

BEN-GURION UNIVERSITY OF THE NEGEV
FACULTY OF ENGINEERING SCIENCES
DEPARTMENT OF INDUSTRIAL ENGINEERING AND MANAGEMENT

EARLY ABIOTIC STRESS DETECTION OF CORN AND SUNFLOWER PLANTS USING SPECTRAL DATA

THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE
M.Sc DEGREE

By: Shahar Gad Shriki

February, 2020

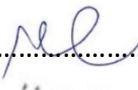
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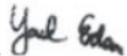
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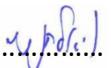
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Abstract

High throughput phenotyping assesses plant status and traits based on advanced nondestructive sensing technologies. Amongst its most important tasks is abiotic stress detection. The present thesis focused on the detection of plants' abiotic stress using leaves spectral reflectance in the visible (VIS), near infrared (NIR) and short-wave infrared (SWIR) region. Two crops were studied, corn and sunflower. Two types of models were developed, binary classification models to discern between healthy and stressed plants and regression models to predict the plants' stress severity.

Abiotic stress was induced to 70 corn plants and 70 sunflower plants that were grown in a controlled environment greenhouse by spraying herbicides that interfered with different plant processes. Plants' leaves spectral reflectance was measured using a spectro-radiometer in the range of 350nm – 2500nm, with an optical spectral resolution of 3nm in the NIR range and 8nm in the SWIR range. The spectral measurements were conducted at six time-points along a 30-day growing period. An expert agronomist visually evaluated eleven phenotypes at the same six time-points and graded each phenotype on a scale between 1-6. For each plant, its phenotypic status (plant under stress or not) and the average value of the 11 phenotypes were calculated (stress severity). The spectral measurements were repeated for two consecutive years (2018 and 2019). Classification and regression models were trained and cross validated on the data acquired in 2018 and validated with the data acquired in 2019.

Binary classification models included logistic regression at one and seven wavelengths, logistic regression using PCA, PLS-DA, random forest and XGBoost. All models were constructed using the 1st derivative of the spectra. The plant's stress severity was predicted using the following models - linear regression with one and seven wavelengths, linear regression on PCA, PLS, random forest and XGBoost models.

Best results were obtained by the random forest algorithm with 88% and 92.5% F1 scores for classification, and regression RMSE of 0.221 and 0.190 for corn and sunflower respectively. These models yielded a F1 score of 79.9% and RMSE of 0.243 on the corn validation data. Linear regression and logistic regression models yielded similar performances using the 1st derivative of the spectra at 7 wavelengths: F1 score 79.9% and 94.7% for classification, and regression RMSE of 0.249 and 0.222 for corn and sunflower respectively. Corn validation results yielded 76.4% F1 score and 0.269 RMSE.

Early prediction models were developed for intervals between 2 and 7 days before appearance for the regression task, and only 2 days before appearance for the classification task. For "two days before" the prediction by the random forest classification yielded a F1 score of 72.9% for corn plants and 85% for sunflower plants. For "Seven days before", the prediction by the random forest regression yielded a RMSE of 0.331 and 0.413 for corn and sunflower plants respectively.

The most important wavelengths were identified and their performance was tested. The best performance was obtained when the 1st derivative of the spectra at the following wavelengths was employed 550nm, 718nm, 734nm, 558nm, 430nm, 702nm, 790nm. 550nm and 734nm. Although the phenotypes were visible to the observer's eye, the results revealed that information from non-visual spectra (above 700nm) is very relevant for abiotic stress detection.

Keywords: Abiotic stress, Phenotyping, Linear regression, Logistic regression, PCA, PLS, PLS-DA, Machine learning, Random forest, XGBoost, Corn, Sunflower, Precision agriculture, Spectroscopy, NIR, SWIR, VIS

Publications

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Classification and regression models for abiotic stress detection of corn and sunflower plants using spectral data.

Conference papers and presentations

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1. INTRODUCTION

1.1. DESCRIPTION OF THE PROBLEM

Current production rates will not satisfy the demands of the world's population by 2050 (An et al., 2016). Abiotic stress is the main cause of crop loss with more than 50% reduction in crop plants worldwide. A future shortage of fresh water could increase intensity of abiotic stresses. Therefore, development of abiotic stress resistant plants is essential to ensure food security and safety in coming years. A major effort in developing abiotic stress resistant cultivars, is stress detection (Gull et al. 2019).

Stress reduces plant growth, performance and fitness, which expressed in plant phenotypes (Sultan E. Sonia 2000). The phenotype is an outcome of complex synergistic developmental systems, influenced by multiple interacting genes and external environments. Phenotypes research seek to understand the mapping from the genotype, the phenotype and the environment to some plant performance, such as yield or disease resistance (Narvaez et al. 2017a).

The standard breeding approach is to apply large-scale experiments, to create new plant varieties. The number of plants that a specialist can evaluate in each growing cycle is limited since it is labor intensive and costly (Bai et al. 2016). This approach requires also specialized training and is hindered by subjectivity resulting from inter-cognitive variability (Ghosal et al. 2018). Automated data collection has the potential to alleviate this bottleneck, increasing the quantity and quality of phenotyping and environmental measurements collected throughout the growing cycle, hence accelerating the overall breeding process (Narvaez et al. 2017a). Many developments focused on automated phenotyping platforms (Bao et al. 2014; Sankaran et al. 2015).

Abiotic stress detection has been exploited by spectral data (Gutiérrez et al. 2016), RGB images (Ghosal et al. 2018), multispectral images (Zaman-Allah et al. 2015) and hyperspectral images (Nansen et al. 2010). Most studies focused on one plant and one abiotic stress. This study aims to develop stress detection models using spectral data, which could be used for several plant species and spectral sensors.

1.2. OBJECTIVES

The purpose of this current study was to develop abiotic stress detection models based on spectral data. Two types of models were developed for corn and sunflower plants:

1. Binary classification models to classify if the plant is under stress or not.
2. Regression models to predict the plant's stress severity.

These models were developed for different prediction sample times and points (leaves). The most important wavelengths were derived.

2. LITERATURE REVIEW

2.1. OVERVIEW

Current production rates will not satisfy the demands of the world's population by 2050 (An et al., 2016). Precision agriculture has been used to improve crop productivity and farm profitability, through improved management of agricultural inputs to deal with this challenge (Mulla 2013).

To facilitate plant growth efforts to increase crop production, genes which are responsible for beneficial traits should be identified (Lu et al. 2017). New plant breeding approaches for the selection of favorable genotypes are required to secure global food supply and cope with climate change (Paulus, et al. 2014).

The use of genomic data must be combined with high quality phenotypic data to fulfill its full potential (Bai et al. 2016). Phenotypes refer to the set of visible traits of a plant emanating from its genetic properties and interaction with the environment. In order to study the relation between the genotype and the environment and create a "genotype-phenotype" map, a "key goal of biology", the phenotypic data must be acquired in detail (Houle et al. 2010).

This section reviews the relevant literature related to precision agriculture (section 2.2.) and stress among plants (section 2.4). Current studies of stress detection (section 2.7) followed by an overview of phenotyping research (section 2.3) follows.

2.2. PRECISION AGRICULTURE

Precision agriculture promotes variable management practices within a field, according to site conditions (Seelan et al. 2003). It is defined as "a management strategy that uses information technologies to bring data from many sources for decision-making related to crop production" (National Research Council, 1997). Precision agriculture deals with better management of agricultural inputs by implementing the right management in the right place and at the right time (Mulla 2013). Whereas large farm fields under conventional management receive uniform applications of fertilizers, irrigation, etc., with precision agriculture, these fields are divided into management zones that receive customized management inputs based on varying soil types, landscape position and management history. In this method, the treatment unit varies according to the characteristics of the phenomenon in space with agro-technical decisions made individually for each unit. By improving the management of inputs, crop productivity and farm profitability are increased (Zhang et al. 2002), thereby contributing to the preservation of the environment.

2.3. PHENOTYPING

Gathering phenotypes is usually referred to as phenotyping (Fiorani and Schurr 2013; Lin 2015). Measuring and evaluating these traits over time (phenotyping) is required for improving selection efficiency in plant breeding and field management. It is also applied to predict yield potential of different genotypes and to investigate their stress tolerance or disease resistance in various conditions (Mack et al. 2017). Phenotyping is currently considered the major operational bottleneck of genetic analysis.

Since phenotypes are often the most powerful predictors of important outcomes, such as fitness, disease and mortality (Houle et al. 2010), there is a high demand for efficient phenotyping techniques in many domains. Population mapping and generations of diversity panels for plant breeding, requires high-throughput genotyping (An et al. 2016). Therefore, high-throughput phenotyping is needed. High-throughput phenotyping is defined as a collection of large datasets of plant samples in order to accurately derive their common structural and physiological features (Lin 2015).

To evaluate the status of crops and plants, agronomists measure different morphology and physical features which have been classified into three categories (Guo et al. 2017):

1. Morphological traits indicating the shape feature of target plant region, such as circumference and eccentricity.
2. Color traits generated from color images, including the pixel value information of R (red), G (green), and B (blue) components.
3. NIR traits, the pixel intensity information of different ranges in NIR images.

There are three main applications for agricultural phenotyping for evaluating the vegetation conditions (Narvaez et al. 2017a):

1. Structural characterization- the estimation of parameters such as canopy volume, plant height, leaf area coverage, biomass, among others, leads to take decisions in order to enhance the agricultural process.
2. Plant/Fruit detection- to achieve this goal, several features of plants and fruits have been used, namely, color, shape, and temperature.
3. Physiology assessment- the physical response of the canopy to sunlight results in characteristic spectral signatures, which provide insights about the physiological status of the plant.

The most popular research phenotypes are plant height, leaf area index/ leaf area/ projected leaf area, stem height/ stem length/stalk count/ stalk width and NDVI/NDVI-spec/red-edge NDVI (Table 1). Several studies focus on evaluating different technologies for phenotyping, such as checking platforms and sensors required to measure features (e.g., Sankaran et al. 2015; Bao et al. 2014)

2.4. STRESS

Stress in plants refers to external conditions adversely affecting growth, development or productivity of plants (Kosová et al. 2011). Plants responses caused by stress can be expressed by gene, cellular metabolism, growth rates and crop yields. Plant stress response is a dynamic process that depends on stress intensity and stress duration (Larcher et al. 2003). There are several stages of plant stress response:

- Initial alarm- when stress causes a shock to a non-acclimated plant and the level of plant stress tolerance decreases.
- Acclimation- establishment of a new homeostasis in plant metabolism under stress. The level of plant stress tolerance increases.
- Maintenance- the newly established homeostasis is maintained under stress conditions. The level of plant stress tolerance remains stable.

- Exhaustion- the plant fails to maintain a stress-induced homeostasis. The level of plant stress tolerance declines. This stage could lead to death. A recovery phase could be observed when a re-establishment of a cellular homeostasis under non-stressed conditions occurs (Kosová et al. 2011).

There are two primary types of stress, abiotic stress and biotic stress.

- Abiotic stress could be physical or chemical. It is caused by environment conditions such as drought caused water stress, excessive watering, extreme temperatures (cold, frost and heat), salinity and mineral toxicity.
- Biotic stress in plants is caused by living organisms such as viruses, bacteria, fungi, nematodes, insects, arachnids and weeds.

Abiotic stress is the main cause of crop loss leading to more than 50% reduction in crop plants worldwide. It can lead to metabolic dysfunction, and if severe, to plants death. A future shortage of fresh water could increase intensity of abiotic stresses. Therefore, development of abiotic stress resistant plants is essential to ensure food security and safety in coming years (Gull et al. 2019).

2.5. HERBICIDES

In this research, herbicides were applied to cause abiotic stress in the plants. Herbicides are chemicals which adversely affect plant growth and development. They are usually used for elimination of weeds (unwanted plants) (Kosová et al. 2011).

Different abiotic stresses have been analyzed such as the proteome change, effects of flumioxazin (herbicide) on grapevine proteome (Castro et al. 2005) and proteome changes of *Triticum tauschii* induced by herbicide (Zhang and Riechers 2004).

There are two types of herbicides: selective and non-selective. Selective herbicides control specific weed species, while leaving the desired crop relatively unharmed. Non-selective herbicides, kill all plant material with which they come into contact. Non-selective herbicides can be used to clear waste ground, industrial and construction sites and railways. In this research we used both types of herbicides to create abiotic stress in corn and sunflower plants.

2.6. MODE OF ACTION (MOA)

Herbicides attack plants differently. The mode-of-action (MOA) is the way which an herbicide affects a plant at the tissue or cellular level. Herbicides with the same mode-of- action will have the same injury pattern and symptoms on the plants.

Plants are complex organisms with integrated sequences vital processes. Photosynthesis, amino acid and protein synthesis, fat (lipid) synthesis, pigment synthesis, growth and differentiation are some of vital metabolic plant processes(Ross et al. 1914).

In this research, three MOAs were examined:

1. Lipid metabolism inhibitors- causes discoloration and disintegration of tissue. The leaves become yellow, redder and will sometimes wilt.
2. Photosynthesis inhibitors: symptoms develop from bottom to top on plants (older leaves show the most injury). Chlorosis first appears between leaf veins and along the margins, which is later followed by necrosis of the tissue.
3. Amino acid metabolism inhibitors- symptoms include yellowing of new growth and the death of treated plants rapidly.

2.7. SENSING

In this research we focused on remote sensing and non-destructive measurements to detect abiotic stress. Remote sensing is the process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance (Campbell et al. 2011). Since stress can cause modifications in tissue color, leaf shape, transpiration rate, canopy morphology and plant density, as well as variation in the interaction of solar radiation with plants (West et al. 2003), this can be measured. There are two types of remote sensing sensors (Figure 1): **Passive**- sensors that measure reflected sunlight emitted from the sun. **Active**- sensors that measure reflected light emitted from external illumination source.

When electromagnetic radiation hits an object, some of it is absorbed by the object, some of it is reflected and some goes through the object (van der Meer 2004).

Absorption radiation is the radiation that stays in the object. The absorption radiation is usually transformed into heat energy. Each substance is responsible for absorption at a different wavelength.

Reflectance is defined as the ratio between the returned radiation by that surface and the radiation received to the surface (Equation 1). The ratio is influenced by the chemical characteristics of the object, the micro topographical surface of the object and the incident's angle of the light source.

The transmittance is defined as the amount of energy that goes through an object. Each object transmittance is depending on the object physical and chemical characteristics.

Equation 1: Reflectance formula.

$$\text{Reflectance} = \frac{\phi_{out}}{\phi_{in}}$$

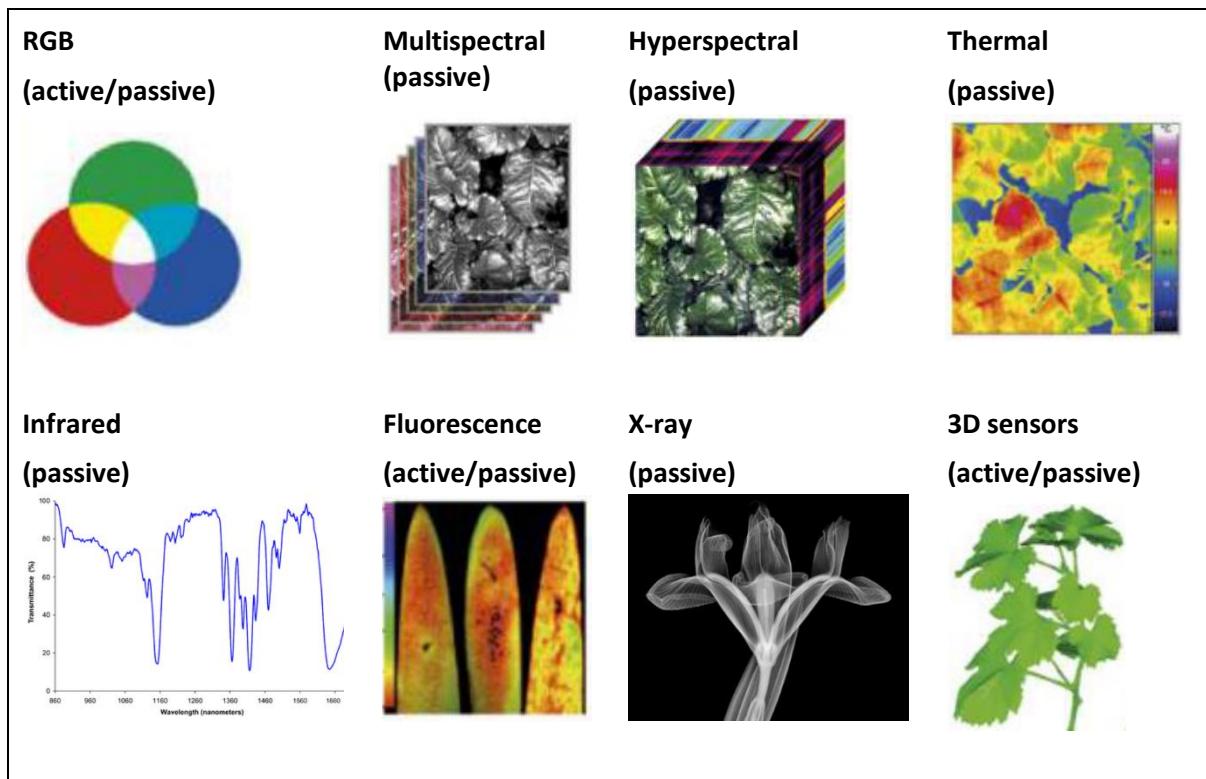


Figure 1: Stress detection sensors

A survey of ranging and Imaging techniques for precision agriculture phenotyping (Narvaez et al. 2017b) differentiated sensors into two main categories: sensing for detection and morphological features and sensing for physiological assessment. The first category consists a range of sensors: ultrasound, time-of-flight (ToF) cameras and light detection and ranging (LiDAR), as well as artificial vision sensors: structured light cameras, color cameras, RGBD and stereo vision cameras. The second category consists the following sensors: thermal cameras, multispectral and hyperspectral cameras and spectroscopy sensors. The most popular sensors in phenotyping research were color cameras and spectroscopy sensors (Table 1).

In this research we used a spectro-radiometer. The wavelength measurements range starts from the visible light to the infrared radiation (IR), as can be seen in (Figure 2).

