strip in each field since the beginning of the growing season. These locations consisted of low and high elevation areas in the field where one of three reference strips were located. These regions were used to calculate a reference canopy temperature, that was considered non water stressed plants (Tc-Tr), where Tr is the canopy temperature of a non stressed measured by IRT. This method was used by Sadler et al. (2002) in corn and Sepulcre-Canto et al. (2006) assessing olive trees leaves temperatures. Next to those reference strips, continuous georeferenced sensors measurements were taken during side-dress (V11 growth stage) in about 10 hectares in each field.

The procedure to be tested consisted of the main assumption that water stress measured with canopy temperature is the major factor affecting the grain yield. To evaluate the assumption two zones in each farmers fields were created: (i) Non-water stressed (NonS) and (ii) Water stressed (S). To delineate these zones it was used the Raster Calculator in ArcGIS considered the following criteria:

NonS = NSI and HSI > 0.95 and Tc-Tr < 0

S = NSI and HSI > 0.95 and Tc-Tr > 0

Where:

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NSI is the nitrogen sufficiency index calculated using the averaged MTCI calculated from the three replications of the N-rich strips; HSI is the height sufficiency index calculated using the averaged plant height measured using ultrasonic sensors from the N-rich strips; Tc – Tr is the canopy temperature minus the average canopy temperature from the N-rich where soil matric potential measured by soil moisture sensors indicated non water limited crop at time of sensing.

The criteria of 0.95 was selected based on previous studies (Varvel et al., 2002 and Solari et al., 2010) where was found that an SI bigger than 0.95 can be considered to N sufficient corn plant. Similarly as observed in chapter 4, a HSI of 0.95 is also a good indicator of N sufficient corn plant.

After the two zones delineation, all points that fall inside the geographical locations inside those zones were used to compare the means of the variables using pairwise comparisons with Tukey – test at $p < 0.05$. To perform a balanced comparison the number of points were randomly excluded from some fields to have the same number for every field.

Correlations between Canopy Temperature, Topographic Features and Soil Attributes

Previous to the reference strips implementation in the producer's fields, apparent electrical conductivity (EC) was mapped using a Veris (Veristech, Salinas, KS) and grid soil sampling was done to map organic matter and others soil nutrients. Detailed elevation was measured using a real kinematic GPS (RTK) associated with the EC mapping. To delineate topographical features (concave and convex areas) it was used the procedure called Focal Statistics from the Spatial Analyst package from ArcGIS 9.3 (ESRI, Redlands, CA). Using the focal statistics it was calculated the difference in elevation from one pixel (5x5 meters) in the raster elevation map and the average of the elevation data inside a radius

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of 10 meters of that pixel (Focal20m). Focal20m = pixel – (average of 10 m radius from that pixel). In the resulting map the negative values in meters represent concave areas and the positive the convex areas, considering one region of influence in the pixel of 20m diameter. It is expected that concave areas and low elevation relative have lower water stress and canopy temperatures compared to convex and high areas. All variables (NSI, HSI, Tc-Tr, grain yield, ECsh, OM, pH, P, $NO_{3,}$ RTK elevation, Focal20m, Tc-Tr) were correlated using Spearman rank correlations to analyze the spatial relationship between these variables inside the zones (NonS and S). As reported by Kitchen et al. (2003) if correlation analysis is used to compare large datasets, as these collected using sensors, the results should be viewed subjectively and mainly used as an indicator of those factors to be included in more scrutinizing analyses. With large datasets statistically significant correlations were common, however, a variable could be found to be significant even with a quite low correlation. For this reason it was decided to analyze the data also using zones comparisons. Then, the Focal20m data was used as input for clustering in Management Zone Analyst 1.0.1 (MZA) (USDA-ARS and University of Missouri, Columbia, MO) (Fridgen et al., 2004) to delineate homogeneous zones of concave and convex areas, and evaluate yield, Tc-Tr and Focal20m values averaged inside each zone delineated. Two performance indices are calculated with the software to determine the number of zones within each field. The Normalized Classification Entropy (NCE) that measures the disorganization created by dividing the data into classes. The Fuziness Performance Index (FPI) is a measure of membership sharing (fuzziness) among classes. The optimum number of classes is when NCE and FPI are minimized.

Spatial Dependence of Crop Canopy Temperature

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The Tc-Ta in the producer's fields was evaluated using geostatistical analysis basically to determine if the maximum distance between passes were adequate for this experiment and also be an indicative on how far can we sample for Tc-Ta and generate a confident krigged map. The semivariograms to determine the model and range were calculated using GS+ (Gamma Design Software, Plainwell, MI), and the models were adjusted and validated using cross validation.

RESULTS AND DISCUSSION

Comparing Ambient and Sensor Tip Temperatures

In the beginning of this project about on-the-go canopy temperature measurements, it was expected that the temperature measured by the tip of the IRT (Tt) should be used as a substitute of Ta for Tc-Ta calculations, but variations obtained during the course of the day were high compared to Ta (Figure 1, 2, 3 and 4). For the small plots experiment where the collection time varied from 3 to 6 hours, the Tt variation was a big concern. For the producer's fields where the data gathering was done in one or two hours, the Tt also varied. When air temperatures are not available, the adjustment used by Evans e al. (2000) can be used, which entails the regression of temperature against time, subtracting the trend, and adding back the average. For this study to calculate the Ta diurnal variations for each Tc reading in different positions (to obtain Tc-Ta for each position), it was used an equation regressing the time and the data available hourly in the automated weather station near the sites, using the same method proposed to obtain the corrected Ta. The hourly air temperature information was downloaded from the High Plains Regional Climate Center. For the small plots the hourly temperatures were recorded in the site and for the producer's fields it was used the closest weather station

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data acquired. It was observed for the producer's sites that the diurnal Ta variation was also a concern for corrections, even with collection in 2 hours interval (Figure 2, 3 and 4). For the BR10 field where the measurements were done early evening, the Ta dropped faster than the crop temperature (Figure 2). To be able to compare with previous studies it was preferred to use Ta estimated from the hourly data from weather stations to calculate Tc-Ta, but more studies should be done to investigate if Tt or some associated temperature device can be used for on-the-go measurements with the same efficiency than Ta.

Another difficult encountered in the canopy temperature data was the filtering process for outliers caused by several issues, e.g. soil background interference, gaps in the plots and inter row sensing due to inadequate orientation during sensing. These outliers can be observed in Figures 1 to 4. Fortunately, the optical measurements and plant height could be used to help this filtering process. Basically it was filtered most of the outliers using the following criteria: Exclude the temperature data when the reflectance was lower than the value at 15% percentile in the check plot (0 kg N ha^{-1}) ; plant height lower than the smaller plant inside the plot (excluding the buffer), and temperatures with coefficient of variation higher than 200% in each plot.

Small Plots

The 2010 growing season had good rainfall delaying the irrigation for the small plot area compared to other years. The canopy measurements started at V7, but the irrigation commenced around V15 and then only later stages of corn were selected to make the statistical analysis to study the canopy temperature effects. Analysis of variance on crop canopy temperature showed significant correlations for irrigation levels and N rates, but no interaction terms were observed (Table 1). The irrigation levels affected the Tc-Ta similarly for both previous crop, and significant differences

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were observed at R3 and R4 growth stages (Table 2). When soybean was the previous crop, the differences in canopy temperature were also observed in R6 (Table 2), maybe due to higher leaf density in vigorous plants. On the other hand as observed by Hatfield (1983) in wheat that non transpiring panicles above the canopy can confound the canopy temperature measurements. There are chances in the R6 stage, that the corn plant had several dry material that could interfered with the readings. Analyzing the N rates effect on canopy temperature across growth stages and previous crop, there were differences between the check plot (0 kg N ha^{-1}) and the other N rates (Table 3). Carefully attention was given during the filtering process to exclude plot alley ways and extremely low plants using the plant height measured by ultrasonic sensors, but as observed by Moran et al. (1994) and Heilman et al. (1981), the canopy temperature can still be interfered by soil temperature if low vegetation cover is sensed. During sensing it was observed that the CS had higher plants than CC, but the ANOVA didn't indicate significant differences between previous crops. The growth stage R4 was the best stage to sense for water stress as showed in Figure 2, showing pronounced differences in Tc-Ta between irrigation levels. In this stage the highest N rate had the lowest temperature also for the 100 % ET. This experiment showed that differences from 0.5 to 3 ºC can be detected when different irrigation levels were used across previous crop and N rates. Overall the experiment showed that intensive data collection of canopy temperature can be viable to detect small differences in irrigation levels across previous crop and N rates.

On-farm research sites

All producers' fields had enough soil moisture in the time of sensing for the reference strip, as assured by measurements taken with soil moisture sensors (Table 4). Normally, in practical situations the trigger point to start an irrigation system for corn planted in a standard size center pivot is around 85 cB, to have enough time for a safe and complete irrigation

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turn. This moisture threshold will change with soil type, clay content and others soil physical properties, but the soil matric potential in all sites were generally very low indicating sufficient soil available water content. The highest measurements for the soil moisture sensors in the BR10, HU10 and BL10 fiels were 15, 61 and 32 cB, respectively (Table 4), so enough moisture was observed in all reference strips, either in the low or high areas in the field. Based on these measurements, the calculation of an average reference temperature (Tr) from these strips was a good representative of a non-water limited crop and that Tc-Tr approach can be used as an indicator of crop water stress for the producers field. As observed in chapter 2, the local variations can still have effect when a reference value is adopted for SI, and certainly the soil spatial variability can also affect the Tc-Tr, but this variability in Tr was not evaluated in this study.

On those areas with SI higher than 0.95 it was observed considerable zones with low and high Tc-Tr, in this case represented by negative and positive numbers (Figure 6). The white areas in the maps represent NSI and HIS < 0.95, and they were not considered in the analysis to determine zones with water stress, because the canopy temperature can be influenced by N deficient plants. All these producer's sites (BR10, HU10 and BL10) had enough N applied before the sensor measurements were conducted (over 180 kg N ha^{-1}). Analyzing the NonS and S zones, it was observed significant grain yield differences between zones in 2 of 3 fields (Table 5). For the BR10 and HU10 the differences in grain yield caused by water stress were around 840 kg ha^{-1} on average; but for BL10 it was only 45 kg ha^{-1} and not statistically significant. The Tc-Tr and Tc-Ta also showed significant differences between the zones delineated, indicating that the crop canopy temperature was higher for the water stressed plants, as expected.

The soil fertility between zones were not different but lower nitrate in the beginning of the season was observed for HU10 and BL10, but after the starter N fertilizer and N sidedressing it was not a concern for these zones because average SI were higher than 0.96 in all zones (Table 5). The organic matter, pH and P were similar to all fields, but slightly lower for the BR10 field.

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The spatial variability observed in Figure 7 for the BR10 field showed that NSI, HIS, Tc-Tr and grain yield had similar spatial patterns when all data was used to make the maps. On the East side of the field it was observed higher yields and in the Tc-Tr map can be observed two different zones of canopy temperatures even with high NSI and HSI. For the HU10 field the spatial patterns were not delineated with big zones as BR10, but it can be seem that lower yields were obtained in higher Tc-Tr (Figure 8). In the BL10 field the spatial pattern was similar for NSI, HIS and yield, but for canopy temperature it seems that the visual correlations were low. In general the procedure proposed to delineate zones of water stress could identify zones in the producer's field where water stress can still be a yield limiting factor other than N derived even with irrigation.

Correlations between Canopy Temperature, Topographic Features and Soil Attributes

Inside the zones where NSI and HIS were higher than 0.95, it was observed that water stress played a major whole, because low correlations between plant height (HSI), plant N status (NSI) and canopy temperature (Tc-Tr) were found, indicating that the canopy temperature had more influence from water stress than vegetation cover (Table 7, 9 and 11). It was observed negative correlations between NSI, HSI and Tc-Tr indicating that higher plants with adequate N nutrition can have lower temperatures, but as also showed by Moran et al., (1994) the vegetation indices can be negatively correlated with canopy temperature because the soil background can influence the canopy temperature measurements.

In the BR10 field (sandy site) it was still observed moderate correlations between yield and NSI (r=0.61), indicating that even zones with SI > 0.95 the N nutrition was important to achieve higher yields (Table 6 and Figure 10). Generally the spatial patterns showed in Figure 10, indicated that RTK, EC shallow and OM had high correlations, but

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the correlation showed in Table 7 also showed correlations of concave and convex areas with grain yield (r=-0.579), where lower yield where observed in convex zones.