Table 1: Popular research phenotypes and sensors

Phenotype	Sensor	Sensor category	Reference	Environment
Plant height	Camera, Kinect-v2, Microsoft	TOF	(Jiang et al. 2016)	lab
	Camera, PMD Cam board nano	TOF	(Li and Tang 2017)	
	2D web-cameras, Logitech HD Webcam C310	Color camera	(Li and Tang 2017)	
	Perceptron Scan, Works V5	LIDAR	(Paulus, Schumann, et al. 2014)	
	Digital single-lens reflex cameras, EOS Rebel T3, Canon Inc	Stereo vision	(Nguyen et al. 2015)	
	2D laser scanners, RPLIDAR (RoboPeak LIDAR)	LIDAR	(Paulus et al. 2014)	
	Camera, SR_4000, MESA Imaging	TOF	(Chaiivatrakul et al. 2014)	
	Camera, Kinect-v2, Microsoft	TOF	(Yang et al. 2017)	
	RGB camera	Color camera	(Yang et al. 2017)	
	Sonic ranging, TS14	Ultrasound	(Enciso et al. 2017)v	field
	Sonic ranging, SR50A	Ultrasound	(Enciso et al. 2017)	
	Sonic ranging, MB7092	Ultrasound	(Enciso et al. 2017)	
	Ultrasonic sensor, ToughSonic30, Senix Corporation, Hinesburg, Vermont	Ultrasound	(Bai et al. 2016)	
	Ultrasonic sensor, Banner U-GAGE Q45U	Ultrasound	(Barker et al. 2016)	
	manually using an electronic bar code scanner with a coded measurement stick		(Thorp et al. 2015)	
	Digital single-lens reflex camera, Canon 500D	Color camera	(Jay et al. 2015)	
	Digital CCD camera, Teledyne Dalsa Genie C1024	Color camera	(Jay et al. 2015)	
	2 RGB cameras, Grasshopper3 by PointGray	Stereo vision	(Shafiekhani et al. 2017)	
	IR (thermal) camera, Flir A625	Spectroscopy	(Shafiekhani et al. 2017)	
	RGB trinocular camera, BumbleBee XB3 by PtGray	Color camera	(Shafiekhani et al. 2017)	
	Multispectral camera, Sentek GEMS	Multispectral	(Neely et al. 2016)	
	RGB camera, DJI P3-005 4K	Color camera	(Neely et al. 2016)	

Phenotype	Sensor	Sensor category	Reference	Environment
	Camera, Kinect-v2, Microsoft	TOF	(Jiang et al. 2017)	
	Hyperspectral camera, MRC-923-001, Middleton Spectral Vision	Hyperspectral	(Jiang et al. 2017)	
	3D NIR laser triangulation scanner, PlantEye F300 by Phenospex B.V.	LIDAR	(Kjaer and Ottosen 2015)	greenhouse
	Multispectral camera, DCC3240N, THORLABS	Multispectral	(Geng et al. 2015)	
Leaf area index/ leaf area/ projected leaf area	Camera, Kinect-v2, Microsoft	TOF	(Jiang et al. 2016)	lab
	Camera, PMD Camboard nano	TOF	(Li and Tang 2017)	
	2D web-cameras, Logitech HD Webcam C310	Color camera	(Li and Tang 2017)	
	Perceptron Scan, Works V5	LIDAR	(Paulus et al. 2014)	
	Perceptron Scan, Works V5	LIDAR	(Paulus et al. 2014)	
	Camera, Kinect-v2, Microsoft	TOF	(Andújar et al. 2016)	
	2D laser scanners, RPLIDAR (RoboPeak LIDAR)	LIDAR	(Wang et al. 2017)	
	Camera, SR_4000, MESA Imaging	TOF	(Chaivivatrakul et al. 2014)	
	LAI meter, LAI-2200 Plant Canopy Analyzer	Spectroscopy	(Thorp et al. 2015)v	Field
	Area meter, LAI-3100	Spectroscopy	(Thorp et al. 2015)	
	Digital single-lens reflex camera, Canon 500D	Color camera	(Jay et al. 2015)	
	Digital CCD camera, Teledyne Dalsa Genie C1024	Color camera	(Jay et al. 2015)	
	2 RGB cameras, Grasshopper3 by PointGray	Stereo vision	(Shafiekhani et al. 2017)v	
	IR (thermal) camera, Flir A625	Spectroscopy	(Shafiekhani et al. 2017)	
	Camera, Kinect-v2, Microsoft	TOF	(Jiang et al. 2017)	
	Multispectral camera, Sentek GEMS	Multispectral	(Neely et al. 2016)	
	Leaf area meter, LI-3100C Area Meter	LIDAR	(Ge et al. 2016)	Greenhouse
	Camera, Canon EOS 450D	Color camera	15	
	3D NIR laser triangulation scanner, PlantEye F300 by Phenospex B.V.	LIDAR	(Kjaer and Ottosen 2015)	
	Leaf area meter, LI-3000, LI-COR	LIDAR	(Kjaer and Ottosen 2015)	
	Perceptron Scan, Works V5	LIDAR	(Paulus et al. 2014)	Laboratory
	Perceptron Scan, Works V5	LIDAR	(Paulus et al. 2014)	

Phenotype	Sensor	Sensor category	Reference	Environment
length/stalk count/ stalk width	Camera, SR_4000, MESA Imaging	TOF	(Lu et al. 2017)	
	Structured-light scanner, DAVID 3D SLA-1 scanner	LIDAR	(Drapikowski et al. 2016)	
	Camera, Kinect-v2, Microsoft	TOF	(Drapikowski et al. 2016)	
	Hand-held scanner, HandyScan EXASCAN	LIDAR	(Drapikowski et al. 2016)	
	Digital camera, Panasonic Lumix DMC-FZ38	Color camera	(Drapikowski et al. 2016)	
	2D laser scanners, RPLIDAR (RoboPeak LIDAR)	LIDAR	(Wang et al. 2017)	
	Camera, SR_4000, MESA Imaging	TOF	(Chaivivatrakul et al. 2014)	
	Camera, Canon EOS 450D	Color camera	(Christian et al. 2015)	Greenhouse
NDVI, NDVI-spec, red-edge NDVI	NDVI sensor, SRS	Spectroscopy	(Enciso et al. 2017)	Field
	RGB camera, Nikon J3	Color camera	(Neely et al. 2016)	
	Multispectral camera, Sentek GEMS	Multispectral	(Neely et al. 2016)	
	NDVI sensor, SRS, Decagon Devices, Pullman, Washington	Spectroscopy	(Bai et al. 2016)	
	Spectrometer, CCS175, Thorlabs Inc., Newton, New Jersey	Spectroscopy	(Bai et al. 2016)	
	GreenSeeker, Trimble 500 with RT200	Spectroscopy	(Barker et al. 2016)	
	GreenSeeker, RT100	Spectroscopy	(Barmeier and Schmidhalter 2016)	
	Bi-directional spectrometer	Spectroscopy	(Barmeier and Schmidhalter 2016)	
	Crop circle multispectral sensor, Holland Scientific ACS 470	Multispectral	(Thorp et al. 2015)	
	Multispectral camera, ADC Micro multispectral camera	Multispectral	(Balota and Oakes 2017)	
	Multispectral camera, DCC3240N, THORLABS	Multispectral	(Geng et al. 2015)	Greenhouse

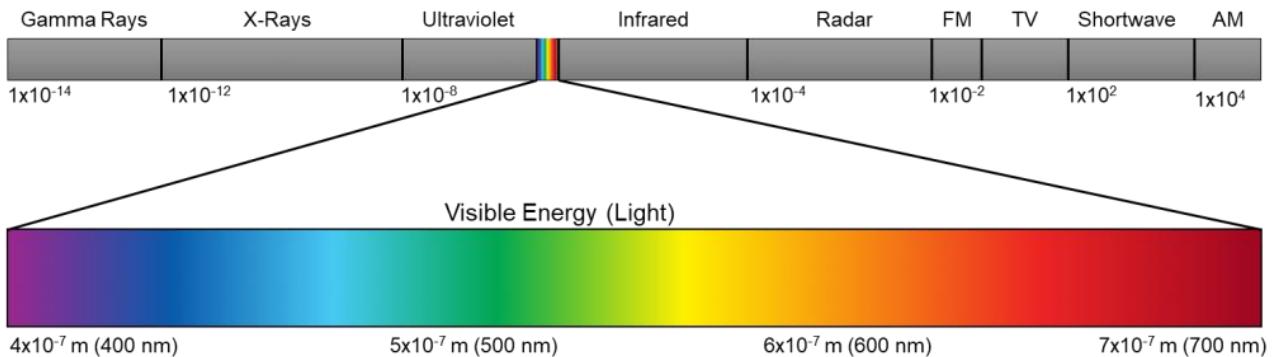


Figure 2: The electromagnetic spectrum

2.8. STRESS DETECTION

One common way for stress detection is using spectral data (more information in chapter 2.8.1). Combine data mining and non-invasive sensing, produce usefulness implementations for industry and precision breeding applications (Gutiérrez et al. 2016).

Water stress of grapevine was detected using NIR spectral data in field condition. An SVM model was developed for variety classification with an average AUC of 0.991. The stem water potential, as an indicator of plant water stress, was using rotation forests and M5 trees resulted with RMSE of 0.165. Due to the use of the same dataset for the training and the testing, this performance could be considered as an upper limit to what may be expected in other settings (e.g., cross- and external validation) (Gutiérrez et al. 2016). Another water stress detection NIR-based model developed using PLS regression for olive trees (Poblete-Echeverría et al. 2014). The PLS regression model was configured with six components and reached a calibrated RMSE of 0.48 MPa and validation RMSE of 1.15 MPa.

Other common way for stress detection is by using images; RGB images (Ghosal et al. 2018), NIR images (Guo et al. 2017), multispectral images (Zaman-Allah et al. 2015) and hyperspectral images (Nansen et al. 2010).

A deep convolutional network for stress identification, classification, and quantification for soybean plants was built (Ghosal et al. 2018). 25,000 images of stressed and healthy soybean leaflets in the field were collected using standard RGB camera. The plants labels were given by expert plant pathologists. The network extract complex features from 16,207 clean images to predict stress source (bacterial blight, bacterial pustule, Septoria brown spot, SDS, frog-eye leaf spot, herbicide injury, potassium deficiency, and IDC). The algorithm reached classification accuracy of 94.13%. The quantitative results were given as the correlation between experts ranking to the network's features. Among herbicide injury, resistant plants had correlation of 47.91%, moderately resistant plants had correlation of 47.91%, susceptible plants had correlation of 64.75% and highly susceptible plants had correlation of 77.28%

Another machine learning model for water stress detection was developed (Guo et al. 2017) to evaluate water status of bok choy roots. Three types of phenotyping traits such as morphological trait, color trait, and near-infrared trait were acquired from RGB and NIR images as the models' inputs. Three machine learning models were developed, Random Forest (RF), Neural Network (NN), and Support Vector Machine (SVM), with an accuracy of

around 90% for all. Overall, SVM model had the highest classification accuracy (92.5%), but a more stable performance was observed in the RF model.

Low nitrogen stress of corn plants was detected using aerial multispectral imaging with a unmanned aerial vehicle (Zaman-Allah et al. 2015). Maize nitrogen status is usually significantly correlated with leaf reflectance at low leaf N concentration under field conditions. Therefore, the low-N stress index compute by the NDVI generated from multispectral imaging. The correlation between aerial NDVI to ground truth was 0.83.

Drought stress levels and spider mite infestation levels analysis of maize plant was conducted (Nansen et al. 2010). Hyperspectral imaging data were acquired from individual maize leaves. Stepwise discriminant analysis was used to identify the five spectral bands with the highest contribution to the drought stress level detection (440nm, 462nm, 652nm, 706nm and 784nm).

2.8.1. VEGETATION SPECTROSCOPY

The main applications for remote sensing of vegetation are based on the following light spectra: (i) the ultraviolet region (UV), which is in the 10 to 380nm range of wavelength; (ii) the visible spectra, which are composed of the blue (450–495nm), green (495–570nm), and red (620–750 nm) wavelength regions; and (iii) the near and mid infrared band (850–1700nm) (Xue and Su 2017).

Spectral reflectance information is related to the chemical composition of the plant, i.e., its physiological status (Behmann et al., 2015). The visible range (VIS 400 to 700 nm) is mainly influenced by leaf pigment content, the near-infrared reflectance (NIR 700 to 1,100nm) depends on the leaf structure, internal scattering processes, and on the water absorption by leaf and the short-wave infrared (1,100 to 2,500 nm) is influenced by the composition of the leaf chemicals and water (Jacquemoud and Ustin 2001).

Each material reflects the electromagnetic radiation differently (*Figure 3*).

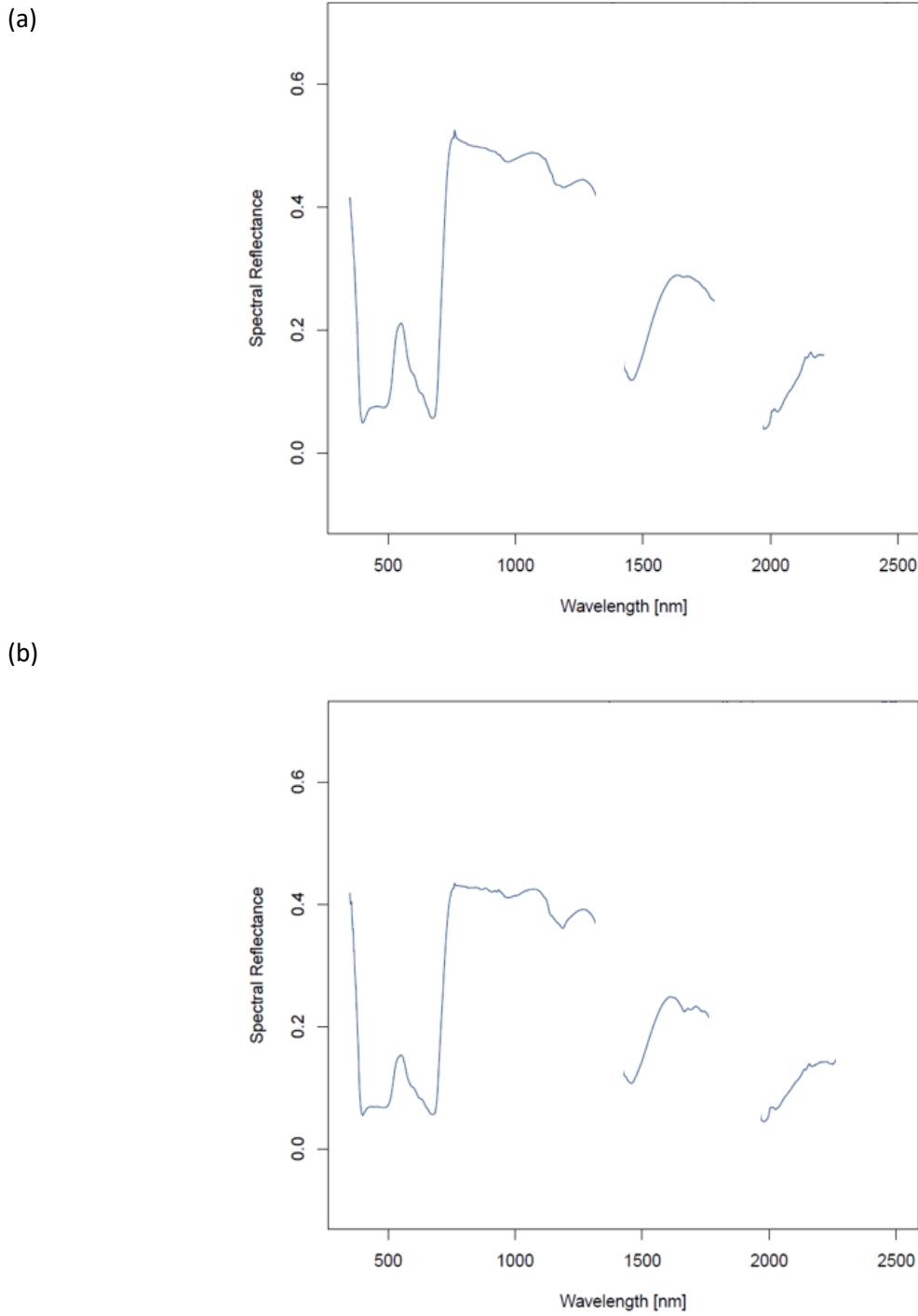


Figure 3: Spectral reflectance of corn (a) and spectral reflectance of wheat (b).

Various combinations between these wavelengths are defined as Index Vegetation (Xue and Su 2017). The index is constructed as a numerical value that defines the power of a general phenomenon, which is too complex to break down into specific known characteristics, found to be well correlated with various vegetation parameters including green leaf area, biomass, percent green cover, productivity, and photosynthetic activity (Huete 1988). The vegetation indices should maximize their sensitivity to the physical parameters of the plant and normalize external influences (such as the angle of the sun) and normalize internal effects (such as the return of radiation not from the measured object) (Bannari et al. 2009). A specific

biophysical index that can be measured in order to conduct quality control of the index. The most common of these indices is to utilize red and near infrared canopy reflectance's or radiances in the form of ratios (normalized difference and ratio vegetation indices) or in linear combination. Equation 2 present a common normalized difference and ratio vegetation indices (NDVI).

Equation 2: NDVI

$$NDVI = \frac{IR - R}{IR + R}$$

The NDVI can be used to estimate the photosynthetic area (biomass) or N-uptake of plant canopies, therefore it is also a biochemical trait. Ge et.al 2016 used the NDVI image to classify the plant into the stem and leaves. They also estimate the average leaf reflectance spectrum with it. Pixels belonging to plant leaves were used as a template to extract pixel intensity from all hyperspectral bands. This gave an average leaf reflectance spectrum for each plant (Ge et al. 2016).

Another vegetation index is the Normalized Green–Red Difference Index (NGRDI, (An et al. 2016)) which is similar to the well-known NDVI. However, NGRDI is more useful in distinguishing healthy vegetation from the background in cameras that have not been modified to be infrared-sensitive (An et al. 2016). The NGRDI equation used in their study:

Equation 3: NGRDI

$$Plant = bw\left(\frac{Green - Red}{Green + Red}\right)$$

Where Green and Red are the respective green and red channel pixel brightness values, and bw() is the Otsu threshold method for binary image transformation.

Most abiotic stress detection studies focused on one plant and/or one abiotic stress.

The present study aims to develop generic stress detection models using spectral data, which could be used for several plant species and spectral sensors.

3. METHODS

3.1. OVERVIEW

Spectral data of plants sprayed with herbicides were collected using a spectro-radiometer ASD point sensor in 2018 (experiment 1). Validation was performed on data collected in 2019 (experiment 2). Two types of models were developed for each of the plants:

1. Binary classification models to predict the phenotypes' status (under stress or not).
2. Regression models to predict the average value of all phenotypes. This field reflects the visual change in each plant.

In this research, plants belonging to two different groups were used: corn and sunflower. Corn plants belong to the C₄ plants category, while sunflower plants belong to the C₃ plants category. The basic difference between these groups is on the way the plants use carbon dioxide (CO₂). C₄ plants process CO₂ in a more complex way and can process more CO₂ when the climate is dry and hot than C₃ plants. Yet most of the plants on earth belong to C₃ category (Pearcy 1984).

3.2. EXPERIMENTAL DESIGN

Experiment 1: Corn (cultivar VIVANI 700) and sunflower plants (cultivar Jerusalem Dwarf Yellow Spray) were grown in pots in a controlled greenhouse (25±2°C day 20±2°C night, flood irrigation of tap water + fertilizer NPK 5:3:8 + 6, 2ml/l at 50% water content) for a period of one month from their seeding time (sunflower-15.10.18 and corn- 25.10.18). The plots were arranged on two tables, one for each crop (Figure 4). Each plot received a number and a bar code for sampling management.

Three seeds were planted in each pot, which were thinned out into one plant. Three days after their emergence, the plants were sprayed with different herbicides. Twenty-five different chemical applications were applied to 250 plots/pots, which comprised of five repetitions for each herbicide type, in a randomized design (Appendix E).

Spectral measurements were conducted on 14 treatments (different chemical applications), 140 plants, due to sampling time constraints. A plant physiologist selected these treatments, to reflect a variety of modes/mechanism of action (MOA) of the herbicides (the primary biochemical or biophysical interference imposed by an herbicide that leads to lethality).

Experiment 2: 99 corn (cultivar VIVANI 700) plants were grown in pots in the same controlled greenhouse with the same environment conditions for a period of one month from their seeding time (10.12.19). Only one chemical application (at lower concentration than experiment 1) was applied to 95 plots. The remaining 4 plants were used as the control group. Spectral measurements were acquired from all plants.



Figure 4: Experimental layout

3.2.1. PHENOTYPES

Experiment 1: Eleven phenotypes were visually evaluated on a 1-6 scale by an expert agronomist at each time point: Pheno 1- Necrosis (spots), Pheno 2- Burning, Pheno 3- Bleaching, Pheno 4- Chlorosis, Pheno 5- Epinasty (curling), Pheno 6- Inhibited growth, Pheno 7- Wilting, Pheno 8- Disturbed apical bud, Pheno 9- Abnormal pigmentation (dark leaf), Pheno 10- Abnormal pigmentation (anthocyanins) and Pheno 11- Disturbed gravitropism.

Experiment 2: Given the previous experiment results, only eight phenotypes were visually evaluated on a 1-6 scale by other expert agronomist at each time point: Pheno 1- Necrosis (spots), Pheno 2- Burning, Pheno 3- Bleaching, Pheno 4- Chlorosis, Pheno 5- Epinasty (curling), Pheno 6- Inhibited growth, Pheno 7- Wilting and Pheno 9- Abnormal pigmentation (dark leaf).

3.3. DATA ACQUISITION

Experiment 1: The measurements were conducted between 09:30 to 15:30 local time (UTC+2) through autumn 2018, at 6 time points (TP): TP1-04.11.18, TP2-06.11.18, TP3-08.11.18, TP4-11.11.18, TP5-13.11.18 and TP6-15.11.18.

Experiment 2: The measurements were conducted between 08:30 to 14:30 local time (UTC+2) through autumn 2019, at 6 time points (TP): TP1-22.12.19, TP2-24.12.19, TP3-25.12.19, TP4-29.12.19, TP5-30.12.19, TP6-31.12.19 and TP7-1.1.20.

Both experiments: spectral reflectance of each leaf was recorded by a spectro-radiometer (ASD FieldSpec 4 hi-res, ASD Inc. Malvern Panalytical, Boulder, Colorado, USA) in the range of 350nm – 2500nm, with an optical spectral resolution of 3nm in the NIR range and 8nm in the SWIR range.

The wavelength measurements range includes the near-infrared range (NIR 700-1000nm) and the short-wavelength infrared radiation (SWIR 100-2500nm).

Each plant was placed on a greenhouse table under direct sunlight, with the ASD fiber probe aimed at a leaf from a distance of a few centimeters without shading it (Figure 5). A white reference was sampled whenever a change in illumination conditions occurred or every fifteen minutes. Four consecutive series' of 10 spectra were acquired for each leaf, and the average value was saved for analysis.

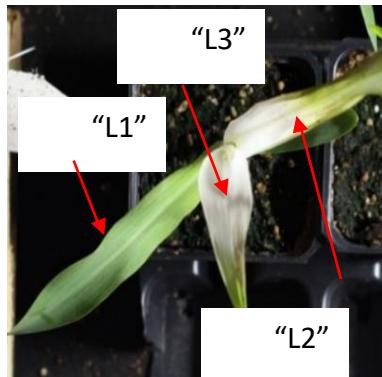


Figure 5: Sensor measurement

Since the sprayed chemicals affect mature or young leaves differently (Figure 7), both young and mature leaves were sampled from each plant. Young leaf, L3, had different spectral signature than mature leaves L1, L2 (Figure 7).