At the HU10 and BL10 fields there were low correlations between N status and plant height with yield, indicating again that water stress was the major yield limiting factor on those zones used to study the water stress effect measured by IRTs (Table 7). For this field the visual correlation of the procedure to determine concave and convex areas (Focal 20 m) had high correlation with EC shallow but the Spearman rank correlation showed r = 0.04 non significant (Table 9). The grain yield was negatively correlated with RTK elevation, with the same trend for BR10. For the BL10 field the elevation was positively correlated with yield and EC shallow (r = 0.22 and 0.20). Generally the canopy temperature was not correlated with yield or NSI on those fields, ensuring that the water stress measured by IRT integrated with the plant N status and height can be a good approach to isolate water effects on corn canopy.

In 2 of 3 fields (BR10 and HU10) the concave and lower elevation areas had higher yields compared to convex and high elevation areas. These fields also had higher Tc-Tr at high elevation zones where the OM was lower. These trends observed on those topographical features delineated by the Focal 20m, showed that mapping these zones with detailed elevation can be a good database stable spatio-temporally.

In general, the soil fertility (pH, P, NO_3, OM) was not correlated with yield as expected, since they were supplied in adequate amounts for the crop (Table 5).

Evaluating the indications that a correlation analysis can provide, the whole dataset for the three producer's field were analyzed clustering zones of Focal20m using MZA to compare different topographical features (concave an convex areas) in terms of grain yield and canopy temperature. The MZA indicated an optimum number of zones of 3 for all sites, minimizing the NCE and FPI (Fridgen et al., 2004). As observed in Figure 13, the lower the Focal20m (concave areas) and Tc-Tr, the higher the yield for all fields. This is a strong indicative that the procedure for zone

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delineation (Focal20m) in concave and convex area can be a good database for delineation of microzones to be considered in variable rate irrigation systems. These zones are stable temporally and likely will behave similarly in terms of water demand and consequently canopy temperature. The zone 1 was the lowest yielding zone across fields, with yields around 7000, 12500 and 9000 kg ha^{-1} for BR10, HU10 and BL, respectively, and zone 3 the highest yields were observed (Figure 13). The lowest increment in yield was for HU10 (500 kg ha^{-1}) but the average yield was much higher than the other fields. The zones 1 and 3 had a difference of 4000 kg ha^{-1} for the BR10 field and 1000 kg ha^{-1} for the BL10 field, indicating again that the zones were very different in terms of yield and canopy temperature as well. In all sites even including the areas with NSI and HIS < 0.95 the zones (which can introduce a bias in the interpretation of canopy temperature as a water stress indicator, because N is the main factor) lower yields were found when the canopy temperature was higher compared to the reference and that concave areas were beneficial in all fields (Figure 14, 15 and 16). This finding confirms that the Focal20m could be a good approach to refine the irrigation optimizing the use of water and could be an important layer to use with optical and ultrasonic sensor for site-specific N management to discriminate water effects from plant N demand.

Spatial Dependence of Crop Canopy Temperature

The spatial dependence of canopy temperature determined by semivariogram analysis was over 65 meters across farmers sites, with varying ranges of 65, 80 and 210 meters for HU10, BL10 and BR10, respectively, showing that the commercial high clearance applicator's swath width was detailed enough to obtain accurate krigged maps during canopy temperature mapping (Figure 17). The resultant maps showed consistent spatial patterns (Figures 7, 8 and 9) compared to the other measurements made for NSI, HSI and yield. For the BR10 field, the model had very low

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semivariance at small distances indicating that the canopy temperature in this field had lower variability at small scale, differently from the other sites where the semivariance was much higher (higher intercept) at small distances. These effects can be observed in the cross validation where BR10 had the best prediction model with low standard error (SE) and higher r^2. But even with higher intercept for the HU10 and BL10, the maps were generated and they could represent well the spatial variability of Tc-Ta, but both sites the model used for interpolation underestimated the canopy temperature, showing that for several estimated points the actual canopy temperature was much higher, almost double (Figure 18 and 19). Probably these high temperatures could be error during mapping where the sensors “see” the inter row or deficient plant stand with long gaps between plants, as observed on those fields. Maybe increasing the IRT field of view angle from nadir to slightly oblique can ameliorate these interferences, but also acute angles can introduce differences of 3 to 5ºC into canopy temperature measurements (Paw E et al., 1989).

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SUMMARY AND CONCLUSIONS

In this chapter we evaluated the use of on-the-go corn canopy temperature measured by infrared sensors integrated with plant N status measured with optical sensors and plant height measured with ultrasonic sensors for crop water status assessment. In the small plots experiment the effect of different irrigation levels, previous crop and N rates were evaluated on crop temperatures. It was found that canopy temperature was influenced by irrigation levels and N rates. Small differences between 70 and 100% irrigation levels could be detected using IRTs and small plants with lower N supply had the highest canopy temperatures. On-farm research plots were mapped and the procedure proposed (where using optical and ultrasonic sensors, the criteria of NSI and HSI > 0.95 as a filter for IRT evaluation on water stress) could identify zones in the field where water stress was the major yield limiting factor, showing differences of about 840 kg ha^{-1} due to water deficit even with irrigation. The correlations between plant, soil, topographical features and canopy temperature on the zones where water was the major yield limiting factor indicated that canopy temperature was important to delineate zones prone to water stress, but the plant N status still affecting grain yield simultaneously. The delineation of zones using the Focal20m procedure could identify great differences in yield and showed that concave areas also had cooler plants. Analyzing the spatial dependence is likely that measurements taken with the IRT used in this study can be used in commercial high clearance machines swath width to map canopy temperature. The integration of plant N status, plant height and canopy temperature was beneficial to detect water stressed zones in the field, affecting yield and possibly promising to delineate stable zones for variable rate irrigation. Opportunities can be foresee also for on-the-go N fertilization using integration of sensors because is likely that water stress can be confounded with different N supply during the growing season and in different zones of the field. More studies have

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to be done to investigate the integration of these active sensors with detailed topography to fine tune the in-season N variable rate fertilization.

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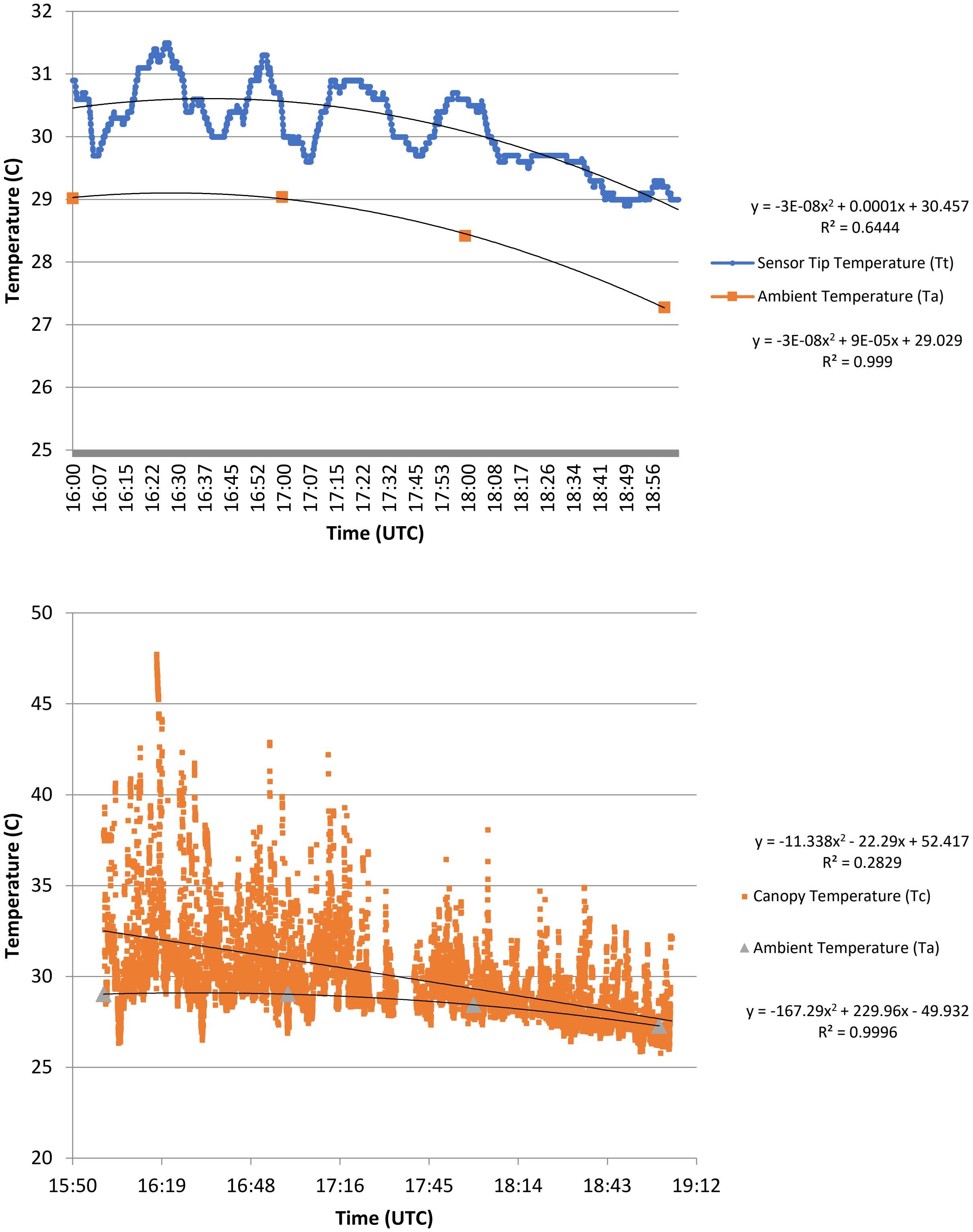

Figure 1. Diurnal temperature variations in the IRT sensor tip (Tt) and ambient temperature (Ta) for the small plots area. Ta was acquired in site using automated weather station.

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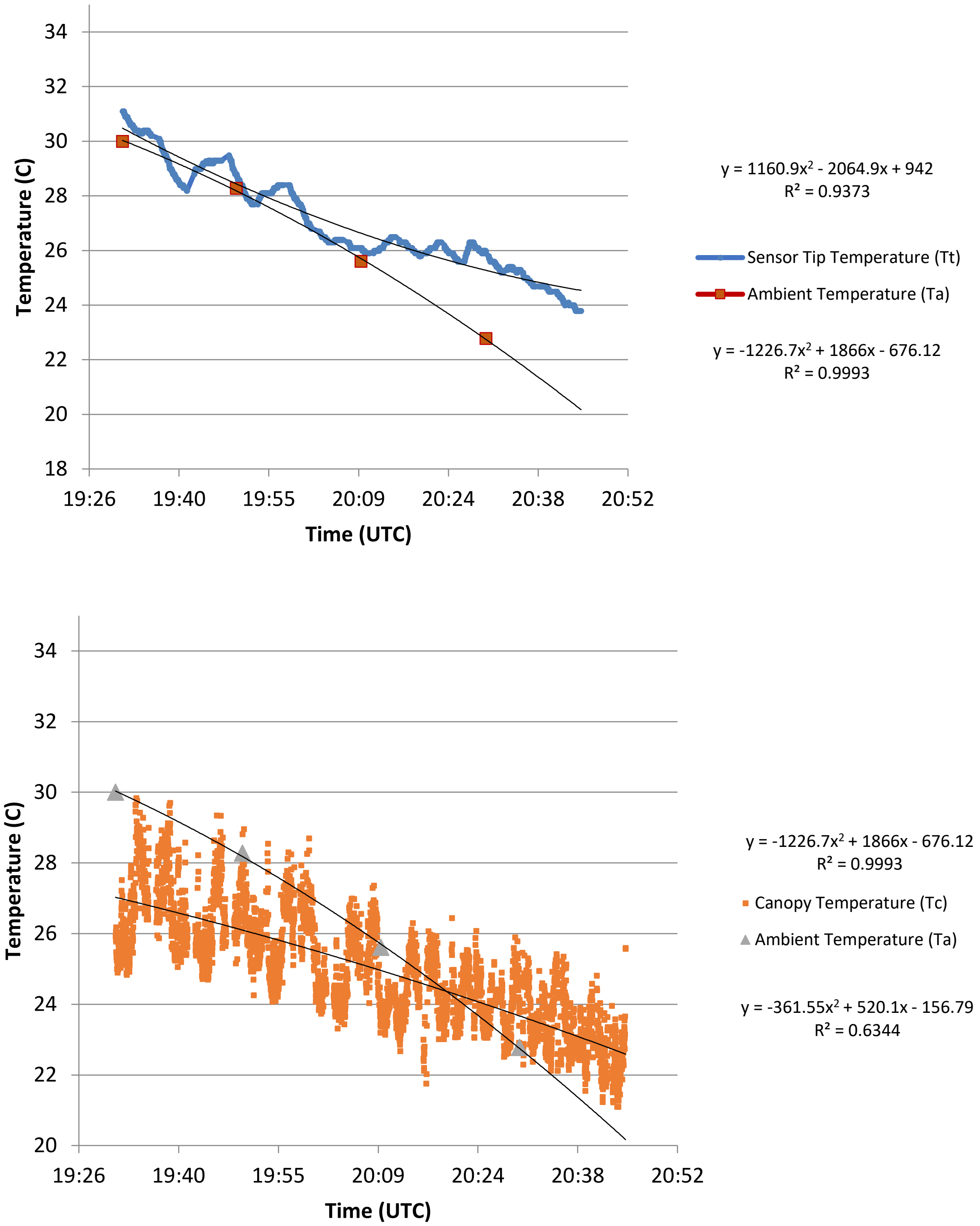

Figure 2. Temperature variations in the IRT sensor tip (Tt), canopy (Tc) and ambient (Ta) for the BR10 field.

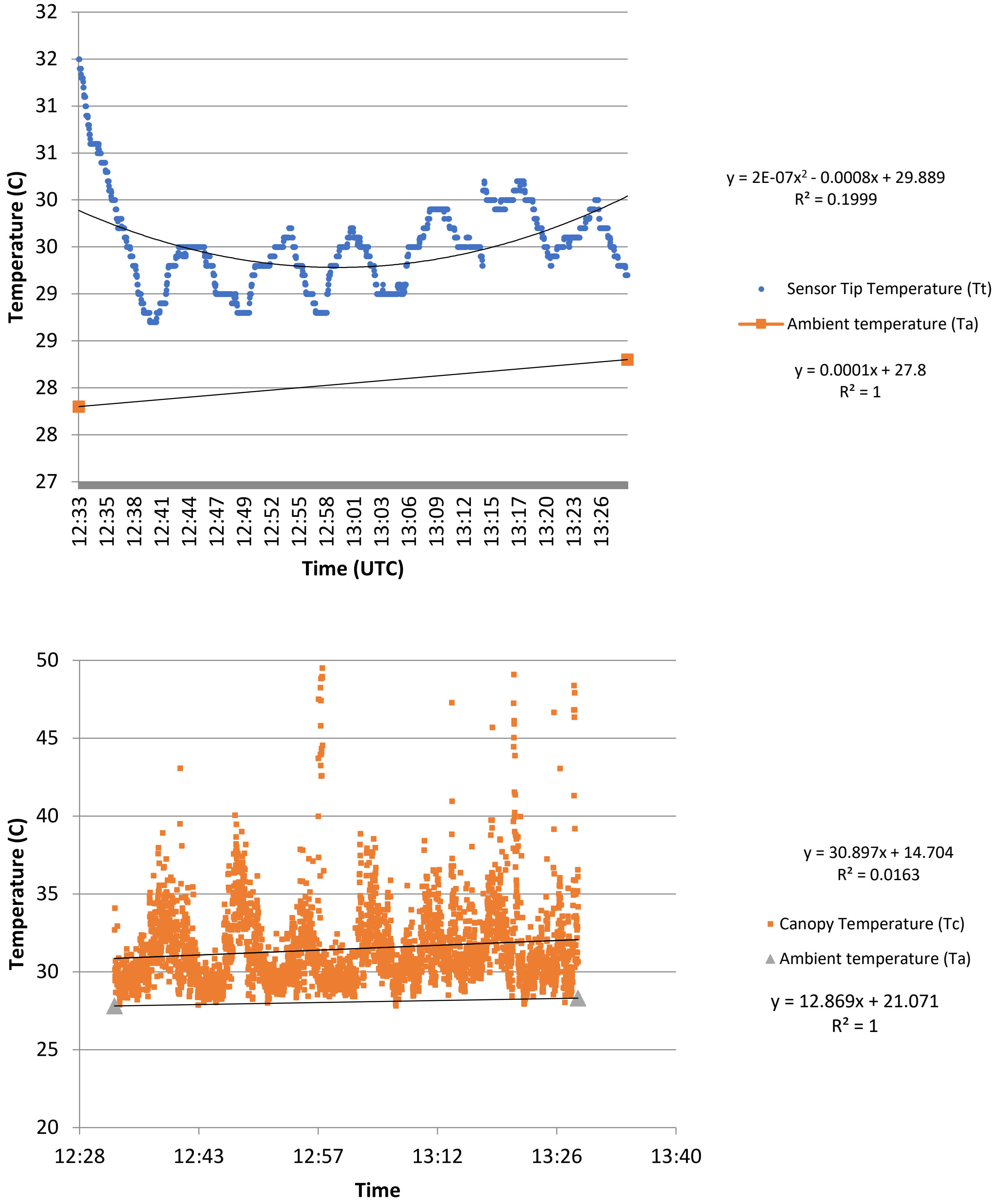

Figure 3. Temperature variations in the IRT sensor tip (Tt), canopy (Tc) and ambient (Ta) for the HU10 field.

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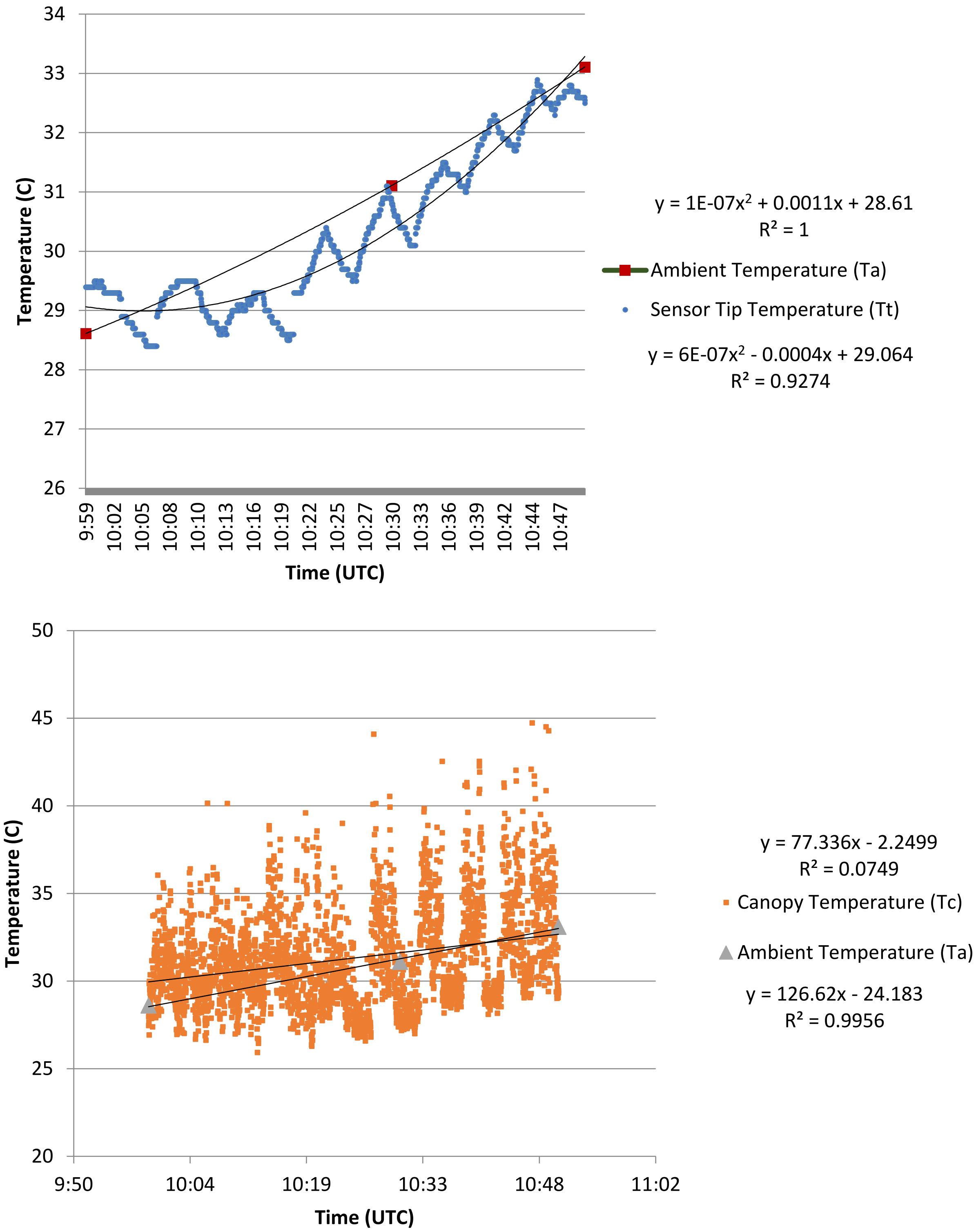

Figure 4. Diurnal temperature variations in the IRT sensor tip (Tt) and ambient temperature (Ta) for the BL10

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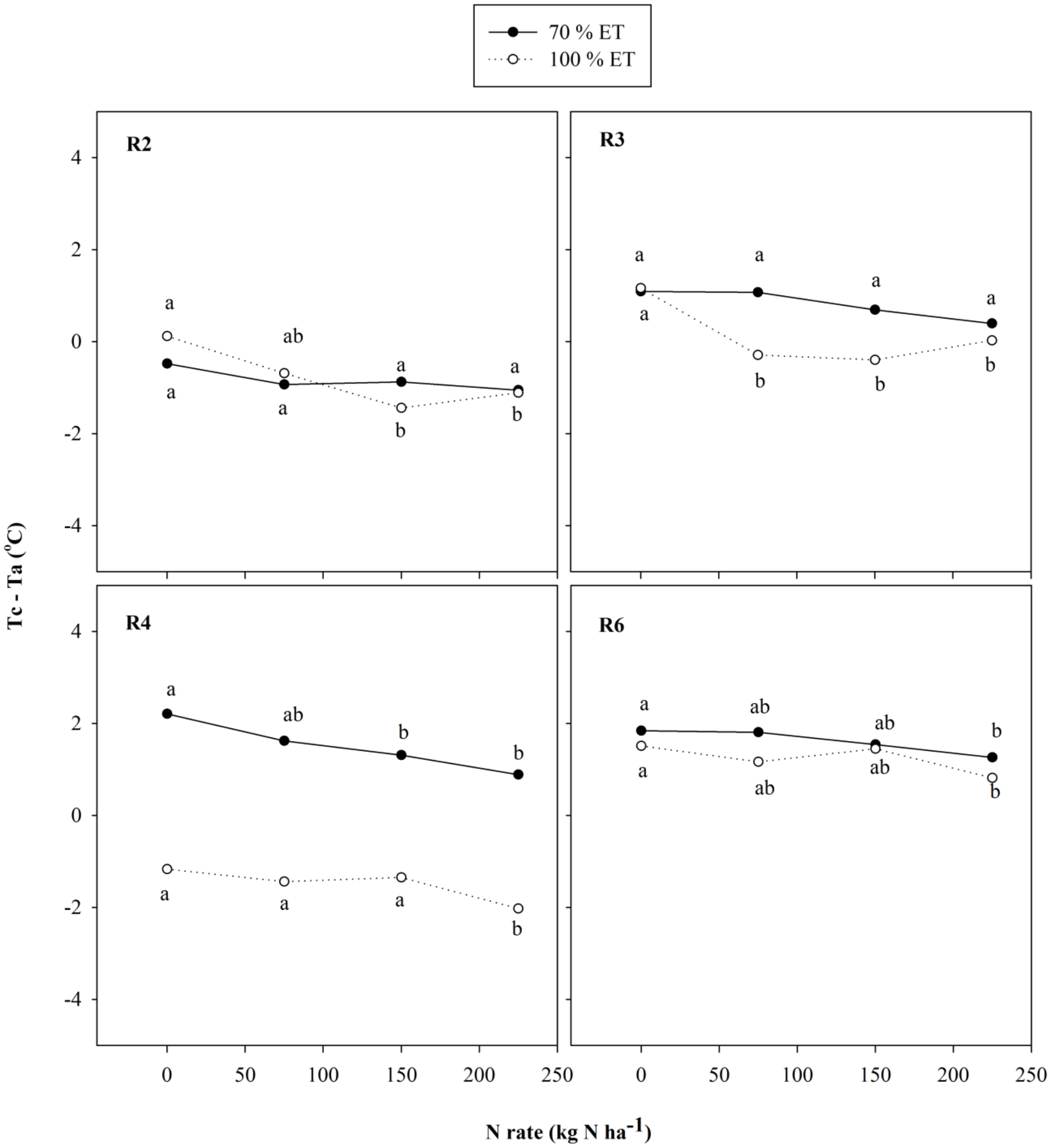

Figure 5. Effects of N rates on Tc-Ta under different irrigation levels and growth stages (R2 – R6).