In corn plants, three leaves were sampled (Figure 6a) starting with one leaf at the first time point, two at the second time point and three leaves from the third time point and so on (in some treatments, a third leaf did not grow due to the chemical effect). In sunflower plants, one mature leaf and one young leaf were measured at every time point (Figure 6b).

(a)



(b)

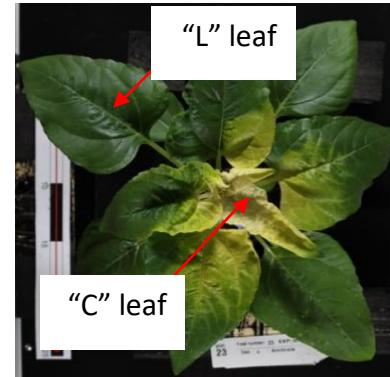


Figure 6: Sampling points of corn (a) and sunflower (b) plants.

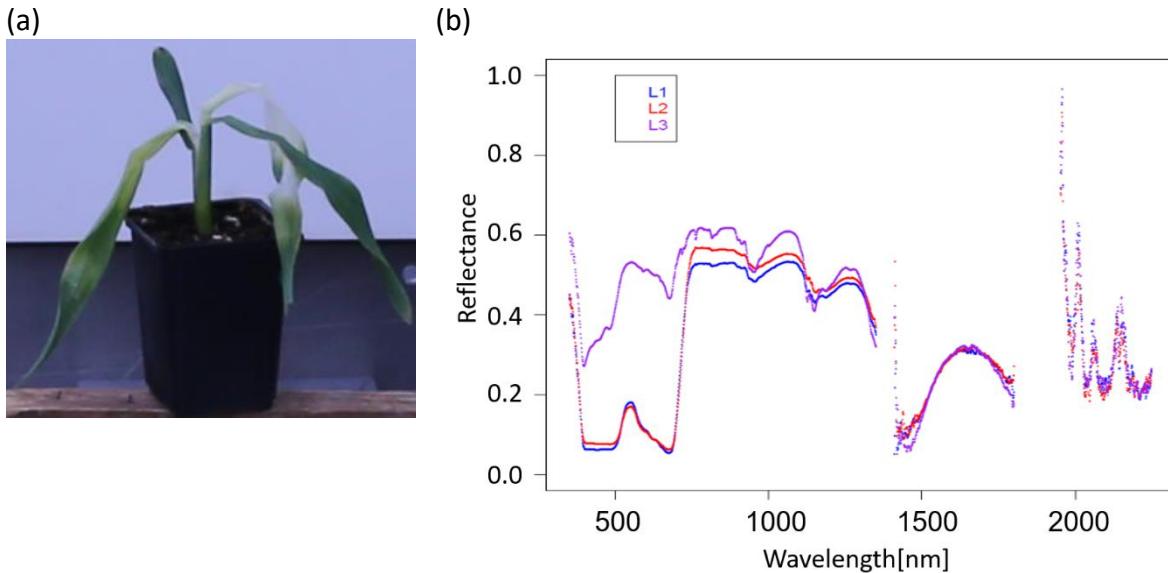


Figure 7: (a) RGB photo of corn leaves, plot 249 at time point 5, (b) Spectral signature of three corn leaves of plot 249 at time point 5.

3.4. PREPROCESSING

3.4.1. PHENOTYPES

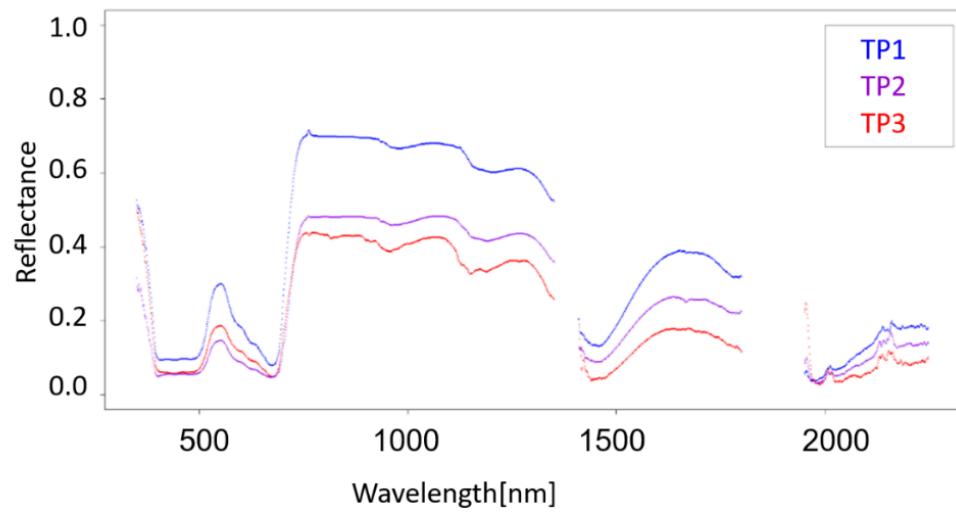
For each plant, two measures were calculated for abiotic stress: the *phenotypic status* (indicating if the plant is under stress or not) and the *phenotypes' average* – the average value of the 11 phenotypes (indicating the stress severity).

When the average value was above one, the *phenotypes' status* was defined as 1 (defining a plant under stress) and when the average value equaled one the *phenotypes' status* was defined as 0 (defining a healthy plant).

3.4.2. SPECTRAL DATA

Due to environmental conditions and the sensor capture angle spectral signatures that were supposed to be identical were found different (Figure 8a). Thus, it would be difficult to attribute the changes in the spectral reflectance only to the chemical treatments. Therefore, a first derivative and smoothing was performed on the data using a procedure defined by Savitzky-Golay with a smoothing polynomial of order 2 and a smoothing window of 11 wavelengths (Savitzky and Golay 1964) (Figure 8b). This was followed by removing water vapor atmospheric absorption windows (1350nm-1410nm, 1800nm-1950nm and 2250nm-2500nm as can be seen in Figure 9) from the spectral data.

(a)



(b)

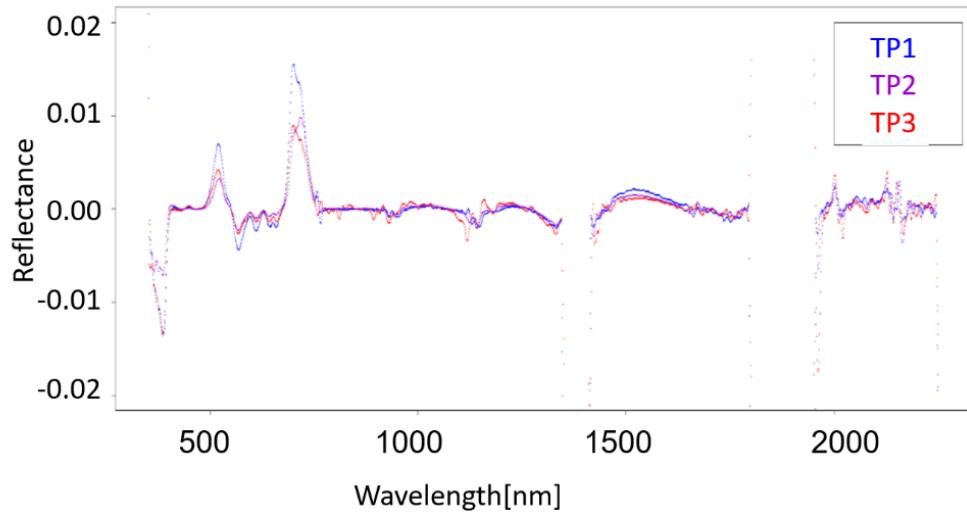


Figure 8: Spectral reflectance of healthy leaves at different dates, before (a) and after (b) Savitzky-Golay procedure.

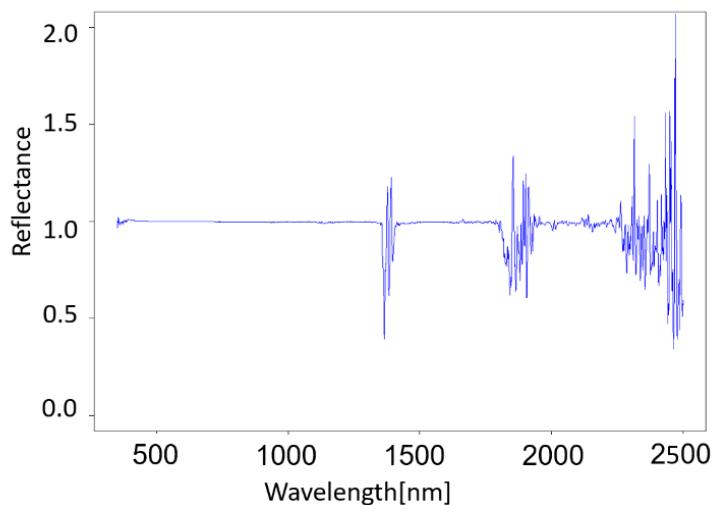


Figure 9: White reference relative reflectance in the greenhouse conditions.

3.5. PREDICTION MODELS

3.5.1. SPECTRAL DATA ANALYSIS

Models were developed separately for each plant dataset (Table 2).

Table 2: Spectral data analysis models

Explanatory variables	Classification	Regression
One band	Logistic regression	Linear regression
Small number of bands	Logistic regression	Linear regression
Entire spectrum	PCA+ Logistic regression	PCA+ Linear regression
	PLS-DA	PLS
	Random forest	Random forest
	XGBoost	XGBoost

For each method, the model was fitted on a training set and evaluated on a test set. Due to the high variability in agriculture data and the small number of the samples, each data division subset influenced the test results. To overcome this, the datasets were divided into 5 subsets. In each iteration the model was built on 4 of the subsets (defined as the training set) and evaluated on the 5th subset (defined as the test set). The average of the 5 iterations score was used as the model's performance result.

An additional model was constructed using all 5 subsets combined.

3.5.2. ALGORITHMS

First, correlations between every wavelength of the first derivative of spectral reflectance (after Savitzky-Golay procedure and noise extraction) and the average of the phenotypes were calculated. With the most correlative wavelength a logistic regression model for phenotypes' status classification was developed and a linear regression model for the phenotypes' average prediction was built.

Second, for phenotypes classification, a stepwise logistic regression limited to 7 bands was calculated. For the phenotypes' average, a stepwise linear regression limited to 7 bands was calculated. Seven bands were selected as the limit of bands used to correspond to a parallel multispectral camera used in this project which employed only 7 bands to lower the costs.

When using all spectra to fit a model, two problems appeared: the high dimensionality versus low sample size and the correlation between the variables (the bands). Therefore, methods were applied to deal with both data reduction and multi-collinearity. These methods included principle components analysis (PCA) and partial least squares regression (PLS) models. PCA is a linear transformation that converts data to a set of orthogonal variables called principal components. Each component is a linear combination of all original variables (coordinate transformation). PCA seeks to rotate the axes, i.e. convert the variables, so that the new axes

will lie along the direction of maximum variation in the data. Thus, the first component, the axis, will lie in the direction of the maximum variation and the last one will lie in the direction of the minimum variation. The number of components was selected by the minimum between the number of components which explains cumulatively 90% of the spectrum variance (X variables), 10% from the number of samples and 10% from the number of features (wavelengths). Later, a logistic regression model was built with these selected principle components (PCs) to predict the phenotype' statues. Additionally, the linear regression model to predict the phenotypes' average value was developed using these PCs.

The second method was PLS regression for average prediction. Unlike PCA which creates components that explain as much of the X variation as possible, PLS searches for components that create a strong relationship between X and Y. i.e. seeking directions in the X space that are associated with high variation in the Y space. Partial least square discriminant analysis is a variant of PLS used when the Y is categorical variable. Thus, the PLS-DA classification model was built for the phenotypes' status. The number of components employed in the PLS-DA was the minimum between the number of components, which maximize the AUC criterion, 10% from the number of samples and 10% from the number of features (wavelengths). The number of components employed in the PLS was the minimum between the number of components which minimize the RMSE criterion, 10% from the number of samples and 10% from the number of features (wavelengths). The AUC in the PLS-DA and the RMSE in the PLS regression was calculated 5 times. The data was split again into 5 subsets, the PLS/PLS-DA model was fitted on 4 subsets and the RMSE/AUC score was calculated on the 5th subset. Then the scores were averaged per each components number and the optimal number was chosen.

Another approach used was supervised machine learning. We used an ensemble method technique to combine predictions from multiple machine learning algorithms together. There are two main types of ensemble learning: Bootstrap Aggregation (Bagging) and Boosting. Bootstrap refers to random sampling of small subset of data from the dataset for each model. Boosting refers to a group of algorithms that trains weak learners sequentially, each trying to correct its predecessor. In this work, two decision tree ensemble algorithms were used; random forest which used bootstrap aggregation and extreme gradient boosting (XGBoost). These methods were trained for both the classification and the regression problems. In both cases the pipeline included the following steps:

- Tuning hyper-parameters by grid search to find the optimal score for the training set. The train set was split into 5 subsets and was fitted by cross validation for every combination of the hyper-parameters. The combination which reached the best averaged score (of the 5 subsets) was chosen. The hyper-parameters range was empirically selected.
- Model fitting with the chosen hyper-parameters, on the training set.
- Model evaluation on the test set. For classification: AUC, F1 and accuracy measures were calculated and for regression: RMSE and MAE metrics.

Random forest algorithm is an ensemble learning method for classification and regression that operates by constructing a large number of decision trees. Each tree predicts a class, the model prediction is the class with the most votes for classification or the mean of the prediction for regression. The key to this model is the low correlation between the models (the trees).

The low correlation is caused by:

- Bagging/Bootstrap Aggregation: as explained before, allowing each individual tree to randomly sample from the dataset with replacement, resulting in different trees.
- Feature Randomness: each tree in the forest considers a subset of features when looking for the best split at each node, instead of considering all the features.

The hyper-parameters which were tuned in this work were the following:

- n_estimators: The number of trees in the forest. Options: 60, 70, 80.
- max_features: The number of features to consider when looking for the best split. Options: 30, 35, 40.
- max_depth: The maximum depth of the tree. Options: 6, 7, 8.

Other parameter's values that were used:

- Criterion: The function to measure the quality of a split was—" Gini" for classification (explained in the next chapter) and "mse" for regression.
- Min_samples_split: the minimum number of samples required to split an internal node. Defined as default- 2.
- Min_samples_leaf: the minimum number of samples required to be at a leaf node. Defined as default- 1.
- Min_impurity_split: threshold for early stopping in tree growth. A node will split if its impurity is above 1e-7, otherwise it is a leaf (as default).
- Bootstrap: whether bootstrap samples are used when building trees. If not, the whole dataset is used to build each tree. We used bootstrap for low correlation as explained earlier.
- Random_state: controls both the randomness of the bootstrapping of the samples used when building trees and the sampling of the features to consider when looking for the best split at each node. To be able to repeat the results, 0 was used as random state.

XGBoost is a gradient boosting algorithm's family. Gradient boosting algorithms correct each weak model by minimizing the loss function of its previous model using a gradient descent procedure (gradient descent is an optimization algorithm used to minimize loss function by iteratively moving in the direction of steepest descent as defined by the negative of the gradient). The XGBoost algorithm trains each new model (tree) to correct the errors made by the previous one (previous tree). Trees are added sequentially until no further improvements can be made (Chen and Guestrin 2016). The hyper-parameters which were used in this work were:

- Colsample_bytree: the subsample ratio of columns (features) when constructing each tree. Options: 0.023, 0.029, 0.035
- Eta/ learning_rate: After each boosting step, we can directly get the weights of new features, and eta shrinks the feature weights to make the boosting process more conservative. This is used to prevent overfitting. Options: 0.5, 0.8, 0.9
- Max_depth: Maximum depth of a tree. Increasing this value will make the model more complex and more likely to overfit. Options: 6, 7, 8.
- Subsample: Subsample ratio of the training instances (subsampling will occur once in every boosting iteration). This will prevent overfitting. Options: 0.6, 0.8, 0.9
- N_estimators: The number of trees in the forest. Options: 60, 70, 80.

Other parameter's values used:

- Objective: specify the learning task and the corresponding learning objective or a custom objective function to be used. We used "reg:squarederror" for the regression case with and "binary:logistic" for the classification case.
- Random_state: to be able to repeat the results, 0 was used as random state.
- Gamma/ min_split_loss: minimum loss reduction required to make a further partition on a leaf node of the tree. Defined as default- 0.
- Min_child_weight: minimum sum of instance weight needed in a child. If the tree partition step results in a leaf node with the sum of instance weight less than min_child_weight, then the building process will give up further partitioning. In linear regression task, this simply corresponds to minimum number of instances needed to be in each node. Defined as default- 1.
- Scale_pos_weight: control the balance of positive and negative weights, useful for unbalanced classes. It was not used due to SMOTE algorithm (will be explained later).

3.5.3. EARLY PREDICTION MODELS

In order to predict the plant phenotypes before they are visually detected by an expert, the datasets were re-organized. The phenotypes' average and status values were moved through time points (

Table 3). We used each spectrum measurement (time point t) to predict the next phenotypes measurement (time point t+i). Four datasets were created: 'two days before dataset', 'four days before dataset', 'five days before dataset' and 'seven days before dataset'. Subsequent time points with a larger gap between them were removed. For example, the gap between 08/11/18 and 11/11/18 was bigger than 2 days, thus these samples were not added to the "two days before" dataset.

Table 3: Early detection datasets

Dataset Name	Spectrum acquisition date (X)	Phenotypes evaluation date (Y)
Dcorn_2Days	06/11/18	08/11/18
	11/11/18	13/11/18
	13/11/18	15/11/18
Dcorn_4Days	11/11/18	15/11/18
Dcorn_5Days	06/11/18	11/11/18
	08/11/18	13/11/18
Dcorn_7Days	06/11/18	13/11/18
	08/11/18	15/11/18

Most of these datasets were extremely imbalanced for the classification task with approximately 80% 'under stress' plants and 20% 'healthy' plants. Additionally, the *phenotype's status* at time points 4, 5, and 6 were the same. The *phenotypes' average* value

had a different value for each time point. Thus, the test dataset containing X and Y from these time points is inappropriate for evaluation. Therefore, the early classification models were fitted only for the ‘two days before’ dataset, which included only the spectra of 6/11/18 and phenotypes’ status of 8/11/18. Moreover, in these datasets there was a lack of healthy plants, therefore a Synthetic Minority Over-Sampling Technique (SMOTE) was used. To use SMOTE, in this work, we created synthetic samples of the healthy plants.

3.5.4. SENSITIVITY ANALYSIS

Sensitivity analyses were conducted for the different leaves and for three of the MOAs.

Since the sprayed chemicals have a different visual effect on mature and young leaves, both young and mature leaves were sampled from each plant. In corn plants, three leaves were sampled, starting with one leaf at the first time point, two at the second time point and three leaves from the third time point and so on (in some treatments, a third leaf did not grow due to the chemical effect). In sunflower plants, one mature leaf and one young leaf were measured at every time point. Filtered datasets were built to analyze leaf sensitivity, i.e., models for each leaf dataset were developed.

Additionally, the datasets were filtered by the following three MOA: lipid metabolism inhibition (LM) inhibition of photosynthesis (IP) and amino acid metabolism inhibition (AAM). Then MOA sensitivity analysis was performed.

3.6. PERFORMANCE MEASURES

The mean and the standard deviation of all 5 iterations were calculated for each dataset separately.

3.6.1. CLASSIFICATION

The classification models’ performance was evaluated by three measures: accuracy, AUC and F1 score. All metrics were calculated using the following four values (Figure 10):

- True Positive (TP)- the proportion of actual positives that were correctly identified as such. The healthy plants which were predicted as healthy.
- False Positive (FP)- The rate of under stress plants which were predicted as healthy.
- True Negative (TN)- the proportion of actual negatives that were correctly identified as such. The plants under stress which were predicted as under stress.
- False Negative (FN)- The rate of healthy plants which were predicted as under stress.

Accuracy: how many times does the model predict the true class from the test dataset divided by test dataset size.

AUC: the Area under the Curve (AUC) of Receiver Operating Characteristic (ROC) curve. ROC curve is the plot of True Positive Rate (TPR) on y-axis versus False Positive Rate (FPR) on the x-axis (Figure 11). Each point on the curve describes the TPR and FPR for a specific probability threshold of classification. The AUC is the area under this curve.