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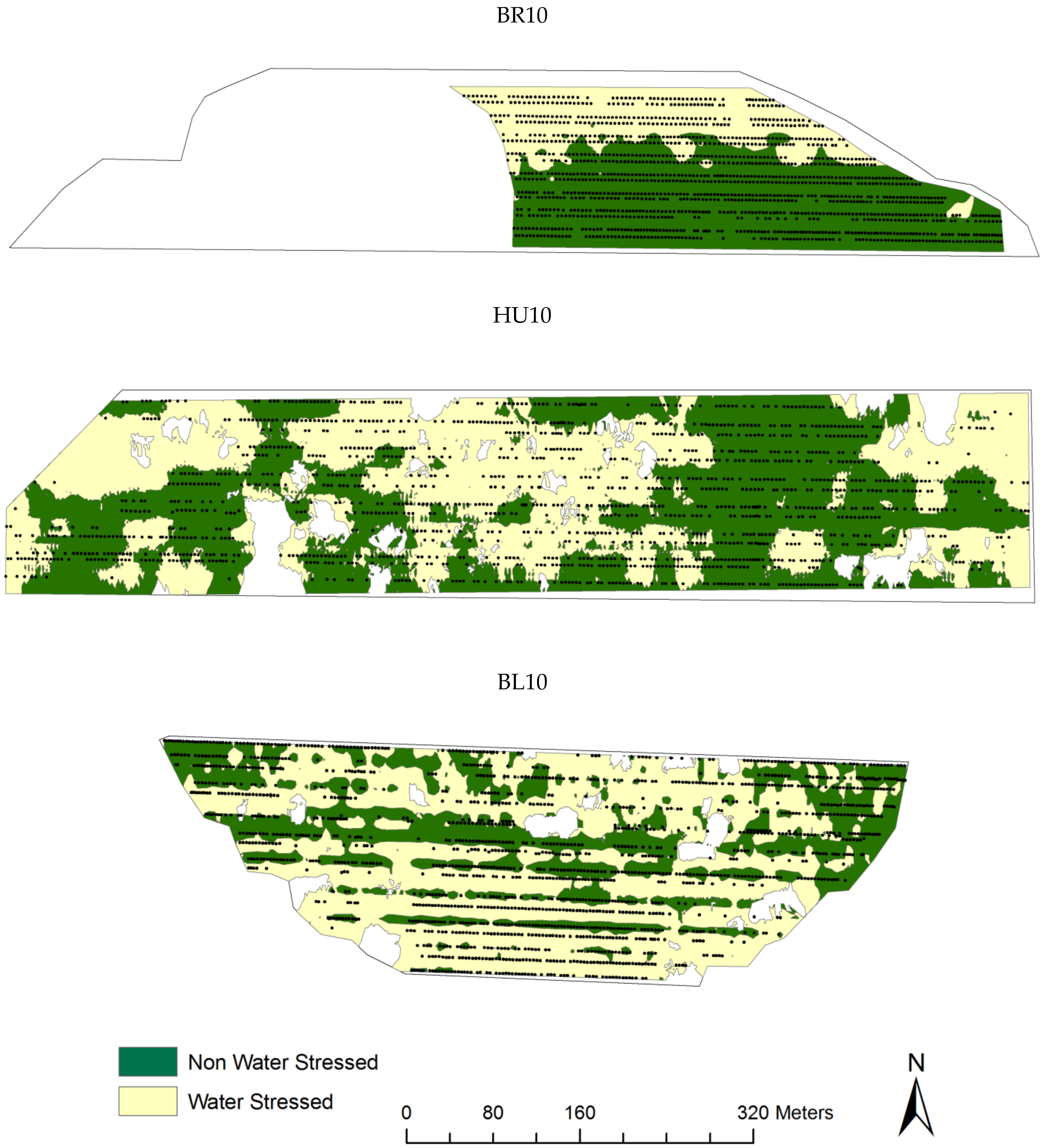

Figure 6. Zones delineated indicating water status based on the procedure proposed. Inside the zones where NSI and HIS > 0.95 the Tc-Tr > 0 represent water stressed zone and Tc-Tr < 0 non water stressed zone.

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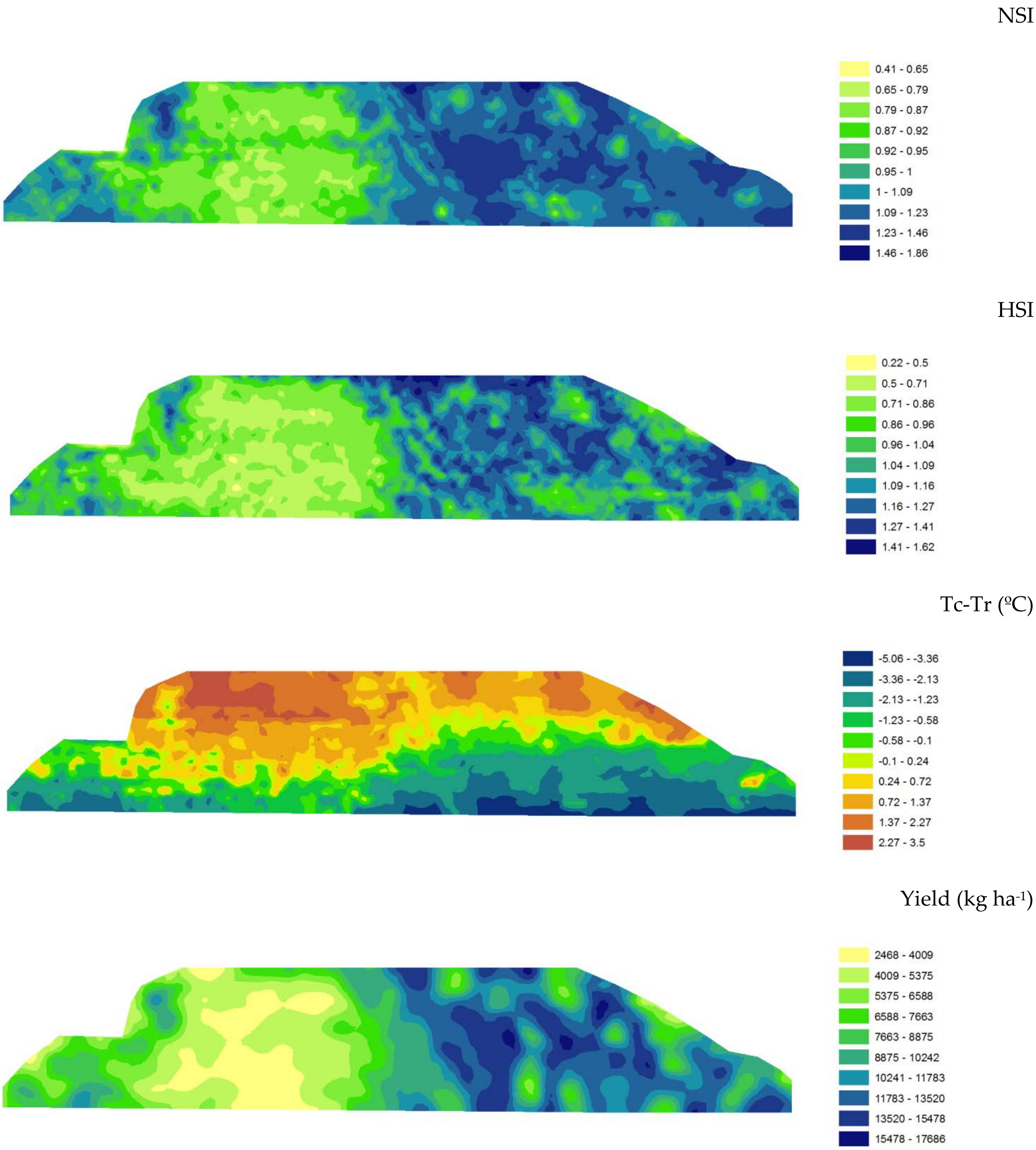

Figure 7. Interpolated maps of NSI, HIS, Tc-Tr and yield for the BR10 field.

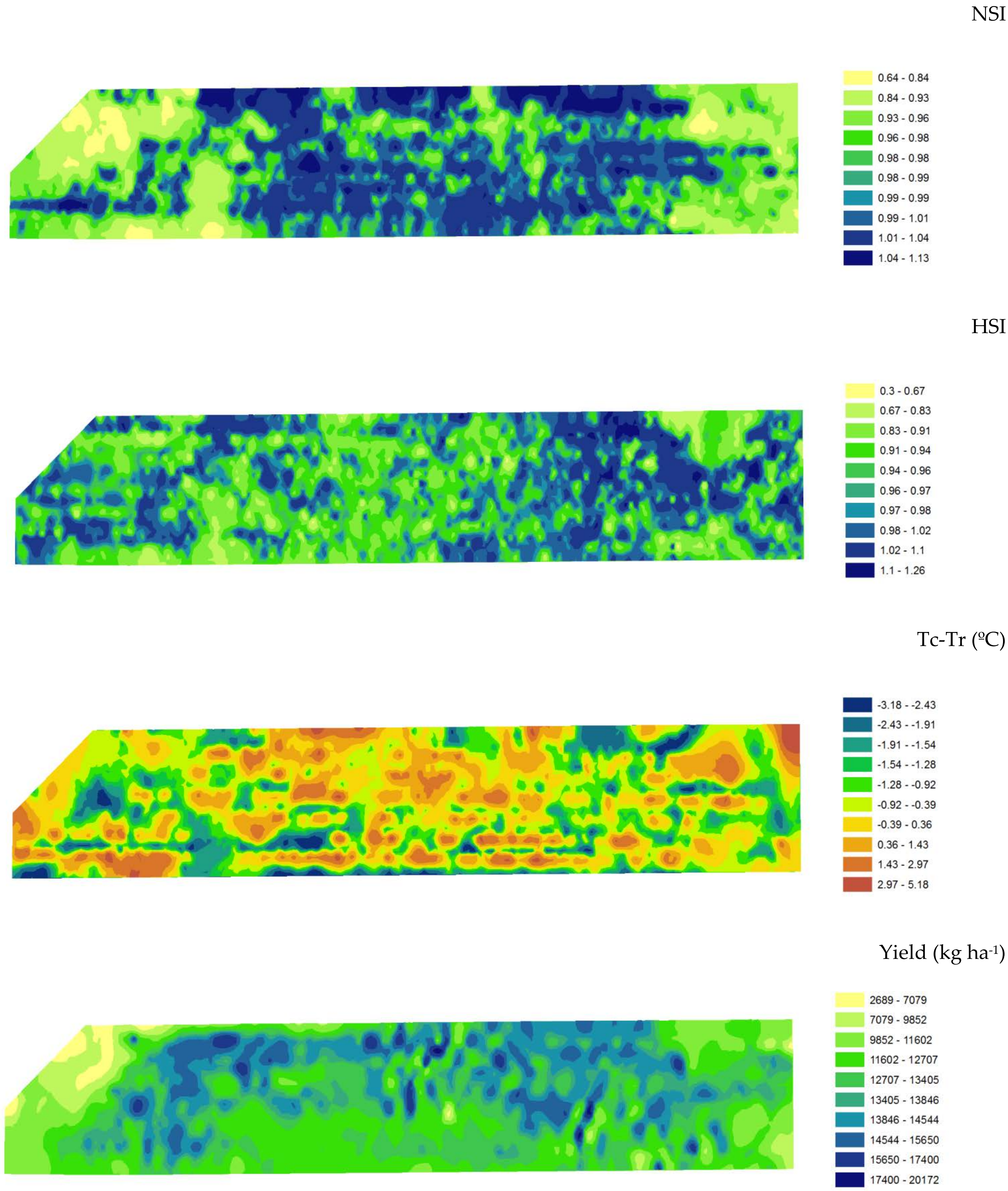

Figure 8. Interpolated maps of NSI, HIS, Tc-Tr and yield for the HU10 field.

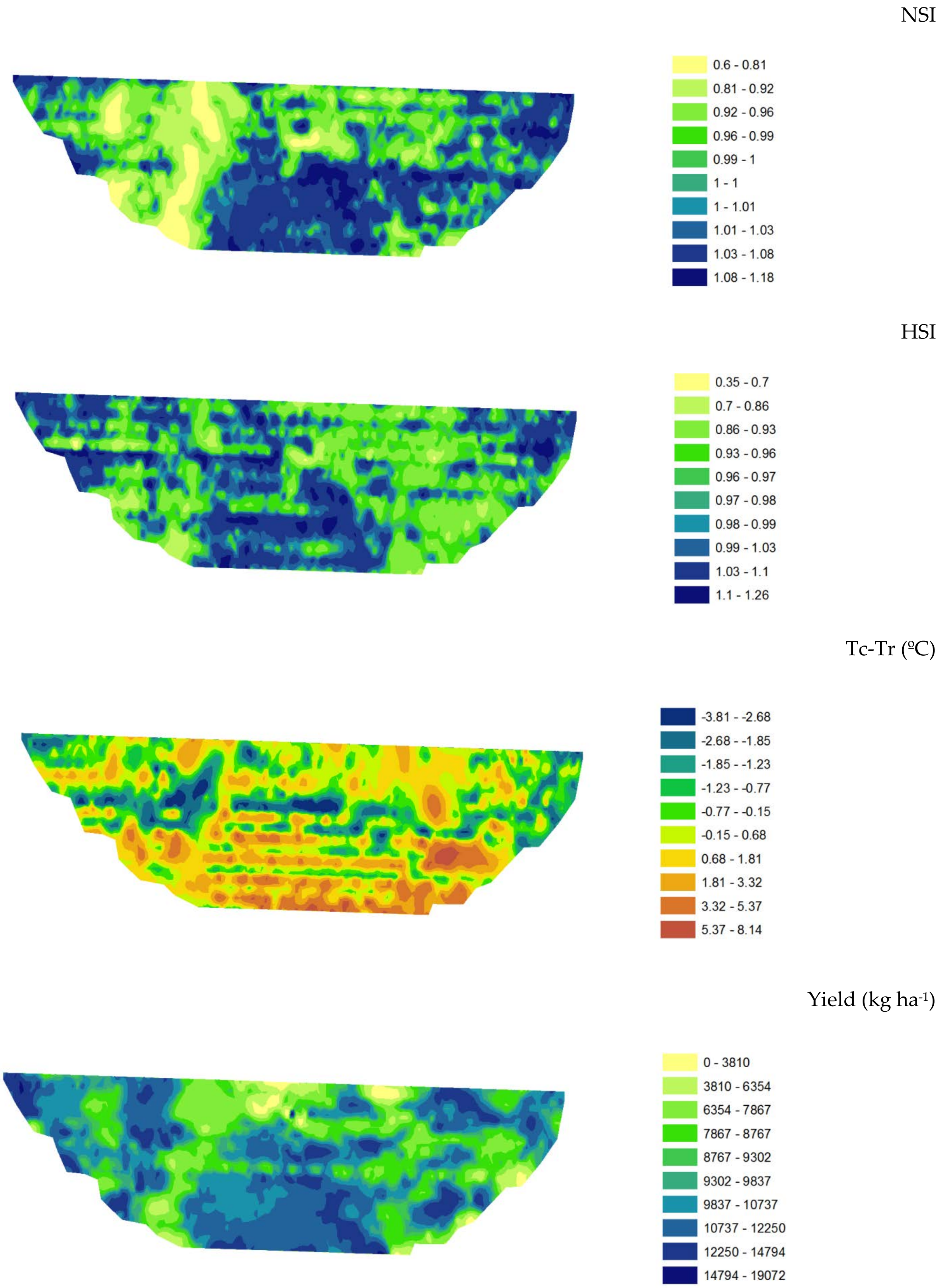

Figure 9. Interpolated maps of NSI, HIS, Tc-Tr and yield for the BL10 field.

RTK Elevation (m)

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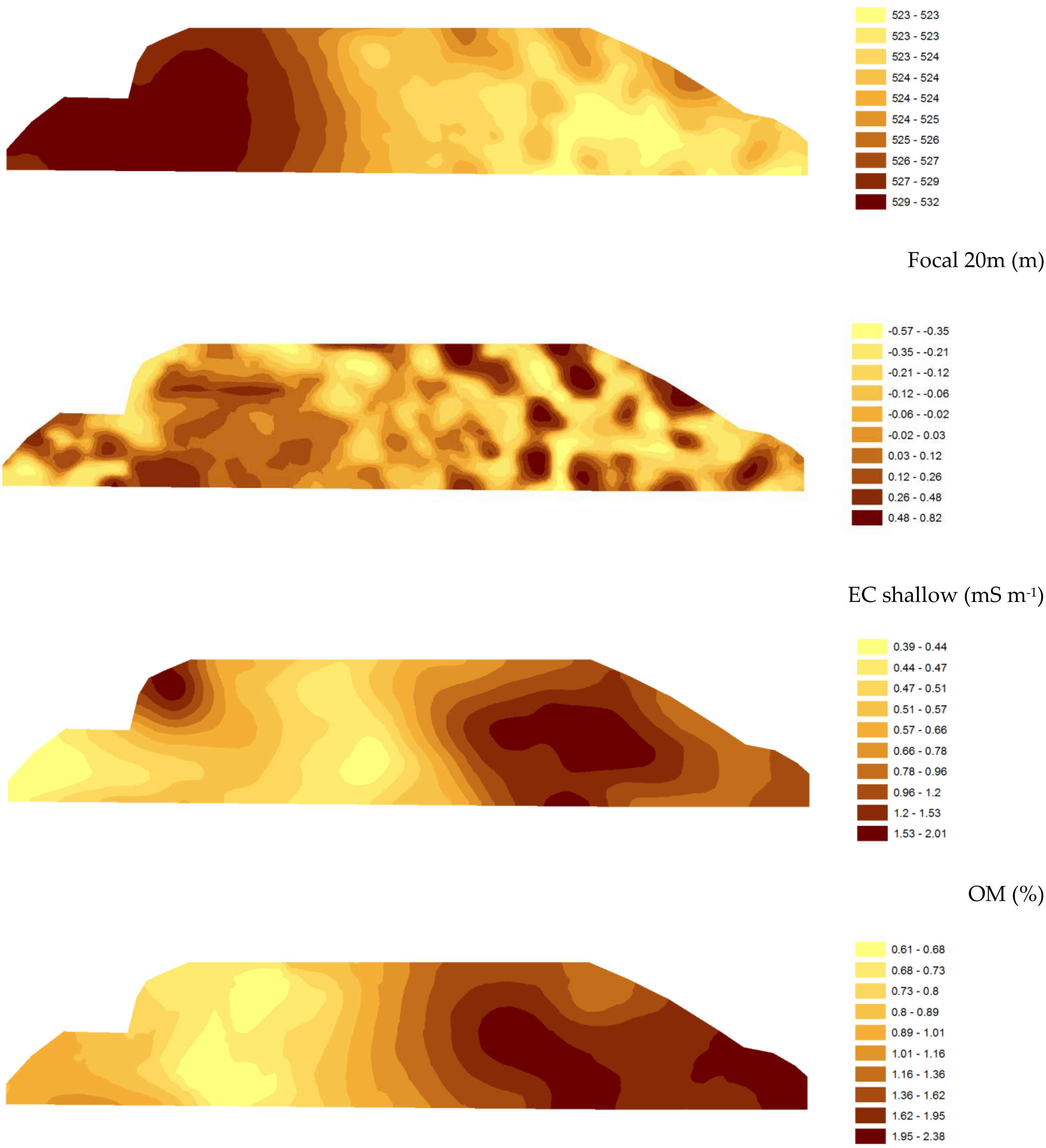

Figure 10. Soil attributes and topographical features for the BR10 field.

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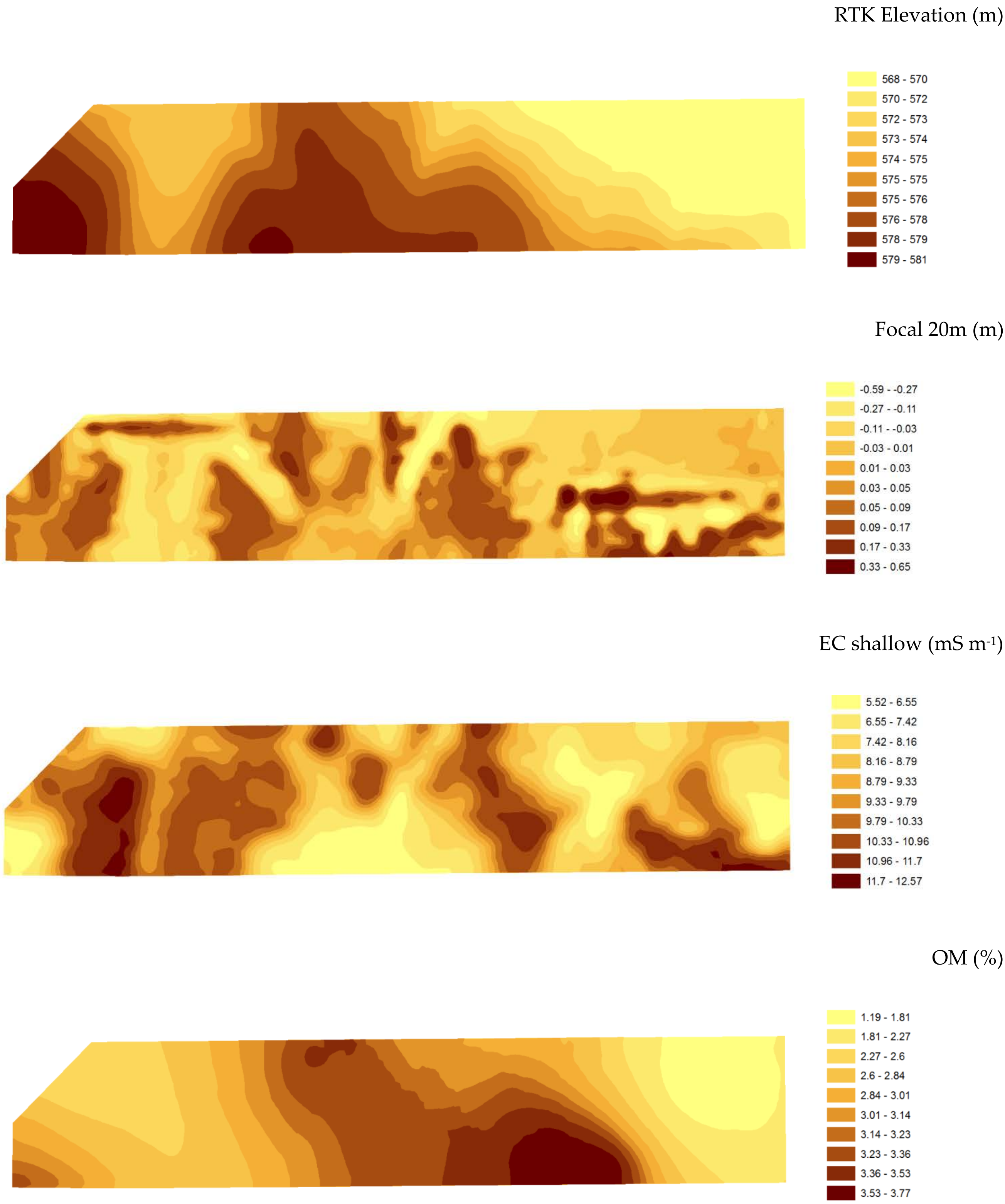

Figure 11. Soil attributes and topographical features for the HU10 field.