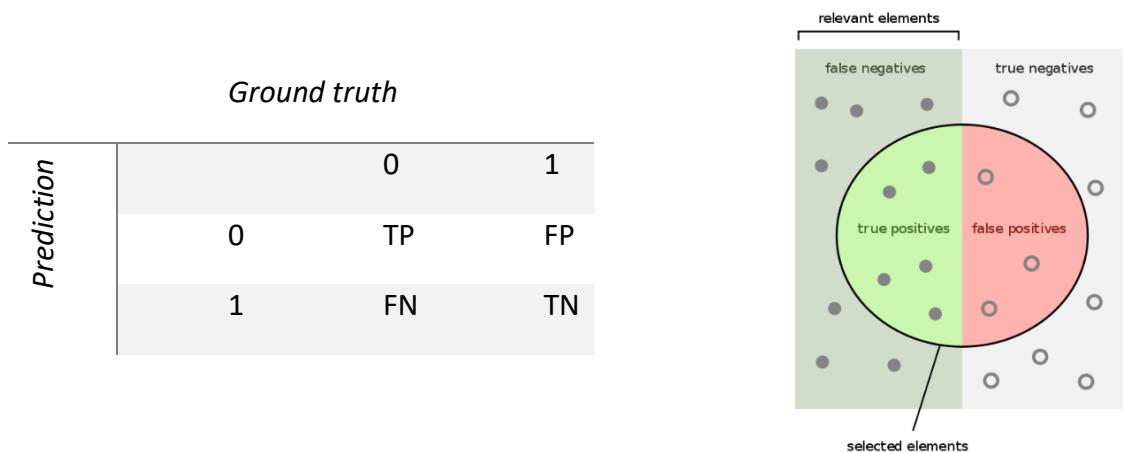
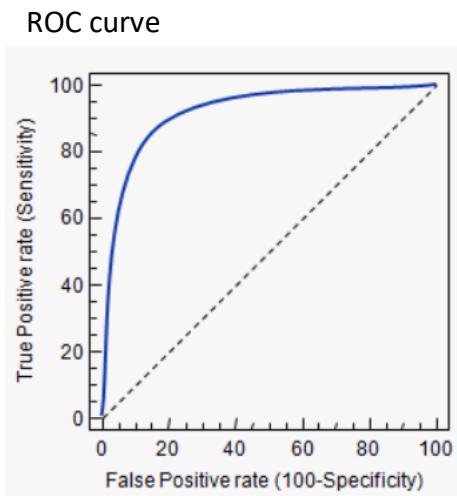


Figure 10: Confusion matrix



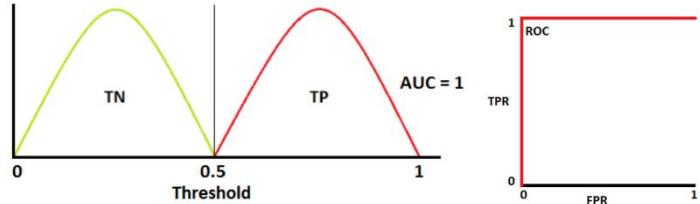
Equation 4: Accuracy, TPR, FPR, Precision

$$\begin{aligned}
 \text{Accuracy} &= \frac{TP + TN}{TP + TN + FP + FN} \\
 TPR &= \text{Recall} = \frac{TP}{TP + FN} \\
 FPR &= \frac{FP}{TN + FP} \\
 \text{Precision} &= \frac{TP}{TP + FP}
 \end{aligned}$$

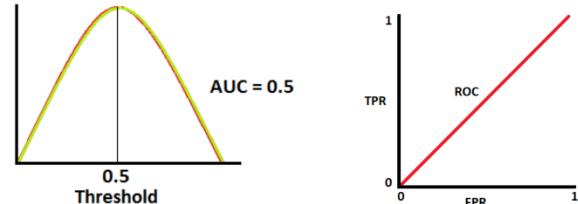
Figure 11: ROC curve

AUC is a value that explains how much the model is capable of distinguishing between classes. The higher the AUC, the better the model is at predicting the actual value. Here, the higher the AUC, the better the model is at distinguishing between under stress plants and healthy plants. The next diagram presents examples of a variety of AUC scores.

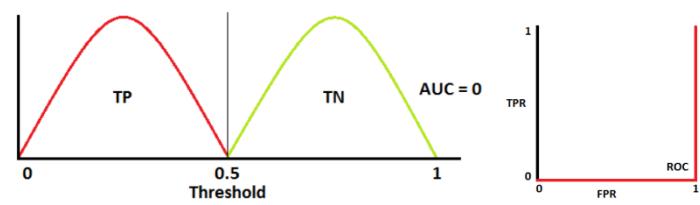
An excellent model has an AUC closest to 1, implying a good measure of separability.



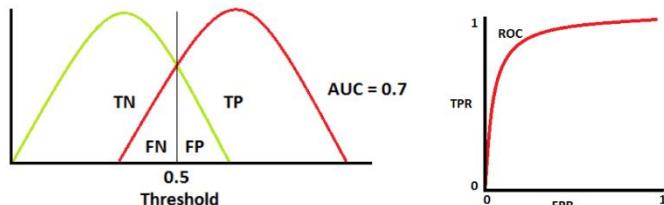
When the AUC is approximately 0.5, the model has no ability to distinguish between positive class and negative class.



A poor model has an AUC close to 0, which implies it has the worst measure of separability.



When the AUC is 0.7, it implies there is a 70% chance that the model will be able to distinguish between positive class and negative class.



F1 score: precision and recall are two important model evaluation metrics. Unfortunately, it is not possible to maximize both these metrics at the same time, as one comes at the cost of another. F1-score is the harmonic mean of precision and recall (Equation 5) and therefore was used. Additionally, F1 Score is a better measure to use if there is an uneven class distribution.

Equation 5: F1 formula

$$F1 \text{ score} = 2 \times \frac{\text{precision} \times \text{Recall}}{\text{precision} + \text{Recall}}$$

3.6.2. REGRESSION

To examine the regression model's performance, two measures were calculated: the root mean square error (RMSE) (Equation 6) and the mean absolute error (MAE) (Equation 7).

Equation 6: RMSE

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2}$$

Equation 7: MAE

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i|$$

RMSE is the standard deviation of the residuals, i.e., it is a measure of how spread out these residuals are. Residuals are a measure of how far the predicted values are from the real data values, i.e., they measure the errors. The MAE is the averaged magnitude of the errors, without considering their direction. This is the average over the absolute differences between prediction and actual observations, where all individual differences have equal weight. We aim to minimize these two indices.

Both MAE and RMSE express average model prediction error (range from 0 to ∞) and are invariant to the direction of errors. However, the RMSE gives a relatively high weight to large errors. In this research, the main metric to compare between the models was RMSE.

3.6.3. FEATURES IMPORTANCE

Amongst the models that include one or several wavelengths (denoted also as bands), the wavelengths which were selected as explanatory variables are the most important.

In the PCA method the most influencing features were selected to maximize the spectrum variance. Thus, they are not necessarily defined as the most relevant for stress detection. We decided to report these bands separately. In contrast, The PLS and PLS-DA models also maximize the stress variance. Every component in the PLS/PLS-DA includes all the spectrum bands. To understand which bands contribute more, the variable importance in projection (VIP) score was calculated (Wold, 1993). VIP scores summarize the influence of individual X-variables on the PLS model. VIP scores are calculated as the weighted sum of squares of the PLS weights, which take into account the amount of explained y-variance in each extracted latent variable (dimension/component) (Chong and Jun 2005). The VIP score for the i^{th} variable is given as:

Equation 8: VIP formula

$$VIP_i = \sqrt{\frac{\sum_{j=1}^h \left(\frac{w_{ij}^2}{\|w_j\|^2} \cdot SSY_j \right)}{SSY_{\text{total}}}}$$

$$\|w_j\|^2 = \sqrt{\sum_{i=0}^p \sum_{j=0}^h |w_{ij}|^2}$$

Where w_{ij} is the weight value for i variable and j component, SSY_j is the sum of squares of explained variance for the j^{th} component and $\|w_j\|^2$ is the Frobenius norm. SSY_{total} is the total sum of squares explained of the dependent variable, h is number of components used in the model and p is number of features (Mehmood et al. 2012).

Variable i can be eliminated if $VIP_i < u$ for threshold $u \in [0, \infty)$. It is generally accepted that a variable should be selected if $VIP_i > 1$, but a proper threshold between 0.83 and 1.21 can yield more relevant variables according to Chong and Jun 2005. Han and Kim 2003, claimed the independent variable has a significant effect on the dependent variable if the VIP value is greater than 1.

The wavelengths' importance within the decision tree algorithms, random forest and XGBoost, was calculated by the "Gini impurity" metric (Zhi et al. 2018). Gini impurity is a measure of how often a randomly chosen element from a set would be incorrectly labeled if it was randomly labeled according to the distribution of labels in the subset. If we have C total classes and $p(i)$ is the probability of picking a point from the data set with class i , then the Gini Impurity is calculated as:

Equation 9: GINI impurity

$$G = \sum_{i=1}^C p(i) \times (1 - p(i))$$

The quality of each split was determined by weighting the impurity of each branch. The weight was defined as the number of elements the branch was divided into by the total number of the elements. The perfect split will reach impurity of 0. The gain between the Gini impurity of data set and the Gini impurity after a specific split is defined the "Gini gain". The higher the Gini gain, the better the split.

4. DATA DESCRIPTION

4.1. DATASETS

4.1.1. EXPERIMENT 1

The size of each dataset and the distribution in each class (“healthy” or “stressed”) were derived (Table 4). The class size is calculated by the number of samples in each phenotypes’ status.

Table 4: Number of samples in different data sets

Dataset Name	Total number of samples	Number of “stressed” samples	Number of “healthy” samples	“Stressed” ratio	“Healthy” ratio
DCorn	875	524	351	0.599	0.401
DSunflower	840	384	456	0.457	0.543
DCorn_train_1	700	410	290	0.586	0.414
DCorn_test_1	175	114	61	0.651	0.349
DCorn_train_2	700	420	280	0.600	0.400
DCorn_test_2	175	104	71	0.594	0.406
DCorn_train_3	700	420	280	0.600	0.400
DCorn_test_3	175	104	71	0.594	0.406
DCorn_train_4	700	421	279	0.601	0.399
DCorn_test_4	175	103	72	0.589	0.411
DCorn_train_5	700	425	275	0.607	0.393
DCorn_test_5	175	99	76	0.566	0.434
DSunflower_train_1	672	301	371	0.448	0.552
DSunflower_test_1	168	83	85	0.494	0.506
DSunflower_train_2	672	316	356	0.470	0.530
DSunflower_test_2	168	68	100	0.405	0.595
DSunflower_train_3	672	302	370	0.449	0.551
DSunflower_test_3	168	82	86	0.488	0.512
DSunflower_train_4	672	309	363	0.460	0.540
DSunflower_test_4	168	75	93	0.446	0.554
DSunflower_train_5	672	308	364	0.458	0.542
DSunflower_test_5	168	76	92	0.452	0.548

The samples distribution among the classes is relatively balanced (Table 4). The size of each dataset and the distribution in each class by sample date were derived for corn plants (Table

5) and for sunflower plants (Table 6). At time point 3 (08/11/18) visual changes appeared in more than half of the samples.

Table 5: Sampling date distribution of the number of samples in corn

Sampling date	Total number of samples	Number of "stressed" samples	Number of "healthy" samples	"Stressed" ratio	"Healthy" ratio
04/11/18	70	0	70	0	1
06/11/18	138	8	130	0.058	0.942
08/11/18	157	96	61	0.611	0.389
11/11/18	170	140	30	0.824	0.176
13/11/18	169	139	30	0.822	0.178
15/11/18	171	141	30	0.825	0.175

Table 6: Sampling date distribution of the number of samples in sunflower

Sample date	Size	Under stress	Healthy	"Stressed" ratio	"Healthy" ratio
04/11/18	140	0	140	0	1
06/11/18	140	20	120	0.143	0.857
08/11/18	140	90	50	0.643	0.357
11/11/18	140	92	48	0.657	0.343
13/11/18	140	92	48	0.657	0.343
15/11/18	140	90	50	0.643	0.357

The size of each early detection dataset and the distribution in each class were derived for corn plants (Table 7) and for sunflower plants (Table 8).

Table 7: Corn early prediction

Dataset Name	Size	Under stress	Healthy	"Stressed" ratio	"Healthy" ratio
Dcorn_2Days	471	360	111	0.764	0.236
Dcorn_4Days	168	138	30	0.821	0.179
Dcorn_5Days	292	245	47	0.839	0.161
Dcorn_7Days	292	245	47	0.839	0.161

Table 8: Sunflower early prediction

Dataset Name	Size	Under stress	Healthy	"Stressed" ratio	"Healthy" ratio
Dcorn_2Days	471	360	111	0.764	0.236
Dcorn_4Days	168	138	30	0.821	0.179
Dcorn_5Days	292	245	47	0.839	0.161
Dcorn_7Days	292	245	47	0.839	0.161

The leaves' datasets were organized by leaves. For corn plants: first leaf (DCorn_L1), second leaf (DCorn_L2) and third leaf (DCorn_L3). For sunflower plants: mature leaf (DSunflower_L)

and young leaf (DSunflower_C). The size of each leaf dataset and the distribution in each class was derived for corn plants (Table 9) and for sunflower plants (Table 10).

Table 9: Corn leaf datasets

Dataset Name	Size	Under stress	Healthy	“Stressed” ratio	“Healthy” ratio
DCorn_L1	420	228	192	0.543	0.457
DCorn_L2	348	228	120	0.655	0.345
DCorn_L3	107	68	39	0.636	0.364

Table 10: Sunflower leaf datasets

Dataset Name	Size	Under stress	Healthy	“Stressed” ratio	“Healthy” ratio
DSunflower_C	420	192	228	0.457	0.543
DSunflowe_L	420	192	228	0.457	0.543

The MOA tables were filtered by MOA:

- Inhibition of photosynthesis (DCorn_IP, DSunflower_IP)
- Inhibition of amino acid metabolism (DCorn_AAM, DSunflower_AAM)
- Inhibition of lipid metabolism (DCorn_LM, DSunflower_LM)
- Control group – not treated

The size of each MOA dataset and the distribution in each class was derived for corn plants (Table 11) and for sunflower plants (Table 12).

Table 11: Corn MOA datasets

Dataset Name	Size	Under stress	Healthy	“Stressed” ratio	“Healthy” ratio
DCorn_IP	260	151	109	0.581	0.419
DCorn_LM	240	98	142	0.408	0.592
DCorn_AAM	242	122	120	0.504	0.496

Table 12: Sunflower MOA datasets

Dataset Name	Size	Under stress	Healthy	“Stressed” ratio	“Healthy” ratio	Ignored
DSunflower_IP	240	140	100	0.583	0.417	0
DSunflower_LM	240	4	236	0.017	0.983	1
DSunflower_AAM	240	120	120	0.500	0.500	0

4.1.2. EXPERIMENT 2

The size of the dataset and the distribution in each class was derived for experiment 2, corn plants (Table 13).

Table 13: Experiment 2 dataset

Dataset Name	Size	Under stress	Healthy	“Stressed” ratio	“Healthy” ratio
DCorn2	1085	750	335	0.691	0.309

4.2. PHENOTYPES

Eleven phenotypes were visually evaluated on a 1-6 scale by an expert agronomist. The descriptive statistics of the phenotypes, the explanatory variables (descriptive statistics of the independent variable will not be given because there are 2150 variables) are presented in Table 14 and Table 15.

EXPERIMENT 1:

Table 14: Corn phenotypes, experiment 1

Phenotype	Mean	Std	Min	25%	50%	75%	Max
Necrosis	1.192	0.735	1	1	1	1	5
Burning	1.419	1.292	1	1	1	1	6
Bleaching	1.447	1.277	1	1	1	1	6
Chlorosis	1.403	1.087	1	1	1	1	5
Epinasty	1	0	1	1	1	1	1
InhibitedGrowth	3.049	2.056	1	1	3	5	6
Wilting	1.403	1.342	1	1	1	1	6
DisturbedApicalBud	1.057	0.532	1	1	1	1	6
AbnormalPigmentationD	1	0	1	1	1	1	1
AbnormalPigmentationA	1.215	0.892	1	1	1	1	6
DisturbedGravitropism	1	0	1	1	1	1	1
Avg	1.381	0.388	1.000	2.273	1.000	1.273	2.273

Table 15: Sunflower phenotypes, experiment 1

Sunflower	Mean	Std	Min	25%	50%	75%	Max
Necrosis	1.226	0.878	1	1	1	1	5
Burning	2.379	2.16	1	1	1	5	6
Bleaching	1.412	1.25	1	1	1	1	6
Chlorosis	1.148	0.699	1	1	1	1	5
Epinasty	1.036	0.186	1	1	1	1	2
InhibitedGrowth	2.583	2.222	1	1	1	6	6
Wilting	1.133	0.8	1	1	1	1	6
DisturbedApicalBud	1.06	0.543	1	1	1	1	6
AbnormalPigmentationD	1	0	1	1	1	1	1
AbnormalPigmentationA	1	0	1	1	1	1	1
DisturbedGravitropism	1	0	1	1	1	1	1

The following phenotypes did not change for corn plants: ‘Epinasty’, ‘AbnormalPigmentationD’ and ‘DisturbedGravitropism’ (Table 14). For sunflower plants the phenotypes which did not change were: ‘AbnormalPigmentationD’, ‘AbnormalPigmentationA’ and ‘DisturbedGravitropism’ (Table 15). The most affected phenotype was ‘InhibitedGrowth’ (Figure 12), i.e., the plant’s size. In the sunflower plant the ‘Burning’ phenotype was also affected, i.e., the leaves edge was damaged.

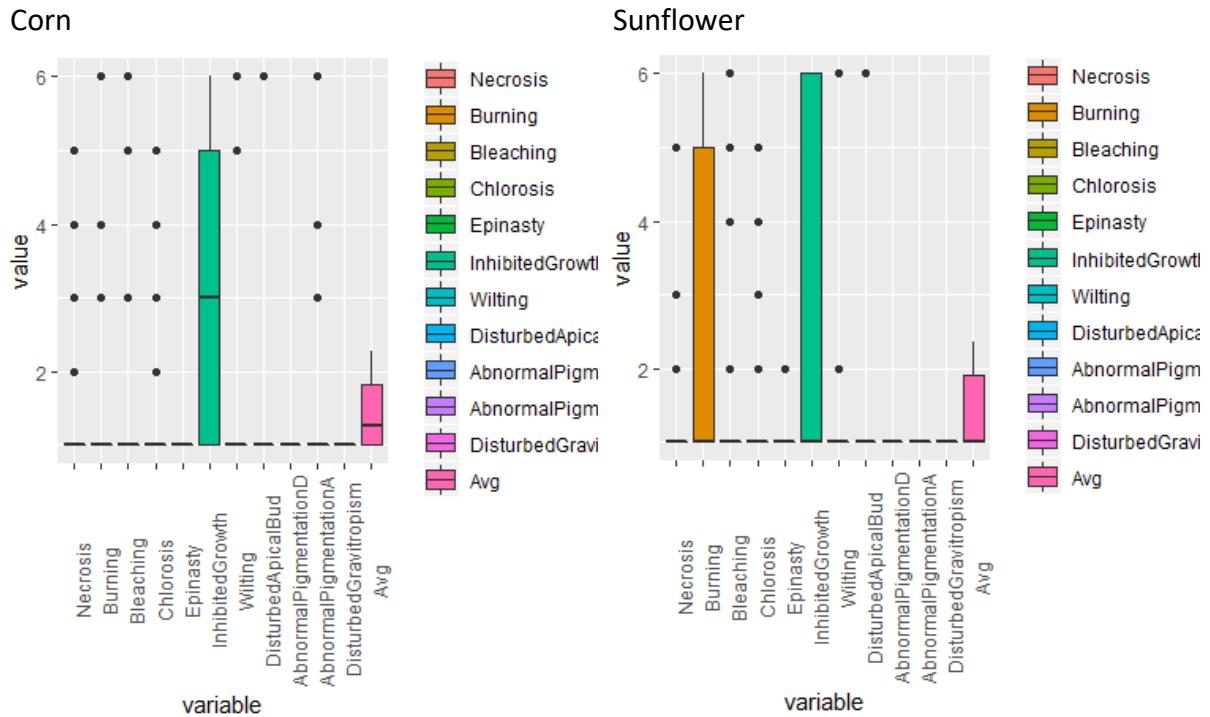


Figure 12: Phenotypes descriptive statistics

EXPERIMENT 2:

Table 16: Corn phenotypes, experiment 2

	Count	Mean	Std	Min	25%	50%	75%	Max
Necrosis	1085	1.957	1.223	1	1	1	3	6
Burning	1085	1.046	0.218	1	1	1	1	3
Bleaching	1085	1.002	0.043	1	1	1	1	2
Chlorosis	1085	2.097	1.263	1	1	2	3	6
Epinasty	1085	1.026	0.217	1	1	1	1	5
InhibitedGrowth	1085	2.731	1.527	1	1	3	4	5
Wilting	1085	2.008	1.557	1	1	1	3	6
DisturbedApicalBud	1085	1.450	0.685	1	1	1	2	4
Avg	1085	1.665	0.694	1	1	1.375	2.250	3.500

All experiment 2 phenotypes were changed (Table 16). The less effected phenotype were 'Burning', 'Bleaching' and 'Epinasty' (Figure 13).

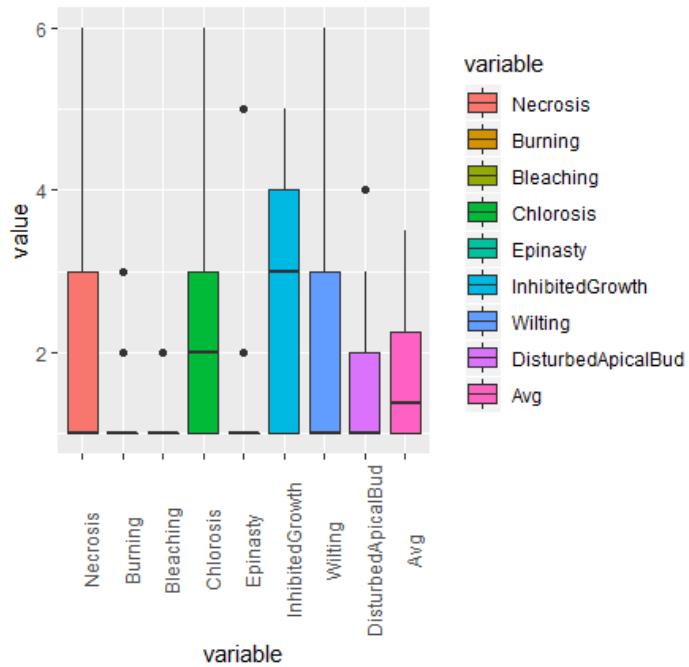


Figure 13: Phenotypes descriptive statistics experiment 2

4.3. SIGNIFICANT WAVELENGTHS

The most correlative wavelengths, by Pearson formula, to the phenotypes' average are: the 1st derivative at **561nm** among corn plants with a 0.554 correlation and the 1st derivative at **722nm** among sunflower plants with a 0.801 correlation (Figure 14).

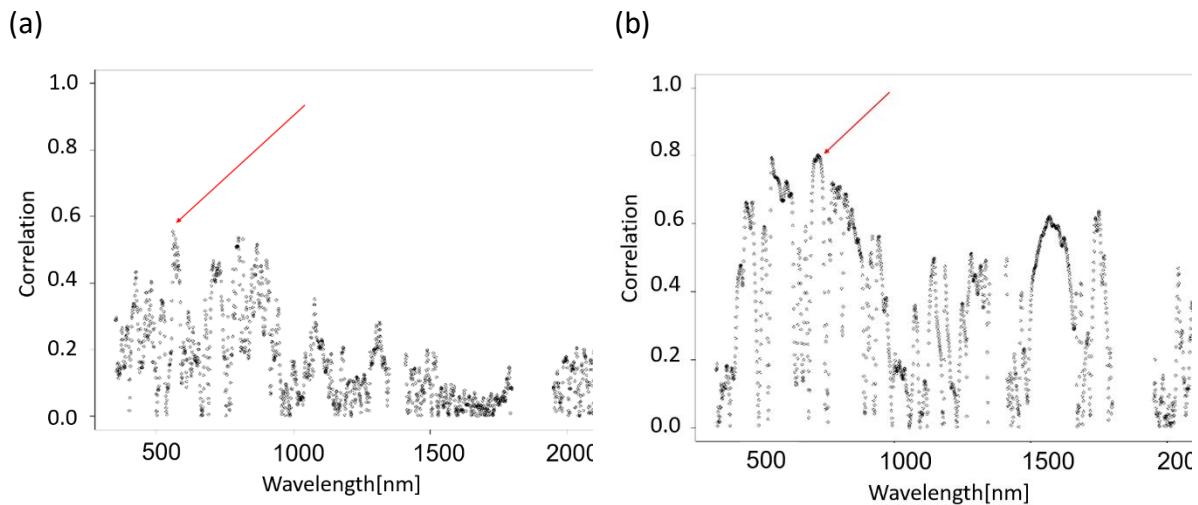


Figure 14: Corn (a) and sunflower (b) bands absolute correlation to the phenotypes' average.

5. CLASSIFICATION

Each score is the average of five iterations with standard deviations noted.

5.1. AVERAGED SCORES

Details of all models are described in Appendix A with iterations scores detailed in Appendix B. The highest F1 score for corn plants was obtained by the XGBoost and random forest algorithms. For sunflower plants the highest F1 score was derived by the logistic regression model with seven bands (Table 17).

Table 17: Classification model results

Plant	Corn			Sunflower		
Model	AUC	Accuracy	F1 score	AUC	Accuracy	F1 score
Logistic regression with one band	0.792	0.688	0.677	0.905	0.876	0.854
Logistic regression with seven bands	0.835	0.927	0.799	0.942	0.986	0.947
Logistic regression on PCA	0.76	0.664	0.654	0.872	0.846	0.805
PLS-DA	0.849	0.765	0.782	0.969	0.921	0.905
Random forest	0.939	0.859	0.88	0.978	0.936	0.925
XGBoost	0.936	0.857	0.882	0.973	0.930	0.920

5.2. CONFUSION MATRIX

Confusion matrices of all models are presented (Figure 16). Logistic regression for instance, had the highest true positive (TP) ratio (89%), but a low true negative (TN) ratio (55%) for corn plants. The PLS-DA model for sunflower plants had perfect true positive ratio (100%) with true negative ratio of only 83%. This means this model classifies more “easily” healthy plants class (0), than under stress plants class (1). The model that had the highest TP+TN for both classes is random forest in corn plants and logistic regression with seven wavelengths in sunflower plants. These were also the lead models by the F1 score (Figure 15 and Figure 16).

Logistic regression with one band

Corn

		Ground Truth	
		Healthy	Under Stress
Prediction	Healthy	313	38
	Under stress	0.89	0.11
Prediction	Under stress	235	289
	Healthy	0.45	0.55

Logistic regression with one band

Sunflower

		Ground Truth	
		Healthy	Under Stress
Prediction	Healthy	431	25
	Under stress	0.95	0.05
Prediction	Under stress	79	305
	Healthy	0.21	0.79

Logistic regression with seven band

Corn

		Ground Truth	
		Healthy	Under Stress
Prediction	Healthy	287	64
	Under stress	0.82	0.18
Prediction	Under stress	80	444
	Healthy	0.15	0.85

Logistic regression with seven band

Sunflower

		Ground Truth	
		Healthy	Under Stress
Prediction	Healthy	440	16
	Under stress	0.96	0.04
Prediction	Under stress	33	351
	Healthy	0.09	0.91

Logistic regression with PCA

Corn

		Ground Truth	
		Healthy	Under Stress
Prediction	Healthy	302	49
	Under stress	0.86	0.14
Prediction	Under stress	245	279
	Healthy	0.47	0.53

Logistic regression with PCA

Sunflower

		Ground Truth	
		Healthy	Under Stress
Prediction	Healthy	443	13
	Under stress	0.97	0.03
Prediction	Under stress	116	268
	Healthy	0.30	0.70

PLS-DA

Corn

		Ground Truth	
		Healthy	Under Stress
Prediction	Healthy	298	53
	Under stress	0.85	0.15
Prediction	Under stress	153	371
	Healthy	0.29	0.71

PLS-DA

Sunflower

		Ground Truth	
		Healthy	Under Stress
Prediction	Healthy	455	1
	Under stress	1.00	0.00
Prediction	Under stress	65	319
	Healthy	0.17	0.83

Figure 15: Classification confusion matrices (logistic regression, PCA and PLS-DA)

Random forest		Random forest					
Corn		Sunflower					
Ground Truth		Ground Truth					
		Healthy	Under Stress		Healthy	Under Stress	
Prediction	Healthy	299	52	Prediction	Healthy	451	5
	Under stress	71	453		Under stress	49	335
	0.14	0.86		0.13	0.87		

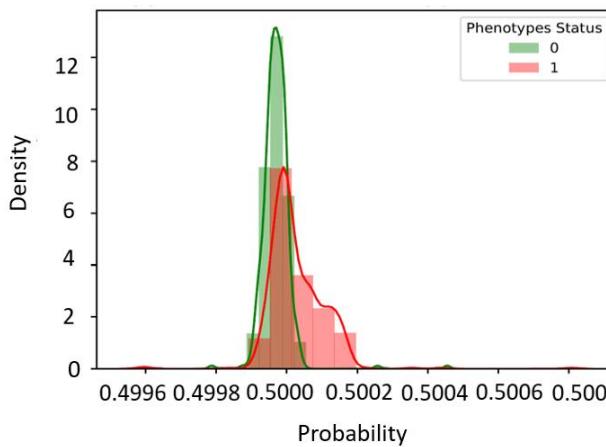
XGBoost		XGBoost					
Corn		Sunflower					
Ground Truth		Ground Truth					
		Healthy	Under Stress		Healthy	Under Stress	
Prediction	Healthy	283	68	Prediction	Healthy	442	14
	Under stress	57	467		Under stress	45	339
	0.81	0.19		0.11	0.89		

Figure 16: Classification confusion matrix (random forest and XGBoost)

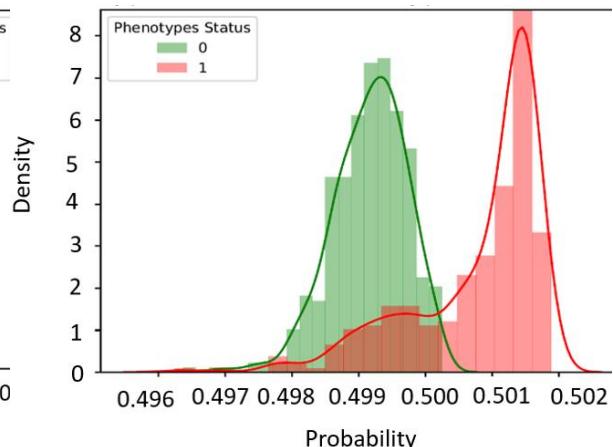
5.3. DENSITY PLOTS

The density plot of each model is presented (Figure 18). This plot was created by the probability output per each sample. As the curves of the classes are further apart, the model separates between classes better. All plots have an overlap between the curves, i.e., there are errors in the classification. The logistic regression model with one band and PCA model have the highest overlap, thus they are the less separating models. Between the random forest, XGBoost and logistic regression with seven bands models it is hard to determine which model yields best separation.

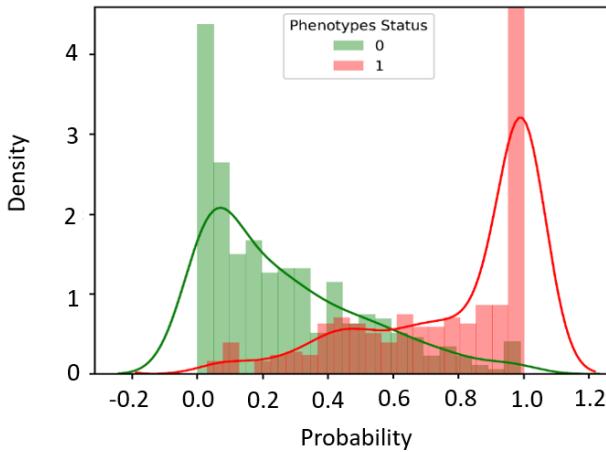
Logistic regression with one band- Corn



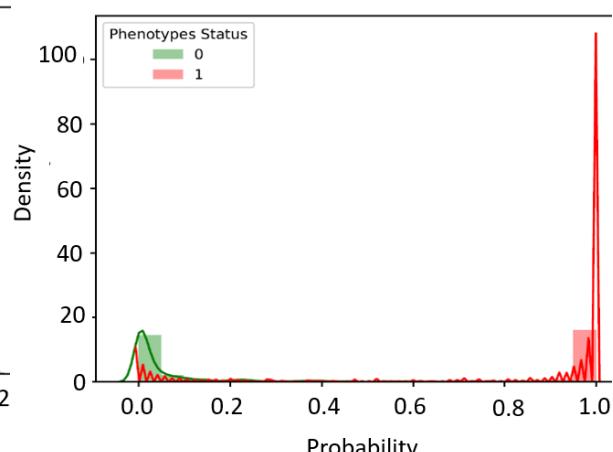
Logistic regression with one band- Sunflower



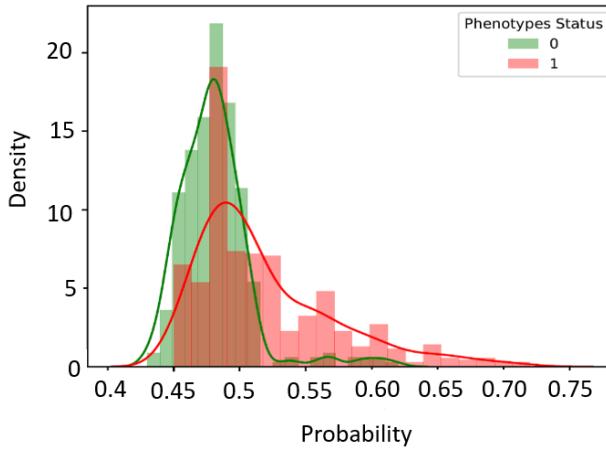
Logistic regression with seven bands- Corn



Logistic regression with seven bands - Sunflower



Logistic regression on PCA- Corn



Logistic regression on PCA- Sunflower

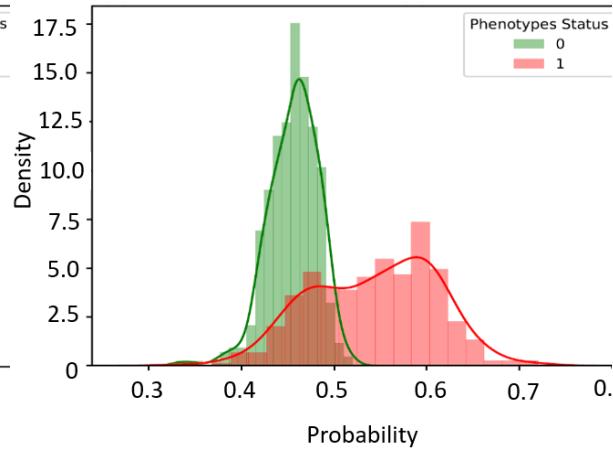


Figure 17: Classification density plots (part A)

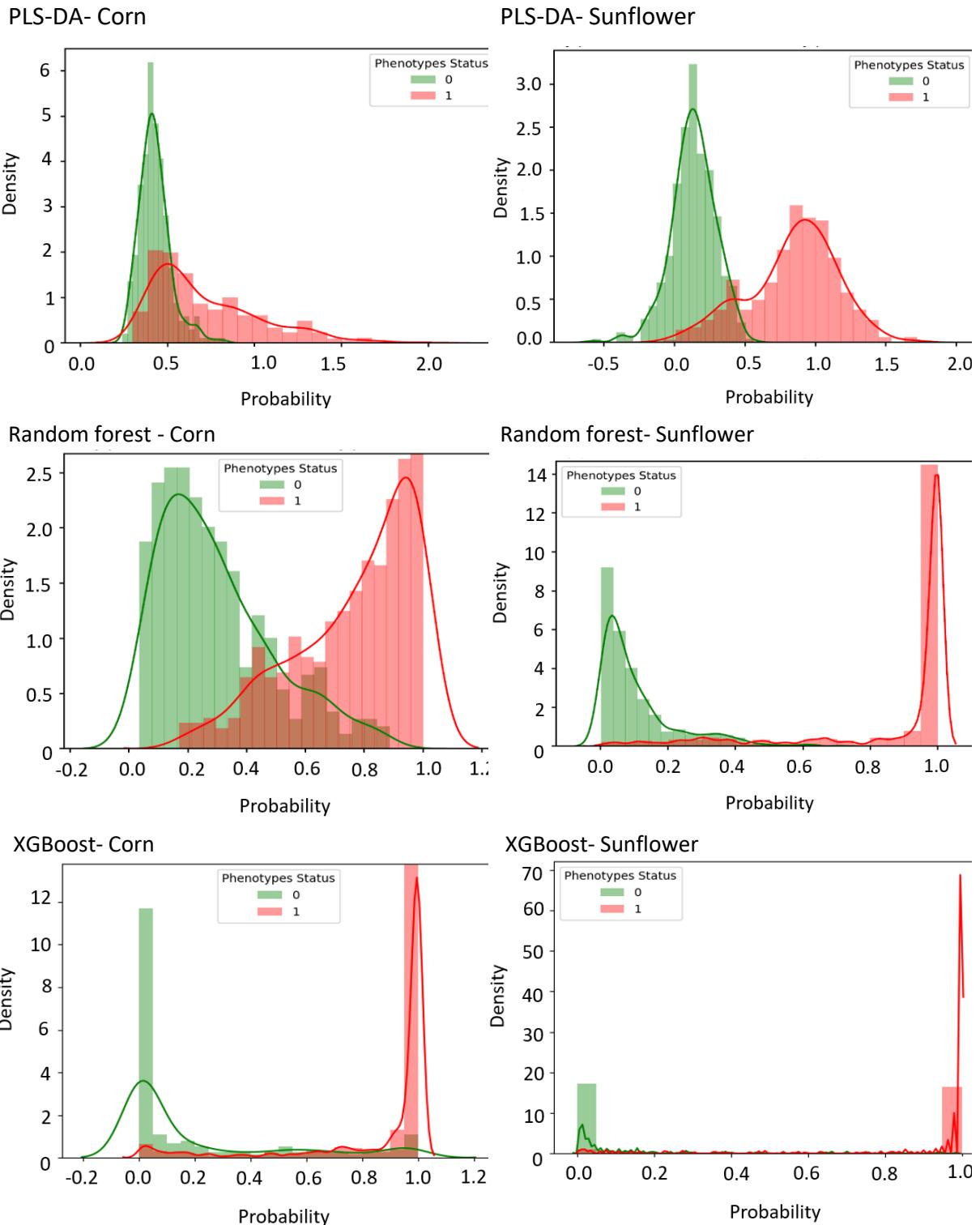


Figure 18: Classification density plots (part B)

5.4. EARLY PREDICTION

Table 18: Two days before classification models results

Plant	Corn			Sunflower		
Model	AUC	Accuracy	F1 score	AUC	Accuracy	F1 score
Logistic regression with one band	0.639	0.602	0.575	0.698	0.629	0.659
Logistic regression with seven bands	0.787	0.851	0.730	0.864	0.958	0.810
Logistic regression on PCA	0.556	0.603	0.664	0.504	0.493	0.556
PLS-DA	0.754	0.669	0.716	0.734	0.686	0.748
Random forest	0.724	0.668	0.729	0.896	0.807	0.850
XGBoost	0.665	0.618	0.686	0.886	0.786	0.836

5.5. TEST ON NEW DATASET

Following the results of experiment 1 (Table 17) XGBoost (88.2%) or random forest (88%) should yield the best scores for corn plant (corn plants). However, the highest F1 score was obtained in experiment 2 by logistic regression with seven wavelengths (Table 19).

Table 19: Test classification results on a new dataset

Model	AUC	Accuracy	F1 score
Logistic regression	0.718	0.511	0.461
N Logistic regression	0.957	0.814	0.846
PCA + Logistic regression	0.599	0.551	0.620
PLS-DA	0.835	0.607	0.606
Random forest	0.865	0.761	0.799
XGBoost	0.852	0.647	0.670

Confusion matrix:

The model that had the highest TP+TN is logistic regression with seven wavelengths and corresponds to the lead model by F1 score (Figure 19).

Logistic regression with one band		Logistic regression with seven band			
Corn		Corn			
Prediction	Ground Truth		Prediction	Ground Truth	
	Healthy	Under Stress		Healthy	Under Stress
Healthy	327	8	Healthy	327	8
	0.98	0.02		0.98	0.02
Under stress	523	227	Under stress	194	556
	0.70	0.30		0.26	0.74

Logistic regression with PCA		PLS-DA			
Corn		Corn			
Prediction	Ground Truth		Prediction	Ground Truth	
	Healthy	Under Stress		Healthy	Under Stress
Healthy	200	135	Healthy	331	4
	0.60	0.40		0.99	0.01
Under stress	352	398	Under stress	422	328
	0.47	0.53		0.56	0.44

Random forest		XGBoost			
Corn		Corn			
Prediction	Ground Truth		Prediction	Ground Truth	
	Healthy	Under Stress		Healthy	Under Stress
Healthy	310	25	Healthy	314	21
	0.93	0.07		0.94	0.06
Under stress	234	516	Under stress	362	388
	0.31	0.69		0.48	0.52

Figure 19: Classification new data confusion matrix.

Density plot:

Based on qualitative analyses the logistic regression model yielded best separation results (Figure 19). This also corresponds to results obtained by the AUC score.