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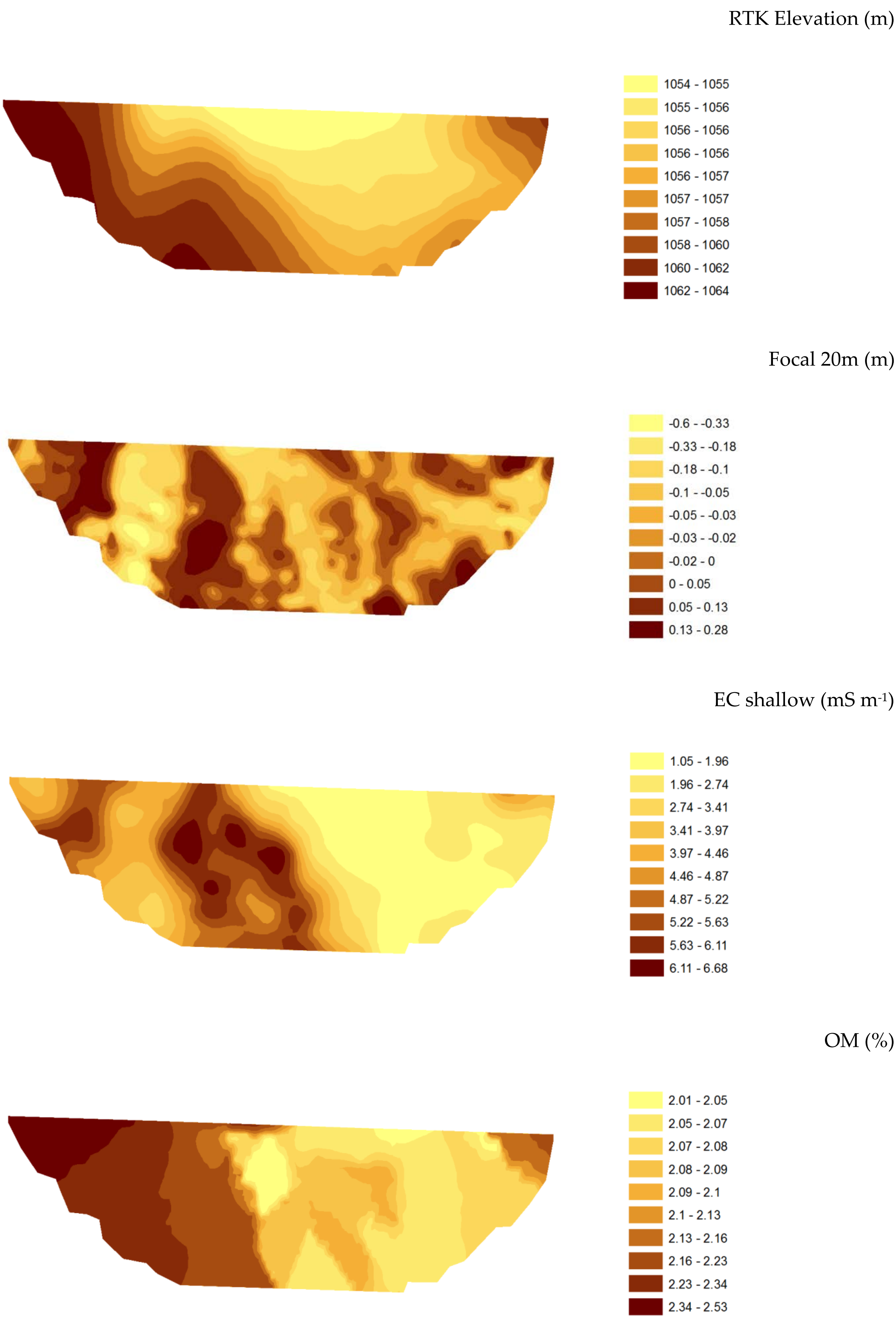

Figure 12. Soil attributes and topographical features for the BL10 field.

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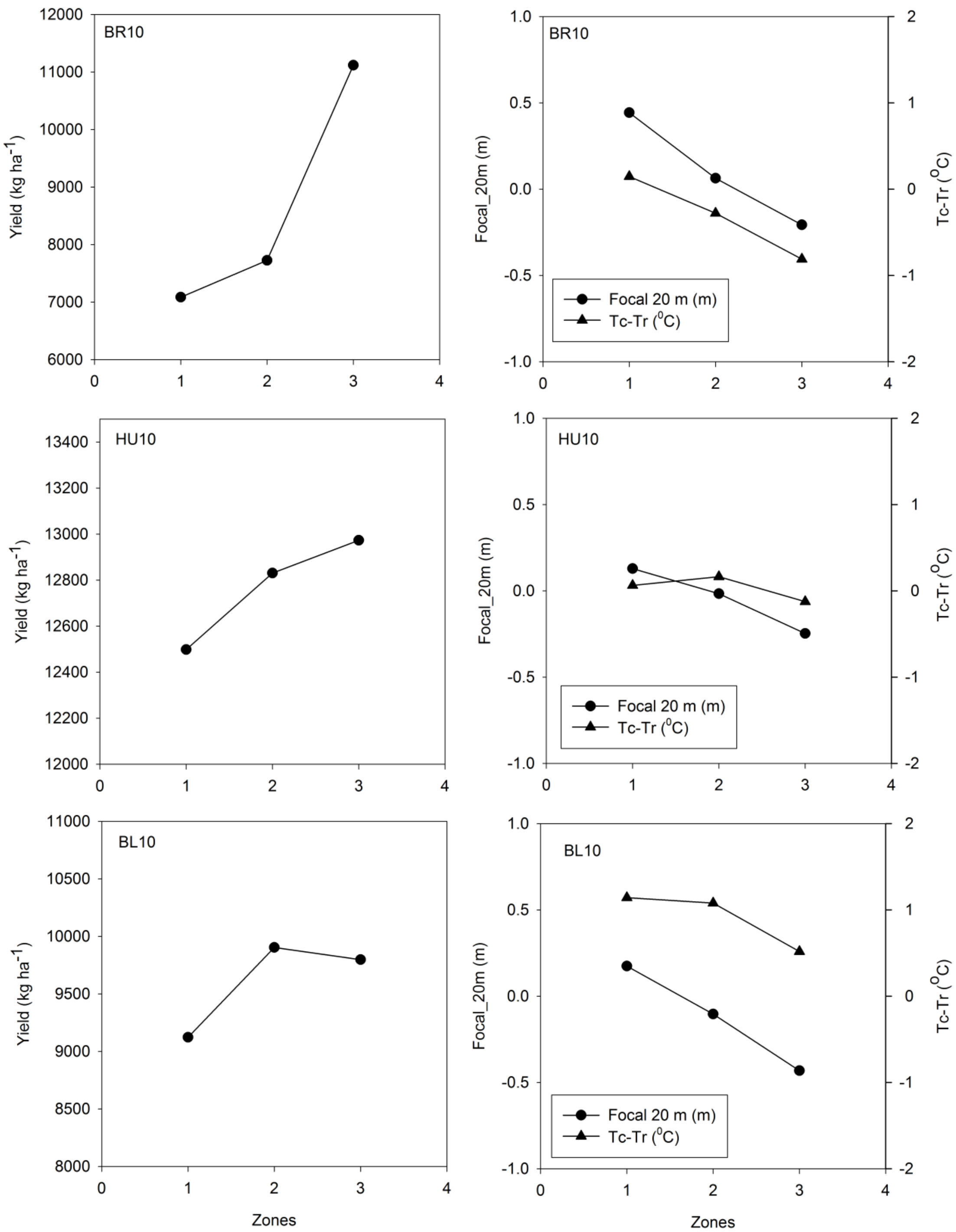

Figure 13. Grain yield, Focal 20 m and Tc-Tr average inside each zone delineated with Focal20m that represents concave and convex areas in the field.

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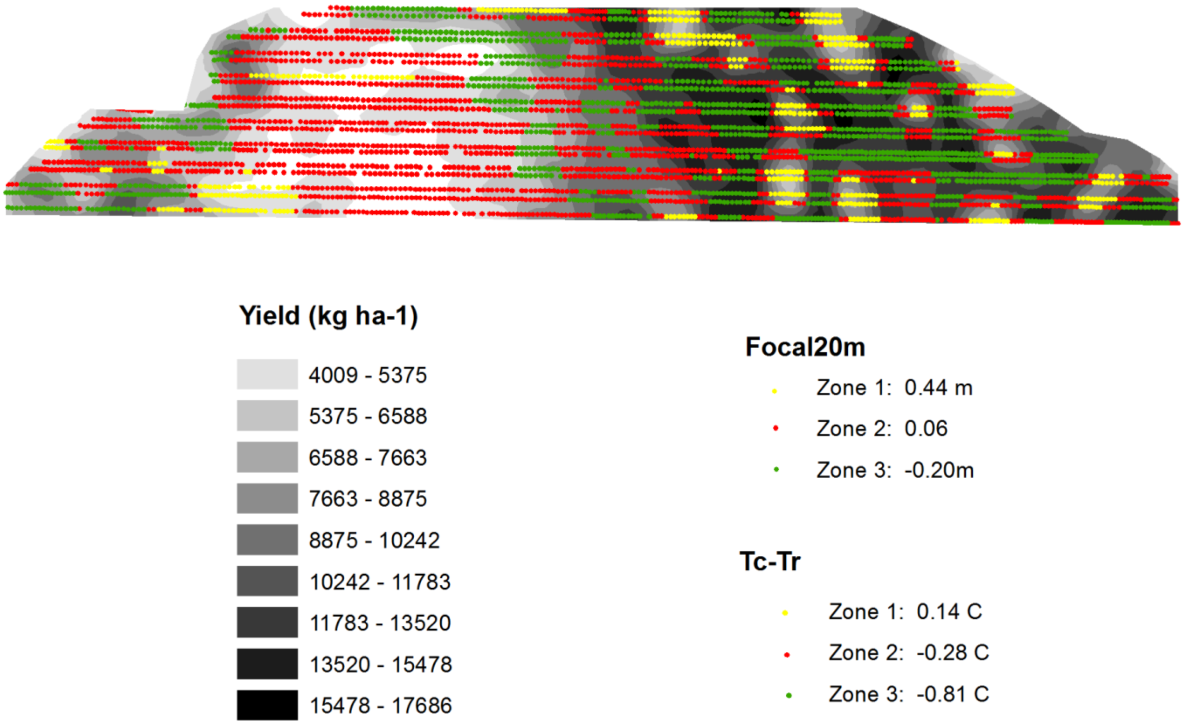

Figure 14. Average of Tc-Tr (ºC) and concave and convex areas in each zone delineated by Focal20m, overlaying yield map (kg ha^{-1}) for the BR10 field.

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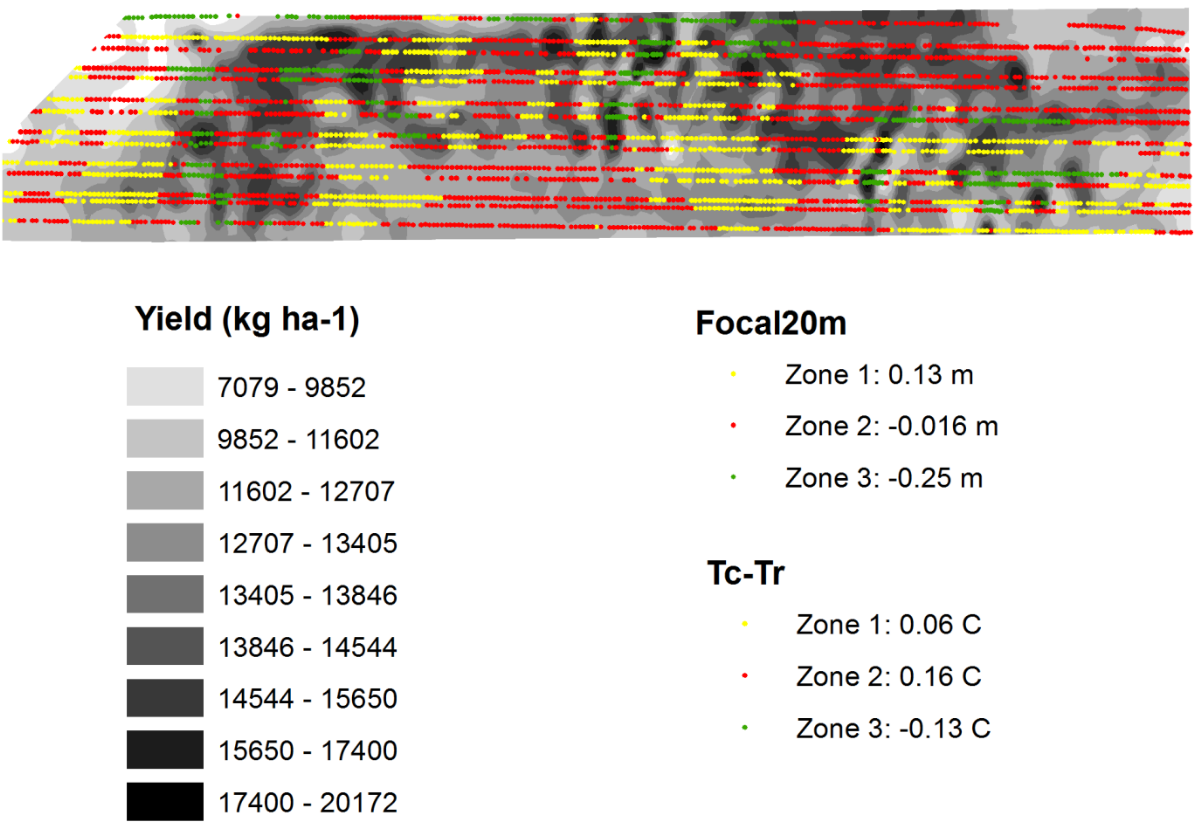

Figure 15. Average of Tc-Tr (ºC) and concave and convex areas in each zone delineated by Focal20m, overlaying yield map (kg ha^{-1}) for the HU10 field.

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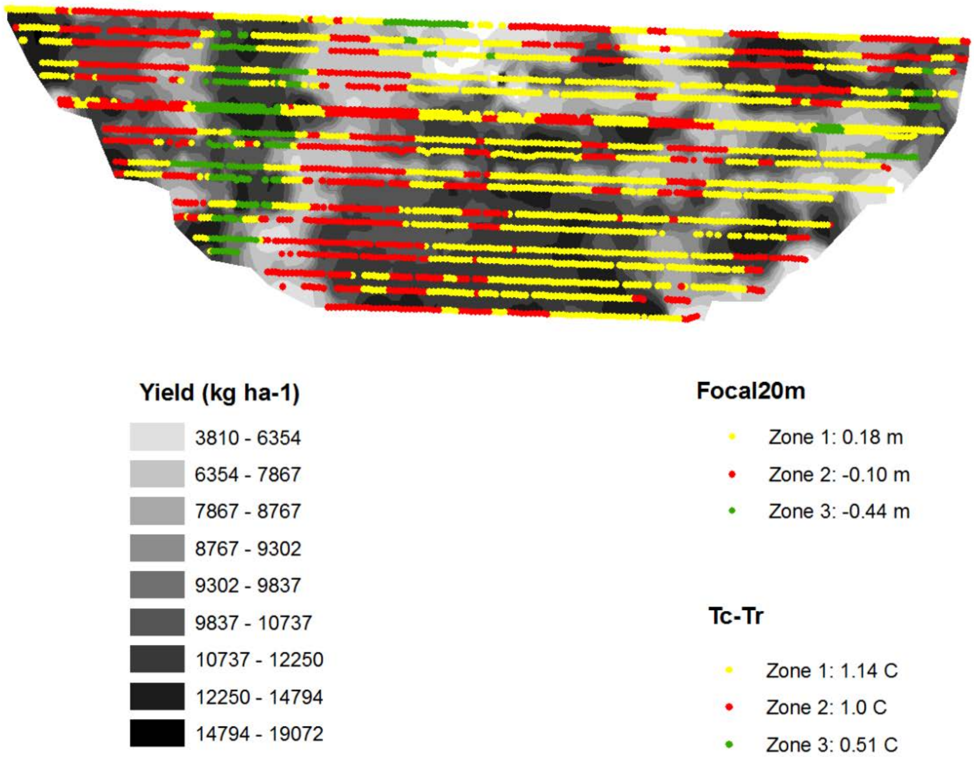

Figure 16. Average of Tc-Tr (ºC) and concave and convex areas in each zone delineated by Focal20m, overlaying yield map (kg ha^{-1}) for the BL10 field.

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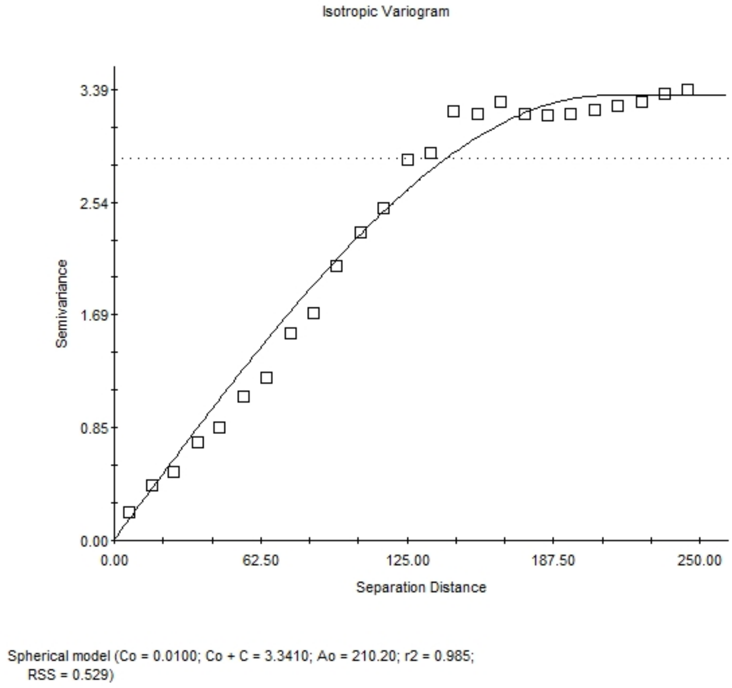


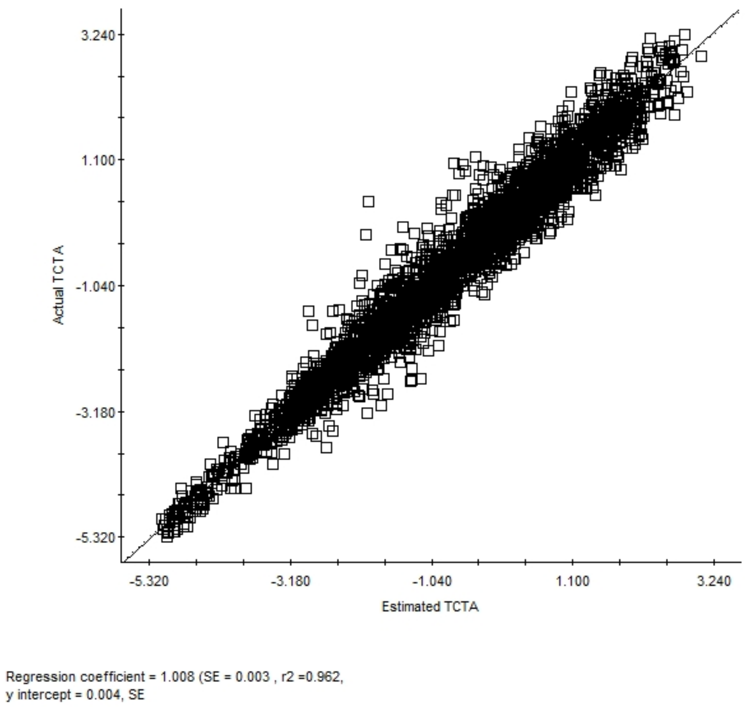
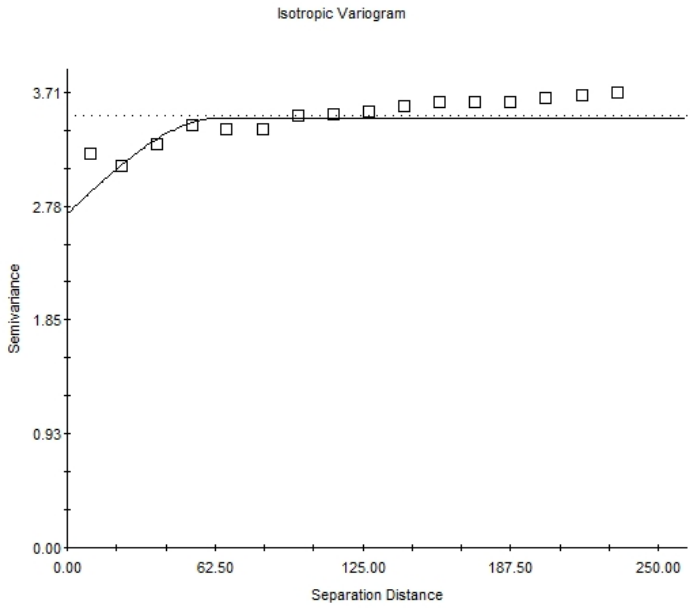
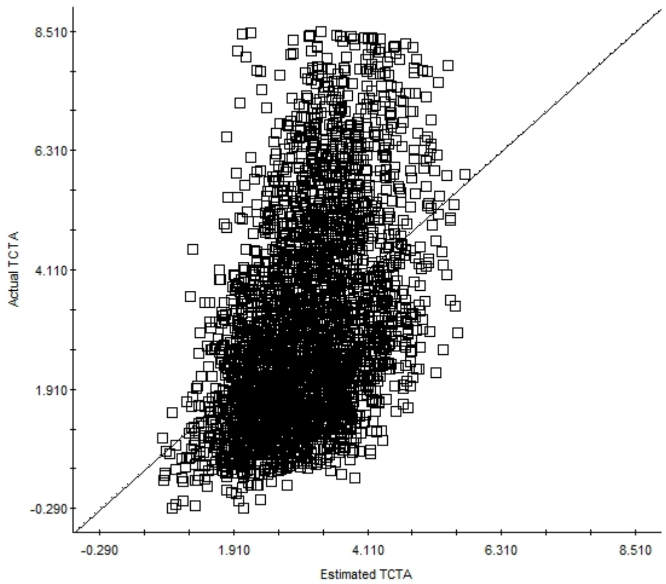


Figure 17. Semivariograms and cross validation for the canopy temperature (Tc-Tr) measured with IRT for the BR10 field.



Spherical model (Co = 2.7180; Co + C = 3.5000; Ao = 65.00; r2 = 0.621; RSS = 0.287)



Regression coefficient = 1.002 (SE = 0.035 , r2 =0.199, y intercept = -0.034, S

Figure 18. Semivariograms and cross validation for the canopy temperature (Tc-Tr) measured with IRT for the HU10 field.

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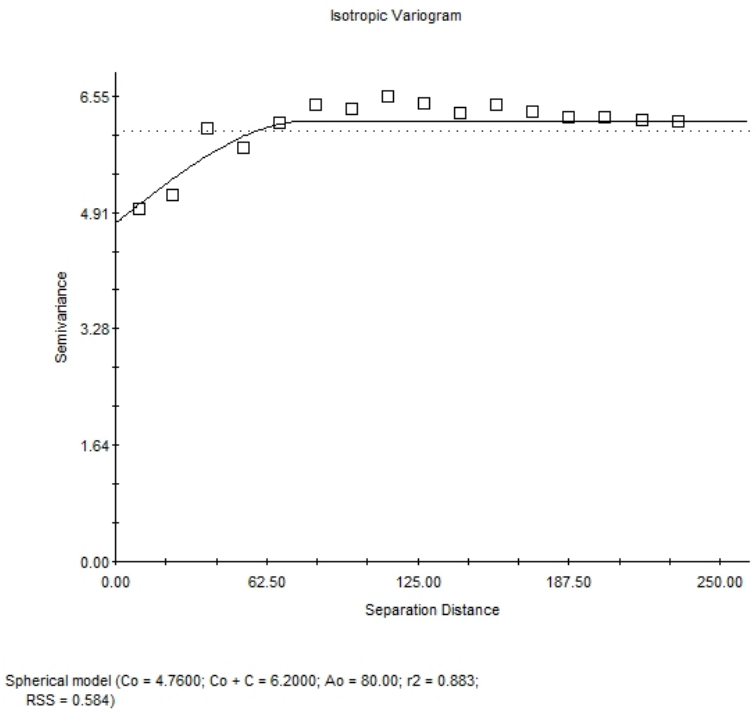

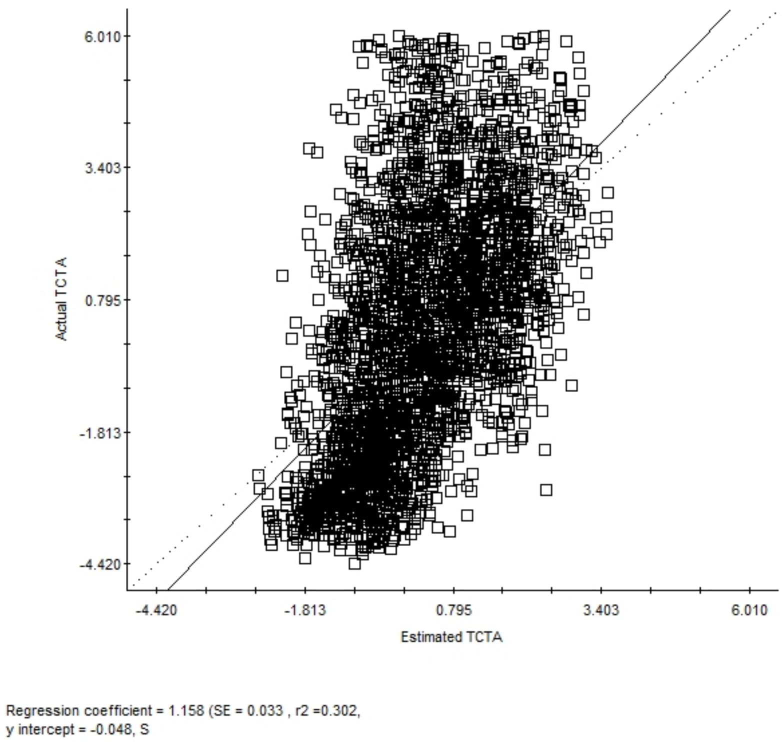

Figure 19. Semivariograms and cross validation for the canopy temperature (Tc-Tr) measured with IRT for the BL10 field.