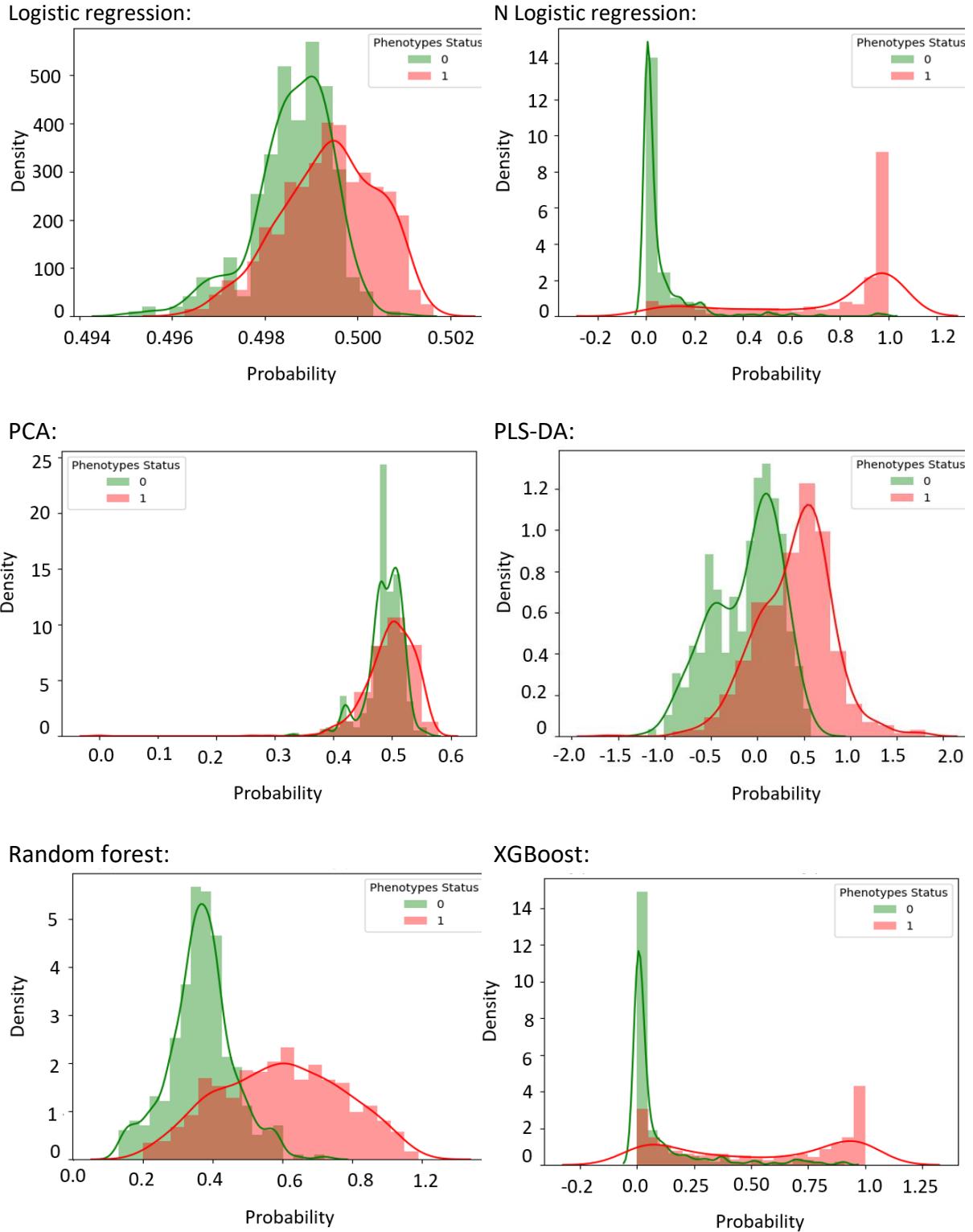
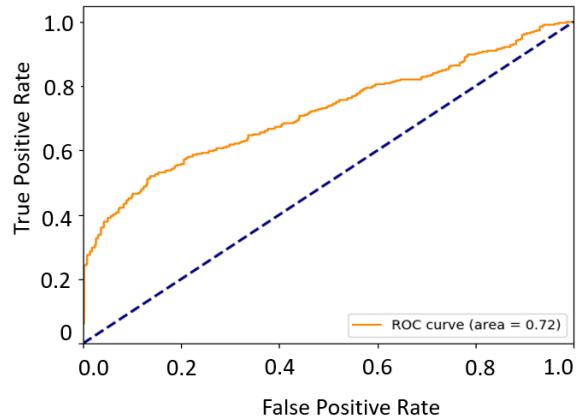


Figure 20: Classification new data density plot.

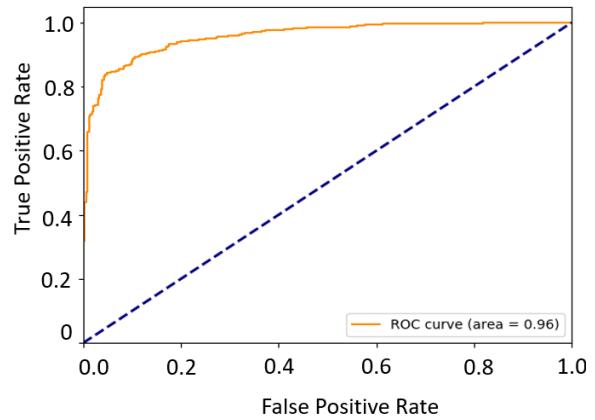
The ROC curve of each model (Figure 21) was created by moving the decision (between classes) threshold. As the curves are high and far from the 45-degree line, the AUC score is

higher, and the model has a better capability to distinguish between classes. As we expected, logistic regression yielded the best ROC plot.

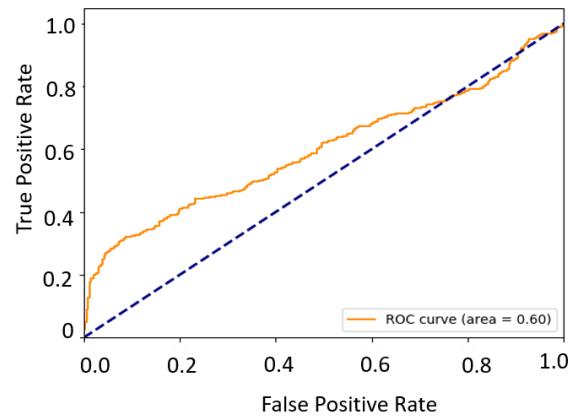
Logistic regression:



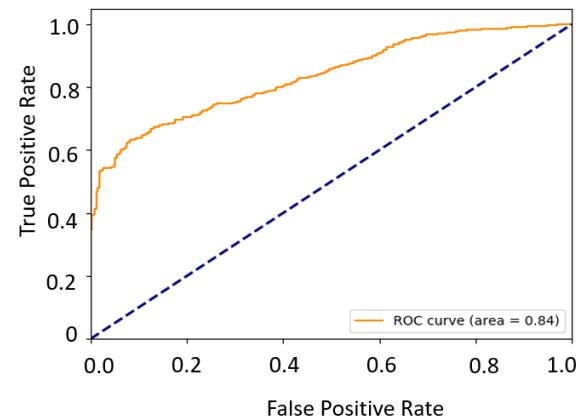
N Logistic regression:



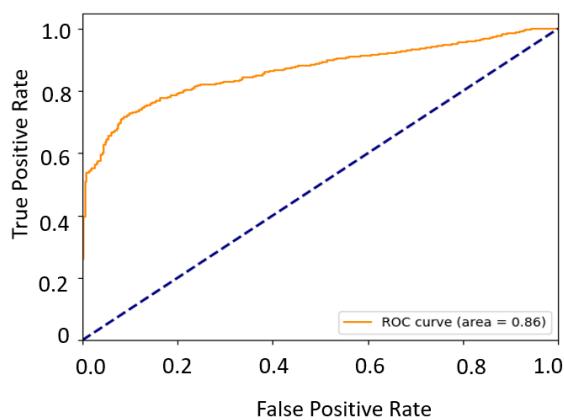
PCA:



PLS-DA:



Random forest:



XGBoost:

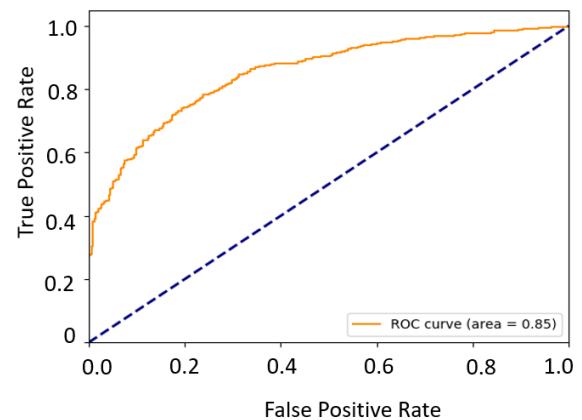


Figure 21: Classification new data ROC curve.

5.6. SUMMARY

XGBoost and random forest models reached the highest results for the 1ST derivative datasets of experiment 1; approximately 88% and 92% for corn and sunflower plants respectively (Table 17). However, the logistic regression model with seven wavelengths for the 1ST derivative dataset of experiment 2 (DCorn2) reached 5% better results than the random forest model and 18% better than the XGBoost model (Table 19).

The logistic regression with one wavelength and the PCA model consistently yielded the poorest results. In the case of the logistic model it makes sense, since it uses only one wavelength. Whereas, the PCA model uses almost all spectrum information, i.e., the PCA transformation reduces information that was needed for the phenotypes' status prediction.

We define the most robust model as the random forest model since it performs best in most cases (0.88 for corn plants, 0.925 for sunflower plants and 0.799 for the validation set) (Figure 22, Figure 23).

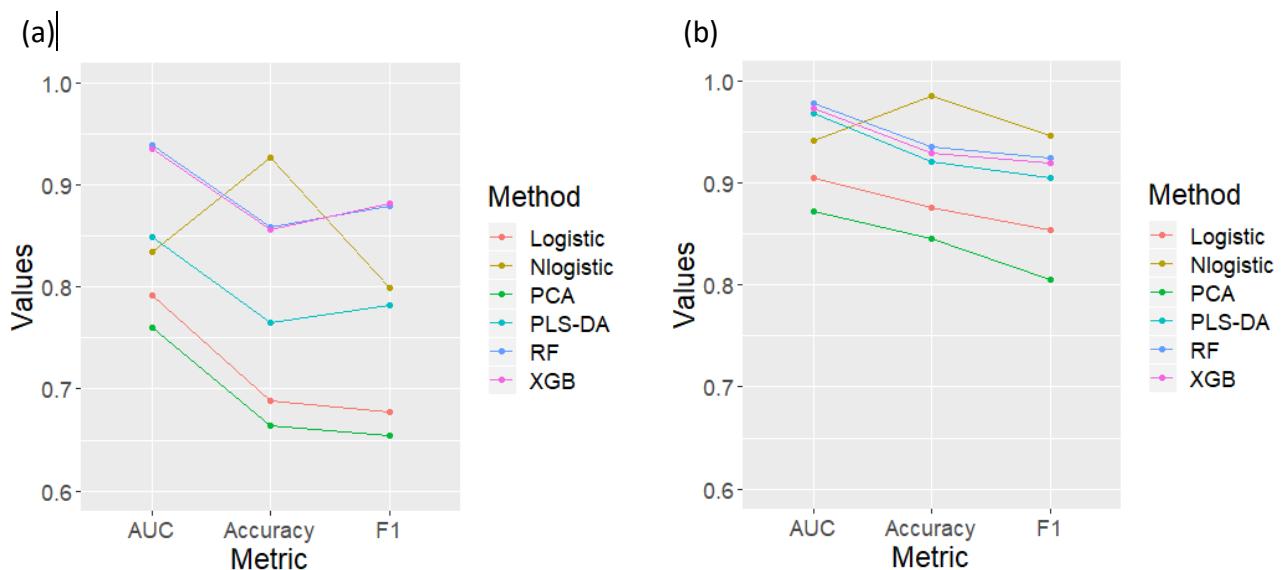


Figure 22: Corn (a) and sunflower (b) summary classification

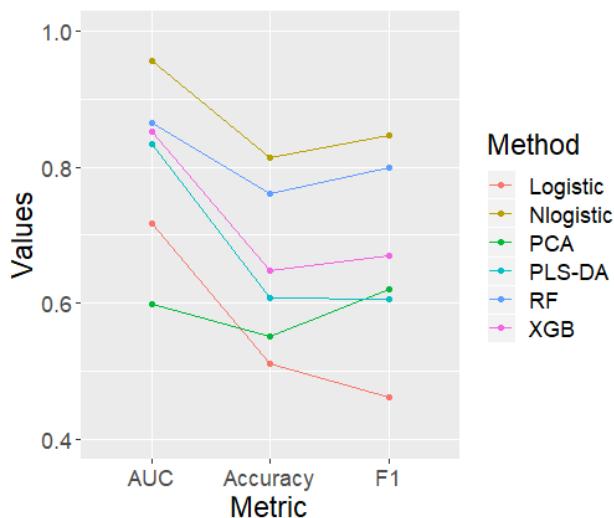


Figure 23: Corn classification model test

The early detection model was tested for samples measured on 6/11/18 and attempted to predict the phenotypes' status observed two days ahead, on 8/11/18.

The same algorithms that reached the best results for the 1ST derivative for current time classification, also reached the best results for the 1ST derivative for two days before classification.

The best performance for corn plants belongs to the random forest and logistic regression with seven wavelengths (approximately 72% F1 score, Table 18).

The best performance for sunflower plants belongs to the random forest and XGBoost (around 84% F1 score, Table 18).

The random forest model is considered the most robust since it performs best in most cases (Figure 24).

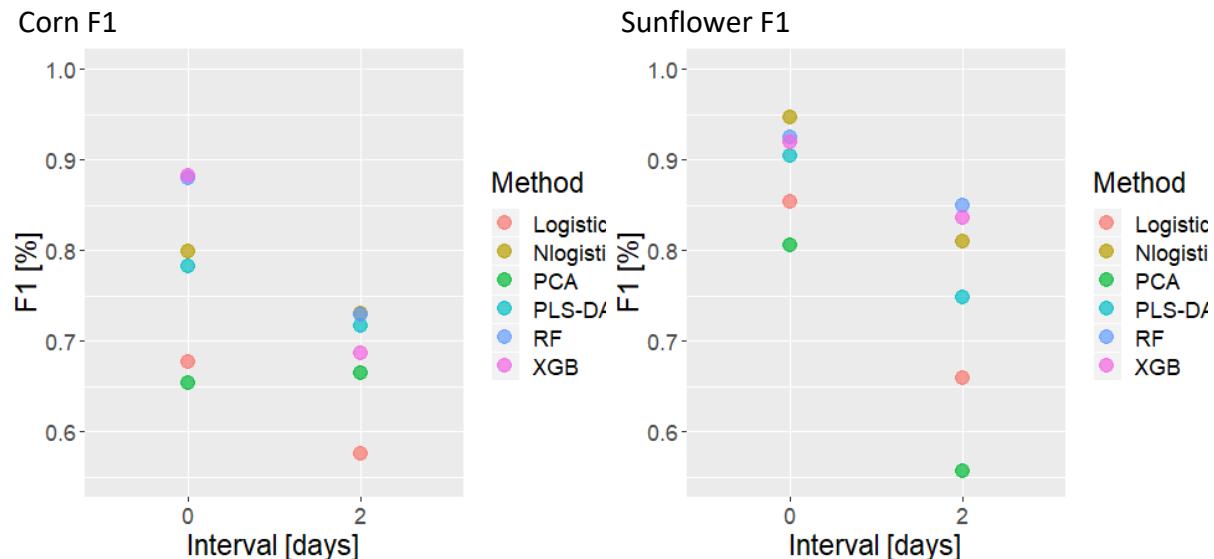


Figure 24: Early classification

6. REGRESSION

Each score is the average of five iterations with standard deviations noted.

6.1. AVERAGED SCORES

The lowest RMSE for both plants was obtained by the random forest model. The lowest MAE in both plants was obtained using the XGBoost algorithm (Table 20).

Details of all models are described in Appendix A with iterations scores detailed in Appendix B.

Table 20: Regression model results

Plant	Corn		Sunflower	
	RMSE	MAE	RMSE	MAE
Linear regression with one band	0.325	0.269	0.281	0.213
Linear regression with seven bands	0.249	0.198	0.222	0.162
Linear regression on PCA	0.282	0.229	0.253	0.180
PLS regression	0.267	0.212	0.231	0.163
Random forest	0.221	0.164	0.190	0.114
XGBoost	0.277	0.147	0.224	0.090

6.2. PREDICTION PLOT

The random forest plots have more samples around the center line i.e., implying better predictions (Figure 26).

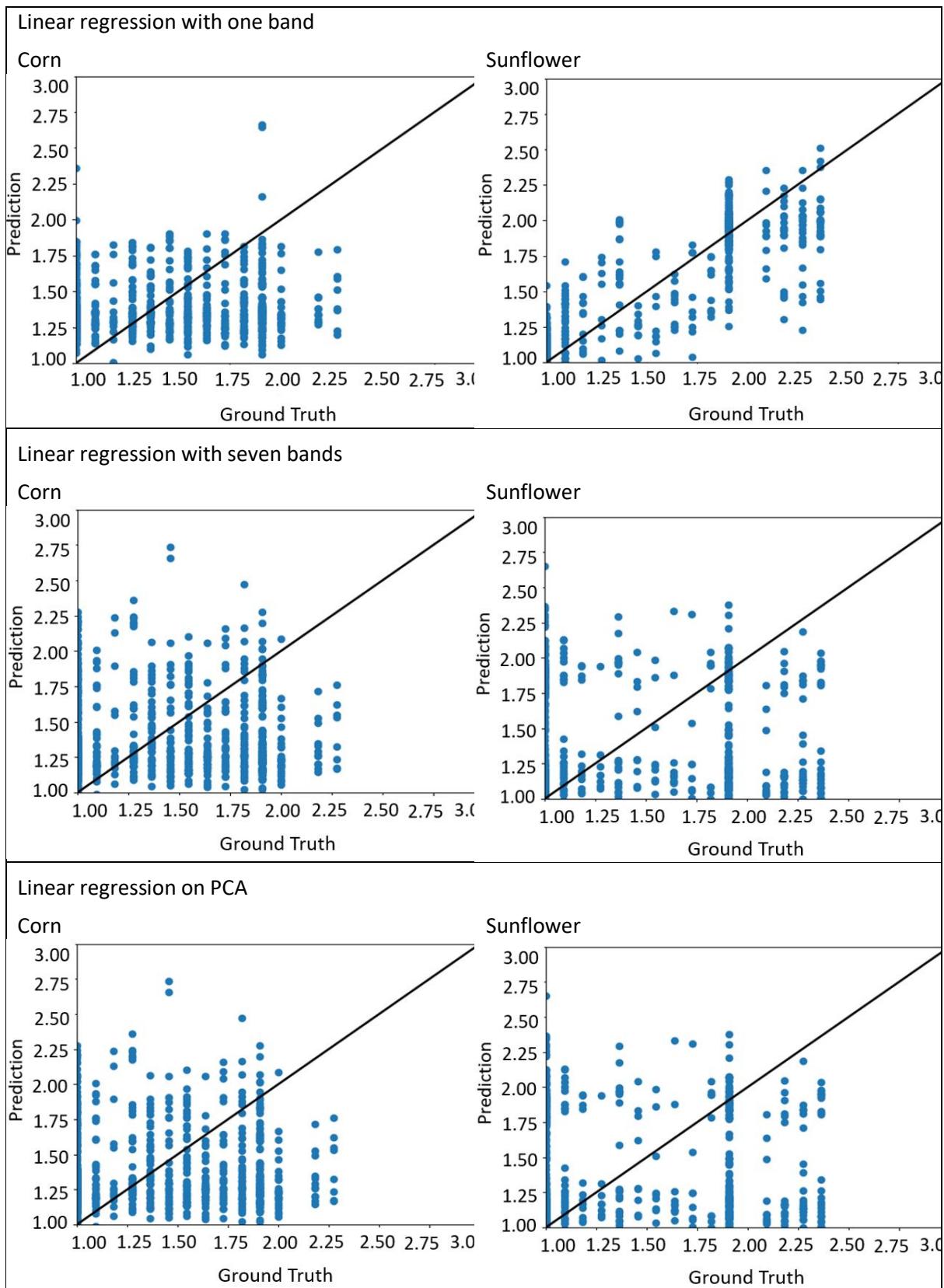


Figure 25: Regression prediction plots (part A)