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Table 1. Analysis of variance calculated for canopy temperature (Tc) minus ambient temperature (Ta) obtained using infrared temperature sensors (IRT) at different irrigation levels (70 and 100 % ET), different previous crop (CC and CS) and nitrogen rates between growth stages R2 and R6.

Source of variation				
Effect	Num DF	Den DF	F Value	Pr > F
Irrigation Level	1	34.9	4.53	0.0404
N	3	174	4.38	0.0053
Irrigation Level*N	3	174	0.29	0.8308
Previous Crop	1	174	3.32	0.0703
Irrigation Level*Previous Crop	1	174	3.19	0.0757
N*Previous Crop	3	174	0.19	0.9047
Irrigation Level*N*Previous Crop	3	174	0.21	0.8869

Table 2. Tc-Ta at different irrigation levels, previous crop (corn after corn – CC and corn after soybeans – CS) and growth stages of corn (R2 to R6).

Tc-Ta (ºC)	**Previous Crop**			
	CC		**CS**	
			Irrigation Levels	
Growth stage	**70% ET**	**100% ET**	**70% ET**	**100% ET**
R2	-0.66a	-0.39a	-1.01a	-1.16a
R3	0.81a	0.68b	0.80a	-0.44b
R4	1.50a	-1.31b	1.50a	-1.68b
R6	1.46a	1.40a	1.75a	1.06b

* Letters in the rows indicate treatment mean differences in canopy temperature between irrigation levels (70 and 100% ET) inside the same previous crop, either CC or CS, using Duncan Multiple Range Test ($p<0.05$).

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Table 3. Treatment mean differences for Tc-Ta measured at different N rates across growth stages, irrigation levels and previous crops. Duncan Multiple Range Test (*p<0.05*).

Differences of TRT Least Squares Means						
N	N	Estimate	Standard Error	DF	t Value	Pr > |t|
0	**75**	0.6301	0.3027	32	2.08	0.0454
0	**150**	0.9773	0.3027	32	3.23	0.0029
0	**225**	0.9025	0.3027	32	2.98	0.0054
75	**150**	0.3472	0.3027	32	1.15	0.2599
75	**225**	0.2724	0.3027	32	0.9	0.3749
150	**225**	-0.07476	0.3027	32	-0.25	0.8065

Table 4. Soil matric potential measured with soil moisture sensors installed at high and low areas delineated from elevation inside the N-rich strip in each of the producer's field in the day of sensing.

Location	**Depth (cm)**	**Soil Matric Potential (cB)**		
High		BR10	HU10	BL10
	30	15	61	15
	60	12	50	20
	92	10	43	23
Low				
	30	15	13	18
	60	3	8	32
	92	3	4	30

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Table 5. Zonal average for the points inside each non water stressed (NonS) and water stressed (S) zones delineated for each producer field.

Variable	BR10		HU10		BL10	
	NonS	S	NonS	S	NonS	S
Yield (kg ha^{-1})	11915*	10850*	13089*	12476*	9883	9838
NSI	1.16	1.11	0.99	0.96	1.01	0.98
HIS	1.15	1.13	0.98	0.95	1.00	0.98
Tc-Tr (ºC)	-1.70*	0.80*	-0.82*	0.90*	-1.39*	2.47*
Tc-Ta (ºC)	-1.96*	0.54*	2.16*	3.83*	-1.80*	1.74*
pH	6.50	6.53	7.23	7.14	7.11	7.24
P (mg kg^{-1})	15.99	16.83	16.31	17.34	17.48	16.93
NO3 (µg g^{-1})	5.26	6.21	1.87	1.86	1.88	1.89
OM (g kg^{-1})	1.83	1.51	2.88	2.85	2.16	2.15
RTK (m)	523.38	523.84	573.76	574.51	1057.63	1057.39
Ecsh (mS m^{-1})	1.22	1.05	8.83	8.99	3.84	3.66
Focal (m)	-0.05*	0.02*	-0.02*	0.01*	-0.03	-0.02

* Pairwise comparisons between NonS and S zones in the field using Tukey-test significant at $p < 0.05$

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Table 6. Descriptive statistics for the variables measured in the BR10 field

Variable	N	Mean	Std Dev	Median	Minimum	Maximum
NSI	1448	1.17	0.10	1.19	0.95	1.42
HSI	1448	1.18	0.12	1.17	0.95	1.54
Tc-Tr	1448	-1.01	1.37	-1.18	-3.71	2.51
Yield	1448	11861	2155	12111	6400	17686
OM	1448	1.74	0.29	1.83	0.88	2.38
RTK_elevation	1448	523.49	0.36	523.49	522.65	524.91
EC_shallow	1448	1.18	0.37	1.14	0.46	2.01
Focal 20 m	1448	-0.05	0.21	-0.07	-0.57	0.73
P	1448	16.25	1.46	15.96	13.47	20.18
pH	1448	6.51	0.04	6.49	6.45	6.61
NO_3	1448	5.48	2.50	5.80	1.68	9.80

Table 7. Spearman rank correlations between variables for the BR10 field

Spearman Correlation Coefficients, N = 1448

Prob > |r| under H0: Rho=0

	NSI	HIS	Tc-Tr	Yield	OM	RTK_elev	EC_sh	Focal20m	P	pH	NO_3
NSI	1.000	0.478	-0.188	0.610	0.243	-0.411	0.356	-0.435	-0.177	-0.145	-0.133
HSI	0.478	1.000	-0.002*	0.294	0.000*	-0.141	0.087	-0.297	-0.103	-0.005*	-0.009*
Tc-Tr	-0.188	-0.002*	1.000	-0.138	-0.373	0.505	-0.066	0.053	0.044*	0.255	0.209
Yield	0.610	0.294	-0.138	1.000	0.249	-0.587	0.495	-0.579	-0.212	-0.174	-0.207
OM	0.243	0.000*	-0.373	0.249	1.000	-0.357	0.531	-0.011*	-0.261	-0.147	-0.190
RTK_elev	-0.411	-0.141	0.505	-0.587	-0.357	1.000	-0.528	0.616	0.209	0.226	0.217
EC_sh	0.356	0.087	-0.066	0.495	0.531	-0.528	1.000	-0.171	-0.212	-0.268	-0.315
Focal20m	-0.435	-0.297	0.053	-0.579	-0.011*	0.616	-0.171	1.000	0.153	-0.016*	-0.077
P	-0.177	-0.103	0.044*	-0.212	-0.261	0.209	-0.212	0.153	1.000	-0.307	-0.337
pH	-0.145	-0.005*	0.255	-0.174	-0.147	0.226	-0.268	-0.016*	-0.307	1.000	0.850
NO_3	-0.133	-0.009*	0.209	-0.207	-0.190	0.217	-0.315	-0.077	-0.337	0.850	1.000

* Correlations were not significant at $p < 0.05$

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Table 8. Descriptive statistics for the variables measured in the HU10 field

Variable	N	Mean	Std Dev	Median	Minimum	Maximum
NSI	1461	0.97	0.01	0.97	0.95	1.00
HIS	1461	0.81	0.04	0.80	0.75	1.00
Tc-Tr	1461	2.80	1.61	2.40	0.00	8.63
Yield	1461	13234	1572	13321	3012	20172
OM	1461	2.97	0.49	3.09	1.31	3.77
RTK_elevation	1461	574.07	3.37	574.18	568.22	580.88
EC_shallow	1461	8.75	1.62	8.82	5.52	12.16
Focal20m	1461	-0.01	0.14	0.01	-0.59	0.65
P	1461	20.51	3.32	19.90	14.99	26.54
pH	1461	5.95	0.12	5.91	5.81	6.43
NO_3	1461	17.58	1.36	17.33	14.78	20.43

Table 9. Spearman rank correlations between variables for the HU10 field

Spearman Correlation Coefficients, N = 1461											
Prob > |r| under H0: Rho=0											
	NSI	**HSI**	**Tc-Tr**	**Yield**	**OM**	**RTK_elev**	**EC_sh**	**Focal20m**	**P**	**pH**	**NO_3**
NSI	1.000	0.118	-0.341	0.042*	0.041*	0.013*	-0.054	0.003*	0.101	0.080	0.009*
HSI	0.118	1.000	-0.198	0.099	-0.236	-0.304	-0.070	-0.159	0.007*	-0.053	0.043*
Tc-Tr	-0.341	-0.198	1.000	0.000*	0.127	0.142	0.082	0.043*	-0.048*	-0.052	-0.013*
Yield	0.042*	0.099	0.000*	1.000	-0.118	-0.295	0.153	-0.230	0.052	0.005*	-0.024*
OM	0.041*	-0.236	0.127	-0.118	1.000	0.469	-0.093	0.246	-0.114	0.046*	-0.013*
RTK_elev	0.013*	-0.304	0.142	-0.295	0.469	1.000	0.087	0.410	-0.060	0.066	-0.039*
EC_sh	-0.054	-0.070	0.082	0.153	-0.093	0.087	1.000	0.034*	0.013*	0.010*	-0.038*
Focal20m	0.003*	-0.159	0.043*	-0.230	0.246	0.410	0.034*	1.000	0.031*	0.009*	0.006*
P	0.101	0.007*	-0.048*	0.052	-0.114	-0.060	0.013*	0.031*	1.000	0.665	-0.571
pH	0.080	-0.053	-0.052	0.005*	0.046*	0.066	0.010*	0.009*	0.665	1.000	-0.482
NO_3	0.009*	0.043*	-0.013*	-0.024*	-0.013*	-0.039*	-0.038*	0.006*	-0.571	-0.482	1.000

* Correlations were not significant at $p < 0.05$

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Table 10. Descriptive statistics for the variables measured in the BL10 field

Variable	N	Mean	Std Dev	Median	Minimum	Maximum
NSI	1570	1.03776	0.04506	1.0365	0.95007	1.18475
HSI	1570	1.03542	0.05714	1.02633	0.9502	1.2558
Tc-Tr	1570	0.38879	2.34457	-0.13	-3.805	8.14
Yield	1570	10242	2105	10448	62.3354	16852
OM	1570	2.15452	0.10902	2.09146	2.01096	2.53076
RTK_elevation	1570	1058	2.5039	1057	1054	1064
EC_shallow	1570	3.89199	1.52492	4.16693	1.0496	6.67878
Focal20m	1570	-0.02584	0.11194	-0.02643	-0.60461	0.27698
P	1570	16.68864	4.42243	15.86671	10.24663	27.39797
pH	1570	7.19001	0.18274	7.1985	6.80091	7.50846
NO_3	1570	1.88149	0.4291	1.72011	0.80253	3.05766

Table 11. Spearman rank correlations between variables for the BL10 field

Spearman Correlation Coefficients, N = 1570											
Prob > |r| under H0: Rho=0											
	NSI	HSI	Tc-Tr	Yield	OM	RTK_elev	EC_sh	Focal20m	P	pH	NO_3
NSI	1.000	0.246	-0.124	0.128	-0.088	-0.033*	-0.086	-0.086	-0.019*	0.188	0.041*
HSI	0.246	1.000	-0.133	0.118	0.191	0.168	0.214	-0.025*	0.012*	-0.034*	0.006*
Tc-Tr	-0.124	-0.133	1.000	0.147	-0.082	0.030*	0.096	0.104	-0.361	-0.266	-0.359
Yield	0.128	0.118	0.147	1.000	0.109	0.222	0.208	-0.011*	-0.264	0.047*	-0.135
OM	-0.088	0.191	-0.082	0.109	1.000	0.701	0.408	0.292	-0.100	-0.077	0.143
RTK_elev	-0.033*	0.168	0.030*	0.222	0.701	1.000	0.562	0.438	-0.307	0.114	0.005*
EC_sh	-0.086	0.214	0.096	0.208	0.408	0.562	1.000	0.322	-0.122	-0.006*	-0.113
Focal20m	-0.086	-0.025*	0.104	-0.011*	0.292	0.438	0.322	1.000	-0.078	-0.032*	0.097
P	-0.019*	0.012*	-0.361	-0.264	-0.100	-0.307	-0.122	-0.078	1.000	0.035*	0.354
pH	0.188	-0.034*	-0.266	0.047*	-0.077	0.114	-0.006	-0.032*	0.035*	1.000	0.178
NO_3	0.041*	0.006*	-0.359	-0.135	0.143	0.005*	-0.113	0.097	0.354	0.178	1.000

* Correlations were not significant at $p < 0.05$