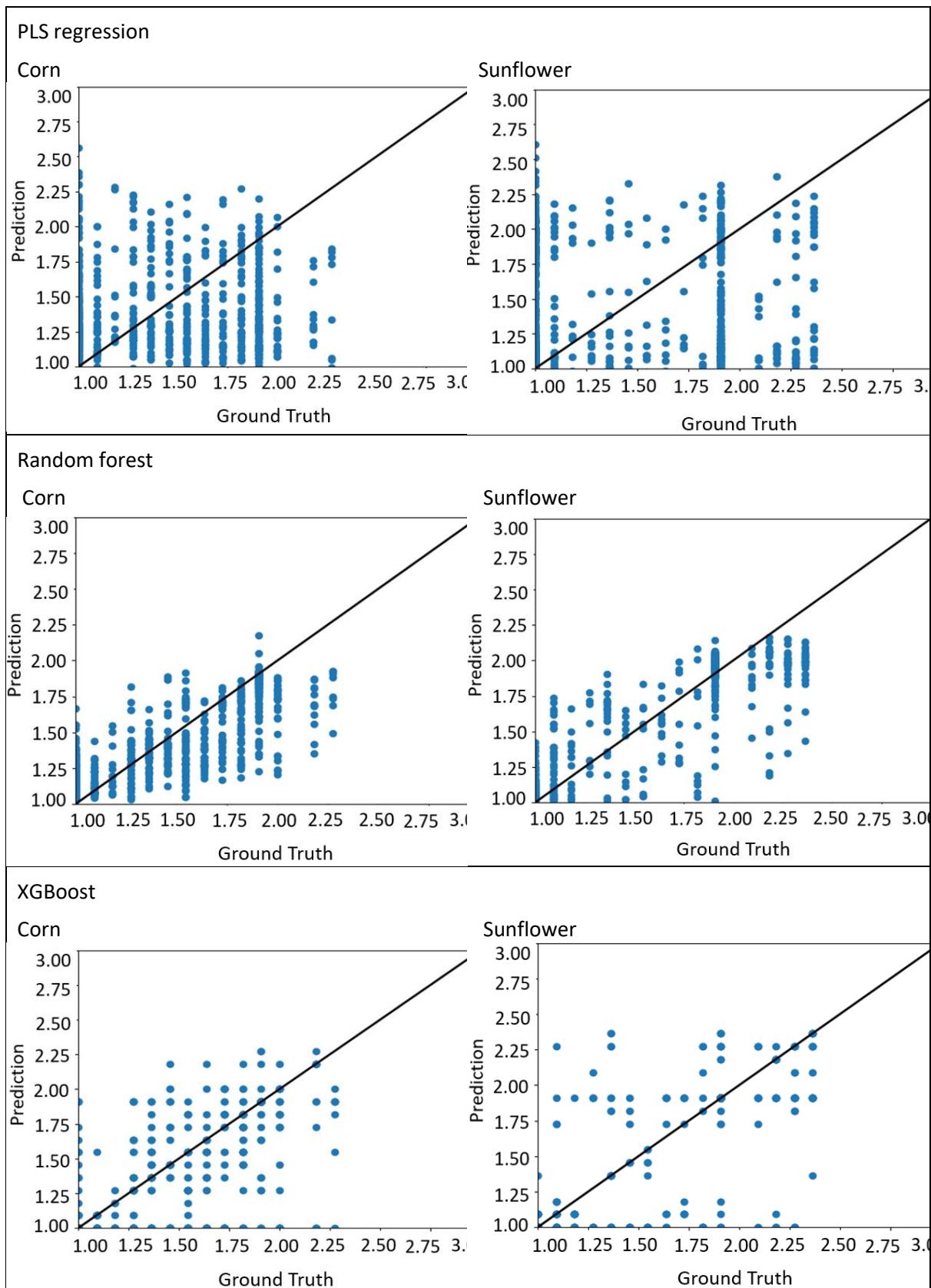


Figure 26: Regression prediction plots (part B)

6.3. EARLY PREDICTION

Table 21: Two days before regression

Plant	Corn		Sunflower	
Model	RMSE	MAE	RMSE	MAE
Linear regression with one band	0.357	0.311	0.297	0.230
Linear regression with seven bands	0.306	0.260	0.228	0.171
Linear regression on PCA	0.334	0.282	0.324	0.256
PLS regression	0.327	0.275	0.268	0.204
Random forest	0.251	0.196	0.229	0.163
XGBoost	0.325	0.186	0.248	0.105

Table 22: Four days before regression

Plant	Corn		Sunflower	
Model	RMSE	MAE	RMSE	MAE
Linear regression with one band	0.310	0.268	0.350	0.283
Linear regression with seven bands	0.257	0.208	0.201	0.151
Linear regression on PCA	0.325	0.280	0.356	0.290
PLS regression	0.325	0.274	0.302	0.231
Random forest	0.298	0.249	0.275	0.205
XGBoost	0.372	0.232	0.331	0.168

Table 23: Five days before regression

Plant	Corn		Sunflower	
Model	RMSE	MAE	RMSE	MAE
Linear regression with one band	0.311	0.258	0.465	0.406
Linear regression with seven bands	0.250	0.206	0.416	0.355
Linear regression on PCA	0.336	0.277	0.490	0.443
PLS regression	0.330	0.275	0.476	0.415
Random forest	0.274	0.224	0.421	0.353
XGBoost	0.376	0.261	0.536	0.318

Table 24: Seven days before regression

Plant	Corn		Sunflower	
Model	RMSE	MAE	RMSE	MAE
Linear regression with one band	0.345	0.287	0.466	0.404
Linear regression with seven bands	0.317	0.262	0.413	0.354
Linear regression on PCA	0.355	0.301	0.494	0.445
PLS regression	0.351	0.297	0.485	0.420
Random forest	0.331	0.279	0.418	0.356
XGBoost	0.451	0.300	0.548	0.331

6.4. TEST ON NEW DATASET

Following the results of experiment 1 (Table 20), the lowest RMSE in experiment 2 was obtained by the random forest algorithm. However, the lowest MAE score was obtained by PLS regression, with very close results (0.2% difference) obtained by the random forest algorithm (Table 25).

Averaged scores:

Table 25: Test regression result on a new dataset

Model	RMSE	MAE
Linear regression with one band	0.269	0.216
Linear regression with seven band	0.269	0.204
Linear regression on PCA	1.082	1.025
PLS regression	0.257	0.200
Random forest	0.243	0.207
XGBoost	0.321	0.216

Prediction plots:

The PCA prediction plot shows that the model has a low fit rate. The random forest plots have more samples around the center implying better predictions (Figure 27).

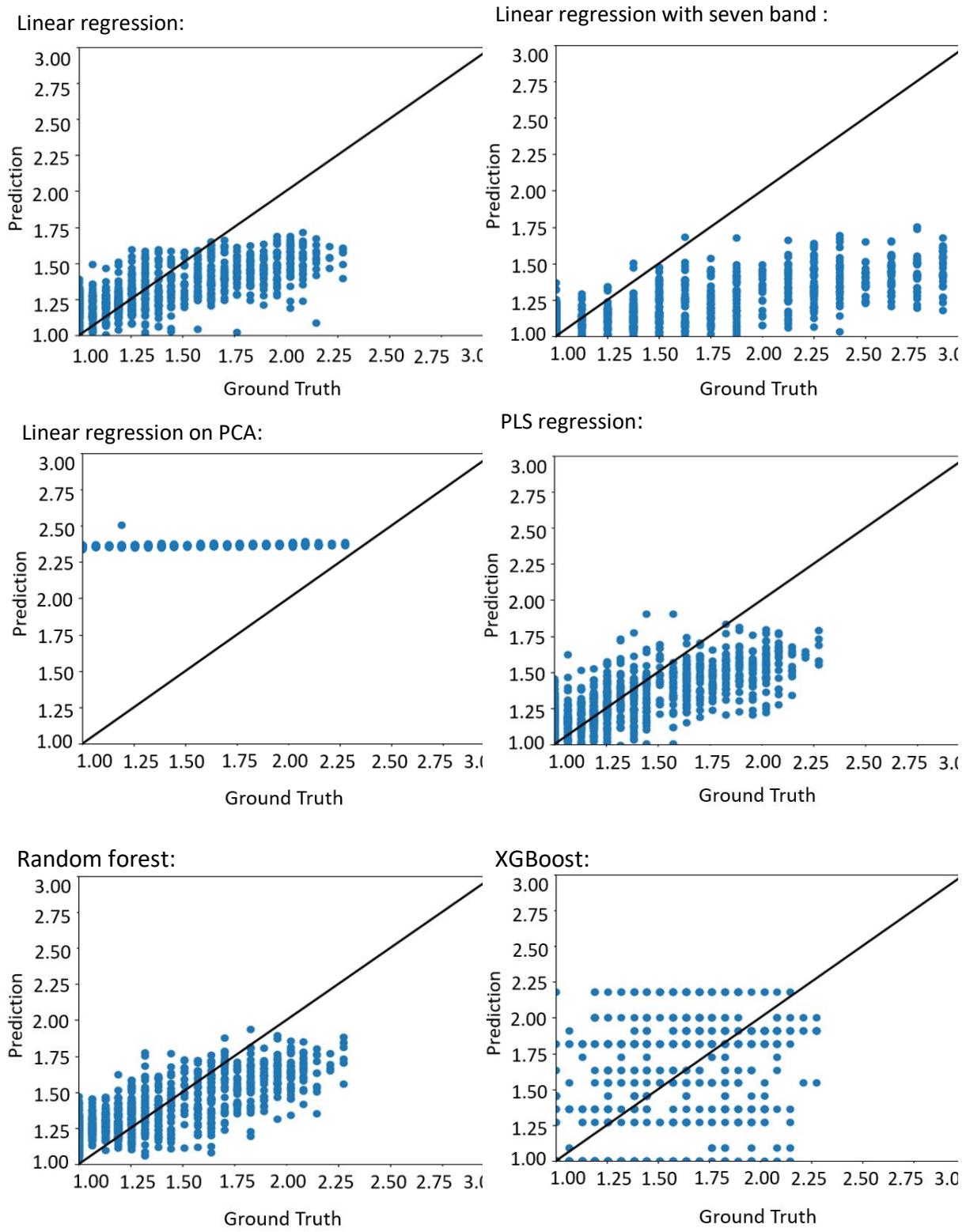


Figure 27: Regression new data performance plots.

6.5. SUMMARY

Random forest algorithm reached the lowest RMSE for the 1ST derivative datasets of experiment 1 (Table 20) and experiment 2 (Table 25). Corn RMSE of 0.221 and sunflower RMSE of 0.19 implying error rates of 17.3% and 14.9% respectively (Equation 10). The second experiment with a *phenotypes' average* range of [1, 3.5], yielded the best RMSE of 0.243 corresponding to a 9.7% error rate with the random forest algorithm.

Equation 10: Error rate

$$\text{Error rate} = \frac{RMSE}{MaxAverage - 1}$$

The next model is the linear regression by 7 wavelengths with only 2% more error rate. The linear regression with one wavelength and the PCA algorithm consistently produced the poorest results. In the case of the linear model it makes sense since it used only one wavelength. As opposed to the PCA algorithm which used almost all spectrum information. Due to the similar result structure (Figure 28) that was obtained for both plants, we note that the most robust algorithm is the random forest (Figure 28,Figure 29).

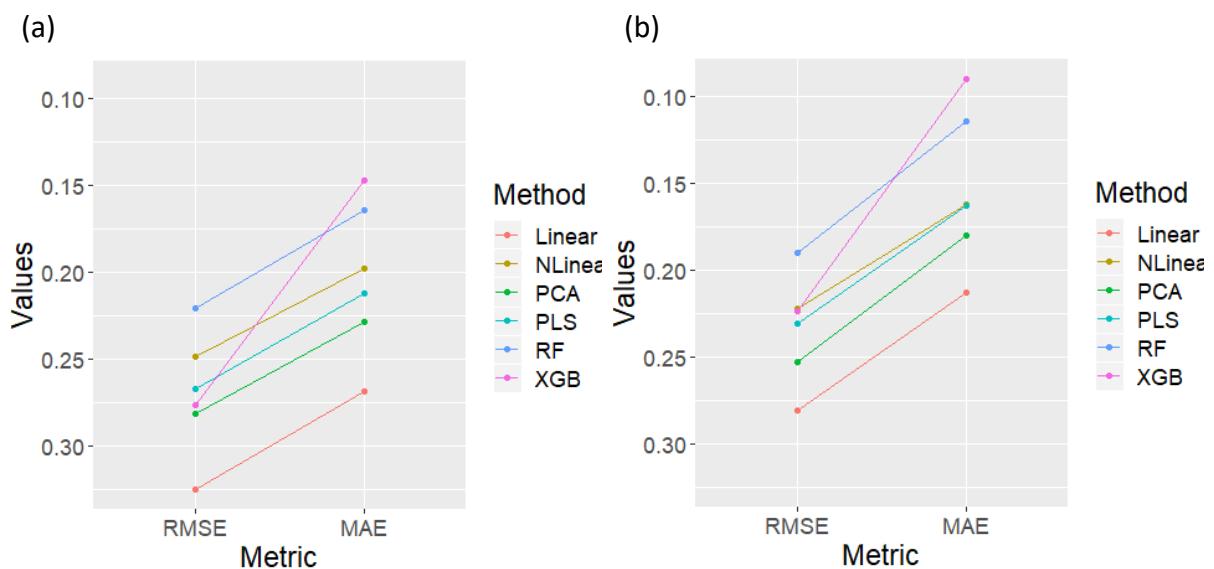


Figure 28: Corn (a) and sunflower (b) summary classification

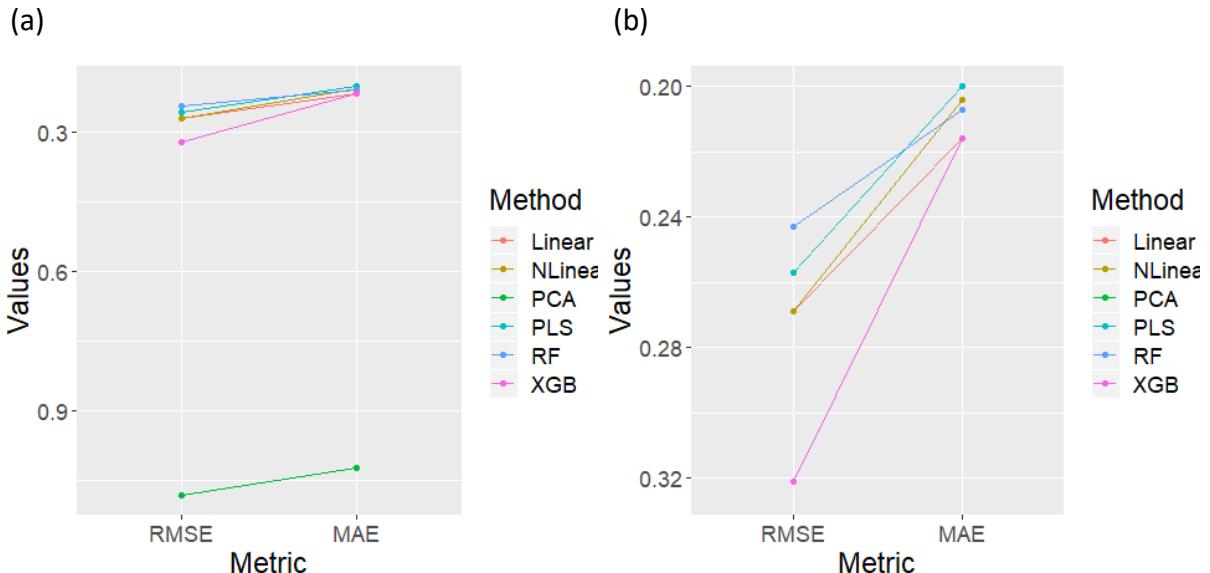


Figure 29: Corn regression model test (a), zoom on the top area (b)

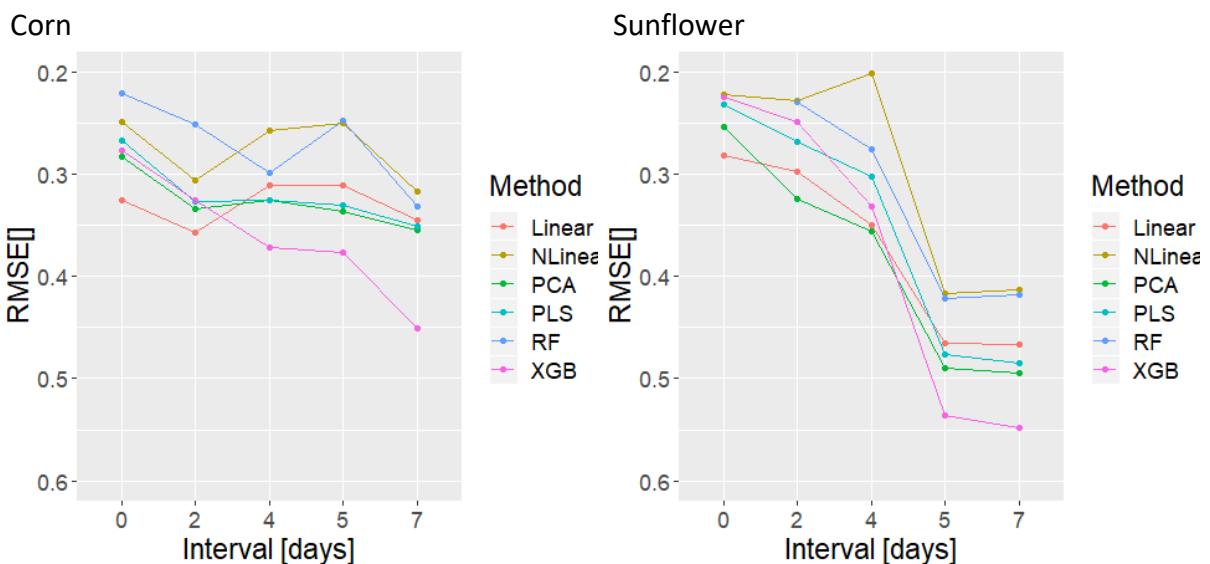


Figure 30: Early regression

The visual change appeared significantly at time point 3 (08/11/18). All early prediction datasets involve data before this time point and after, except for 'Dcorn_4Days' in the regression task. Therefore, in this dataset the success is highest, but less interesting.

Generally, the earlier we predict, the harder it is (Figure 30). The same algorithms reached the lowest RMSE for the 1ST derivative current time regression, reached the lowest RMSE for the 1ST derivative early prediction (Table 21,

Table 22, Table 23, Table 24).

It is possible to predict stress severity two days before appearance with a 20% and 18 % error rate for corn and sunflower plants using random forest or linear regression with 7 bands. It is possible to predict stress severity five days before appearance with an error rate around 20% for corn plants, and around 33% for sunflower plants by random forest or linear regression with 7 bands. It is possible to predict stress severity seven days before appearance with a 25% and 33% error rate for corn and sunflower plants using random forest or linear regression with 7 bands models (Table 24).

7. SENSITIVITY ANALYSIS

In this section the interaction between the leaves (section 7.1), MOAs (section 7.2) and the other variables was tested. Details of all models are described in Appendices A.2, A.3, A.6, A.7 and Appendix C.

7.1. LEAF ANALYSIS

The F1 score for each leaf in each classification method (Figure 31) and the RMSE score for the regression task (Figure 32) are presented. The highest F1 and the lowest RMSE score belong to the young leaf- L3 in corn, C in sunflower (Table 26,

Table 27, Table 28, Table 29). Additionally, visual analysis of the results reveal a trend- the younger the leaf is, the better the score. Thus, we can conclude that the young leaves contain the most information for the abiotic stress detection, implying that at the time of the sampling it is best to measure the last leaf that grew.

Table 26: Corn leaves classification

Plant	L1			L2			L3		
	AUC	Accuracy	F1 score	AUC	Accuracy	F1 score	AUC	Accuracy	F1 score
Logistic regression with one band	0.842	0.702	0.635	0.767	0.658	0.669	0.98	0.887	0.901
Logistic regression with seven bands	0.940	0.869	0.859	0.936	0.856	0.796	0.983	0.981	0.975
Logistic regression on PCA	0.712	0.627	0.594	0.747	0.684	0.707	0.822	0.728	0.75
PLS-DA	0.828	0.738	0.735	0.825	0.73	0.798	0.956	0.851	0.888
Random forest	0.912	0.822	0.838	0.903	0.827	0.872	0.966	0.897	0.915
XGBoost	0.904	0.819	0.833	0.907	0.830	0.875	0.972	0.887	0.911

Table 27: Sunflower leaves classification

Plant	L			C		
	AUC	Accuracy	F1 score	AUC	Accuracy	F1 score
Logistic regression with one band	0.879	0.853	0.821	0.97	0.936	0.923
Logistic regression with seven bands	0.976	0.917	0.924	0.997	0.983	0.985
Logistic regression on PCA	0.827	0.838	0.798	0.904	0.843	0.801
PLS-DA	0.941	0.888	0.862	0.991	0.962	0.956

Random forest	0.953	0.898	0.88	0.991	0.983	0.981
XGBoost	0.955	0.884	0.867	0.986	0.979	0.976

Table 28: Corn leaves regression

Plant	L1		L2		L3	
Model	RMSE	MAE	RMSE	MAE	RMSE	MAE
Linear regression with one band	0.302	0.249	0.311	0.250	0.235	0.192
Linear regression with seven bands	0.248	0.190	0.232	0.188	0.162	0.133
Linear regression on PCA	0.298	0.237	0.263	0.216	0.277	0.233
PLS	0.277	0.199	0.271	0.220	0.261	0.223
Random forest	0.239	0.173	0.214	0.161	0.203	0.163
XGBoost	0.374	0.208	0.259	0.149	0.300	0.186

Table 29: Sunflower leaves regression

Plant	L		C	
Model	RMSE	MAE	RMSE	MAE
Linear regression with one band	0.263	0.196	0.257	0.196
Linear regression with seven bands	0.215	0.160	0.184	0.130
Linear regression on PCA	0.286	0.216	0.230	0.165
PLS	0.236	0.171	0.203	0.146
Random forest	0.198	0.125	0.156	0.087
XGBoost	0.241	0.104	0.212	0.081

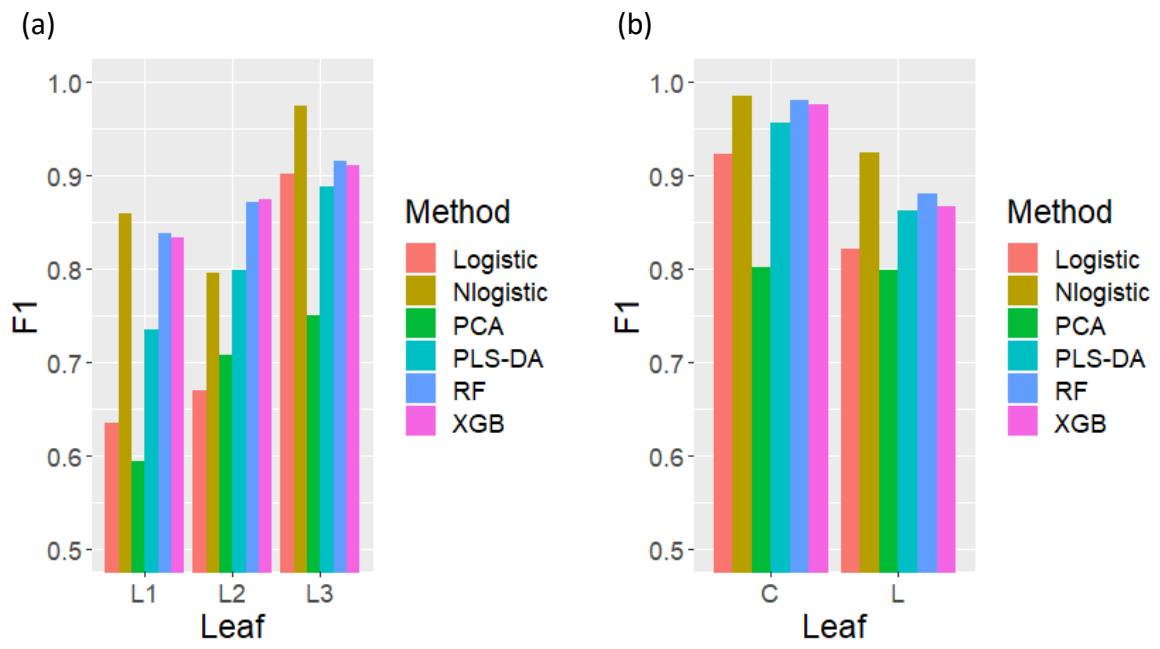


Figure 31: Corn (a) and sunflower (b) leaves classification plots

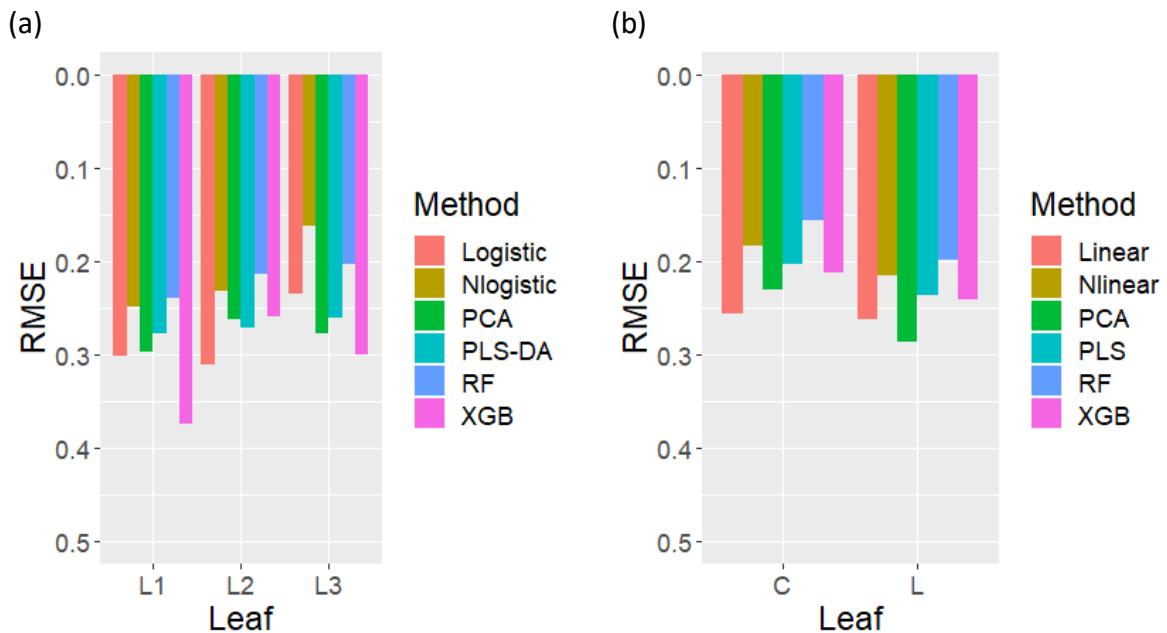


Figure 32: Corn (a) and sunflower (b) leaves regression plots

7.2. MOA ANALYSIS

The F1 score for each MOA in each classification method (Figure 33) and the RMSE score for the regression task (Figure 34) are presented. It is hard to determine which inhibition mechanism is more detectable (Table 30, Table 31, Table 32, Table 33). Therefore, all “under stress” plants are filtered and labeled by their chemical MOA category. After that, the random forest algorithm is used to classify between Inhibition of Photosynthesis (IP), Inhibition in Lipid Metabolism (LM) and Inhibition in Amino Acid Metabolism (AAM). We tried to determine which mechanism has been damaged (Figure 36).

The classification between 167 LM, 185 IP and 167 AAM plants reached accuracies of 65.9%, 69% true lipid metabolism detections, 69% true photosynthesis detections and 60% true amino acid metabolism detections (using the normalized confusion matrix) (Figure 36).

The model probabilities were manipulated as follows- for LM prediction samples, the probability to predict LM was calculated, for IP prediction samples, the probability to predict IP plus 1 was calculated and for AAM prediction samples, the probability to predict AAM plus 2 was calculated. The density plot of a good classification model should include LM predictions between 0 to 1, IP predictions between 1 to 2 and AAM predictions between 2 to 3. Unfortunately, the predictions of each class spread across the range. This implies that these models cannot determine which mechanism has been damaged. For more details, see Appendix C.

Table 30: Corn MOA classification

Plant Model	IP			LM			AAM		
	AUC	Accuracy	F1 score	AUC	Accuracy	F1 score	AUC	Accuracy	F1 score
Logistic regression with one band	0.848	0.742	0.716	0.904	0.796	0.712	0.741	0.632	0.532
Logistic regression with seven bands	0.858	0.943	0.832	0.912	0.985	0.927	0.930	0.991	0.930
Logistic regression on PCA	0.837	0.757	0.769	0.724	0.671	0.517	0.584	0.528	0.45
PLS-DA	0.866	0.777	0.788	0.898	0.834	0.757	0.867	0.806	0.802
Random forest	0.921	0.846	0.863	0.959	0.879	0.839	0.951	0.876	0.876
XGBoost	0.925	0.854	0.869	0.945	0.866	0.822	0.940	0.880	0.881

Table 31: Sunflower MOA classification

Plant	IP			AAM		
Model	AUC	Accuracy	F1 score	AUC	Accuracy	F1 score
Logistic regression with one band	0.986	0.946	0.951	0.888	0.871	0.86
Logistic regression with seven bands	0.996	1.000	0.995	0.971	0.990	0.970
Logistic regression on PCA	0.929	0.842	0.854	0.837	0.825	0.797
PLS-DA	0.996	0.95	0.955	0.986	0.933	0.933
Random forest	0.999	0.988	0.989	0.982	0.933	0.932
XGBoost	0.999	0.988	0.989	0.975	0.933	0.931

Table 32: Corn MOA regression

Plant	IP		LM		AAM	
Model	RMSE	MAE	RMSE	MAE	RMSE	MAE
Linear regression with one band	0.244	0.209	0.312	0.236	0.190	0.159
Linear regression with seven bands	0.181	0.145	0.219	0.162	0.143	0.107
Linear regression on PCA	0.215	0.177	0.307	0.243	0.194	0.154
PLS	0.223	0.182	0.295	0.189	0.163	0.115
Random forest	0.184	0.136	0.233	0.164	0.140	0.097
XGBoost	0.212	0.097	0.305	0.145	0.165	0.072

Table 33: Sunflower MOA regression

Plant	IP		AAM	
Model	RMSE	MAE	RMSE	MAE
Linear regression with one band	0.195	0.149	0.285	0.226
Linear regression with seven bands	0.152	0.116	0.227	0.171
Linear regression on PCA	0.234	0.170	0.277	0.207
PLS	0.172	0.132	0.255	0.187
Random forest	0.115	0.059	0.191	0.113
XGBoost	0.145	0.042	0.203	0.077

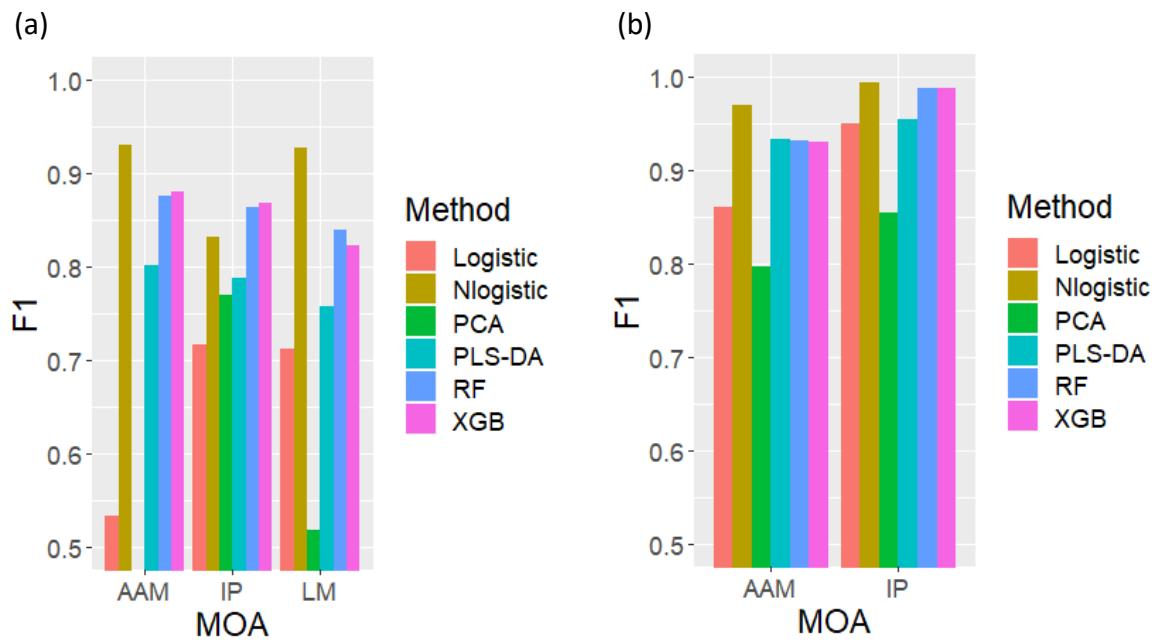


Figure 33: Corn (a) and sunflower (b) MOA classification plots

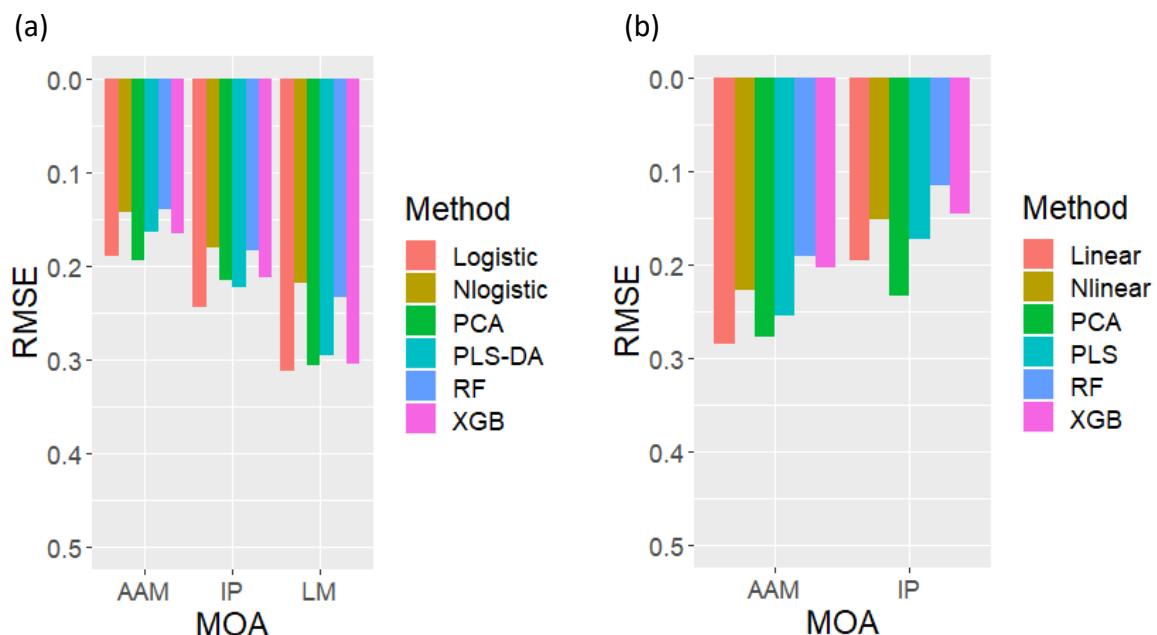


Figure 34: Corn (a) and sunflower (b) MOA regression plots

MOA classification:

Label 1- lipid metabolism, label 2- photosynthesis and label 3- amino acid metabolism.

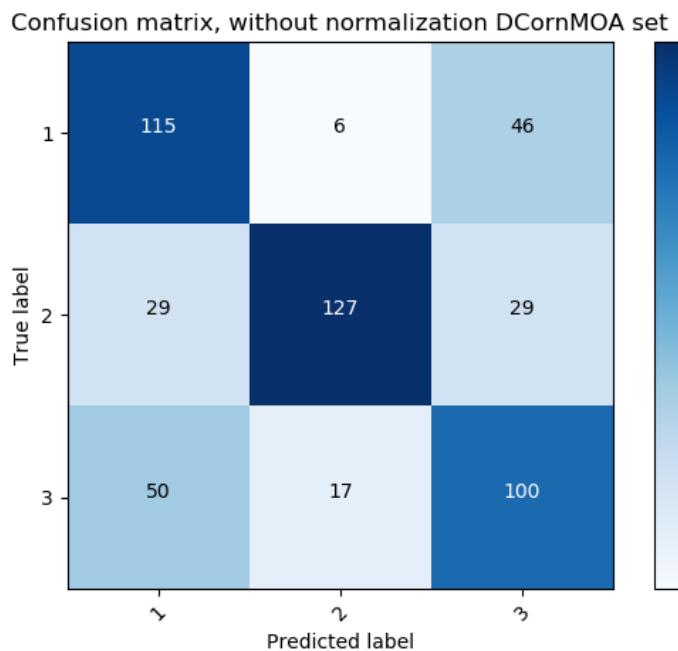
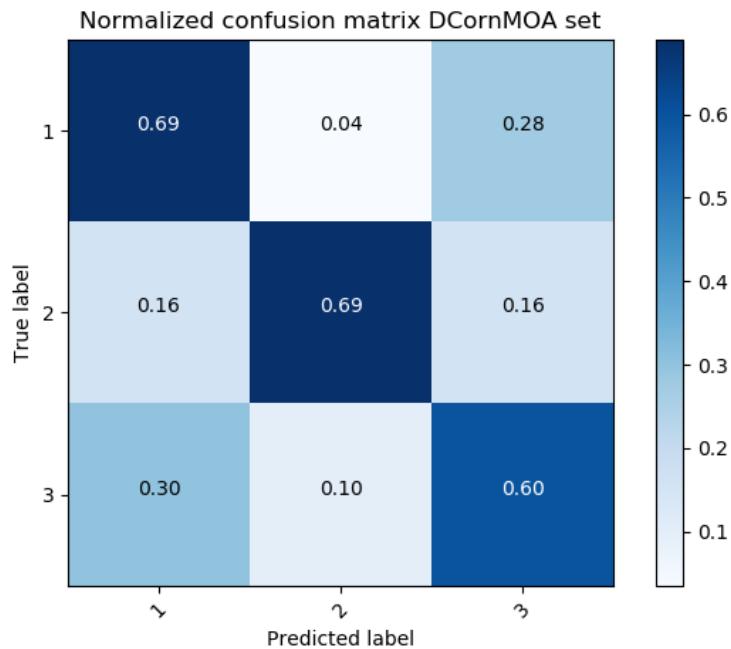


Figure 35: MOA classification, confusion matrix

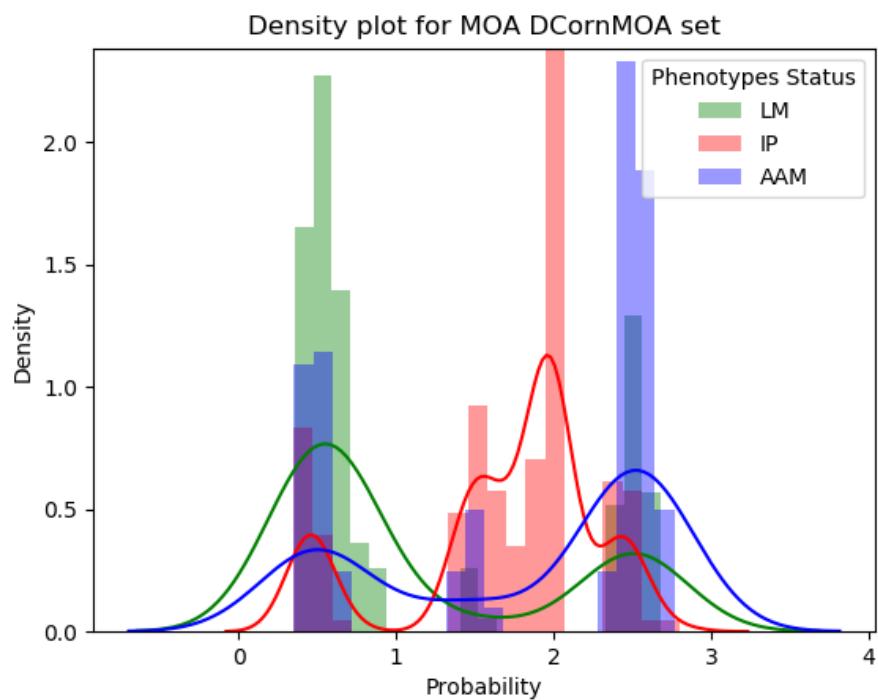


Figure 36: MOA classification, density plot

8. FEATURES (WAVELENGTHS) IMPORTANCE

8.1. OVERVIEW

Results reveal different wavelengths' importance for the different corn and sunflower models.

The most correlated wavelength to the *phenotypes' average*, which used both linear and logistic regression with one variable (1^{ST} derivative at 561nm), belongs to the visible light near the green color. The seven wavelengths, which used logistic regression, belong to the visible light and the NIR (1^{ST} derivative at: 562nm, 794nm, 683nm, 656nm, 535nm, 703nm and 542nm). The linear regression model also used bands in the SWIR range (1^{ST} derivative at: 561nm, 901nm, 684nm, 703nm, 373nm, 525nm and 1996nm).

Among sunflower plants, the most correlated wavelength to the *phenotypes' average*, which used both linear and logistic regression with one variable (1^{ST} derivative at 722nm), belongs to the NIR. The seven wavelengths, which were used in logistic and linear regression, spread throughout all measurement ranges (logistic- 1^{ST} derivative at: 551nm, 734nm, 1516nm, 1074nm, 739nm, 1651nm and 2136nm. linear- 1^{ST} derivative at: 722nm, 755nm, 1504nm, 437nm, 550nm, 354nm and 404nm).

The 1^{ST} derivative of the wavelengths between 550nm to 850m reached the highest VIP score in the PLS/PLS-DA plots (Figure 37). The 1^{ST} derivative of the wavelengths between 450nm to 850m reached the highest GINI score in the random forest classification and regression (Figure 38). The 1^{ST} derivative of the wavelengths spread all over the spectrum with peaks around 600nm-800nm among XGBoost classification and regression (Figure 39). For more details, see appendix E.

The wavelengths are defined as follows:

- blue colour - wavelengths under 500nm
- green colour - wavelengths between 500nm and 600nm
- red colour - wavelengths between 600nm and 700nm
- NIR - wavelengths between 700nm and 1000nm
- SWIR - wavelengths above 1000nm.

The blue, green and red colours belong to the visible field.

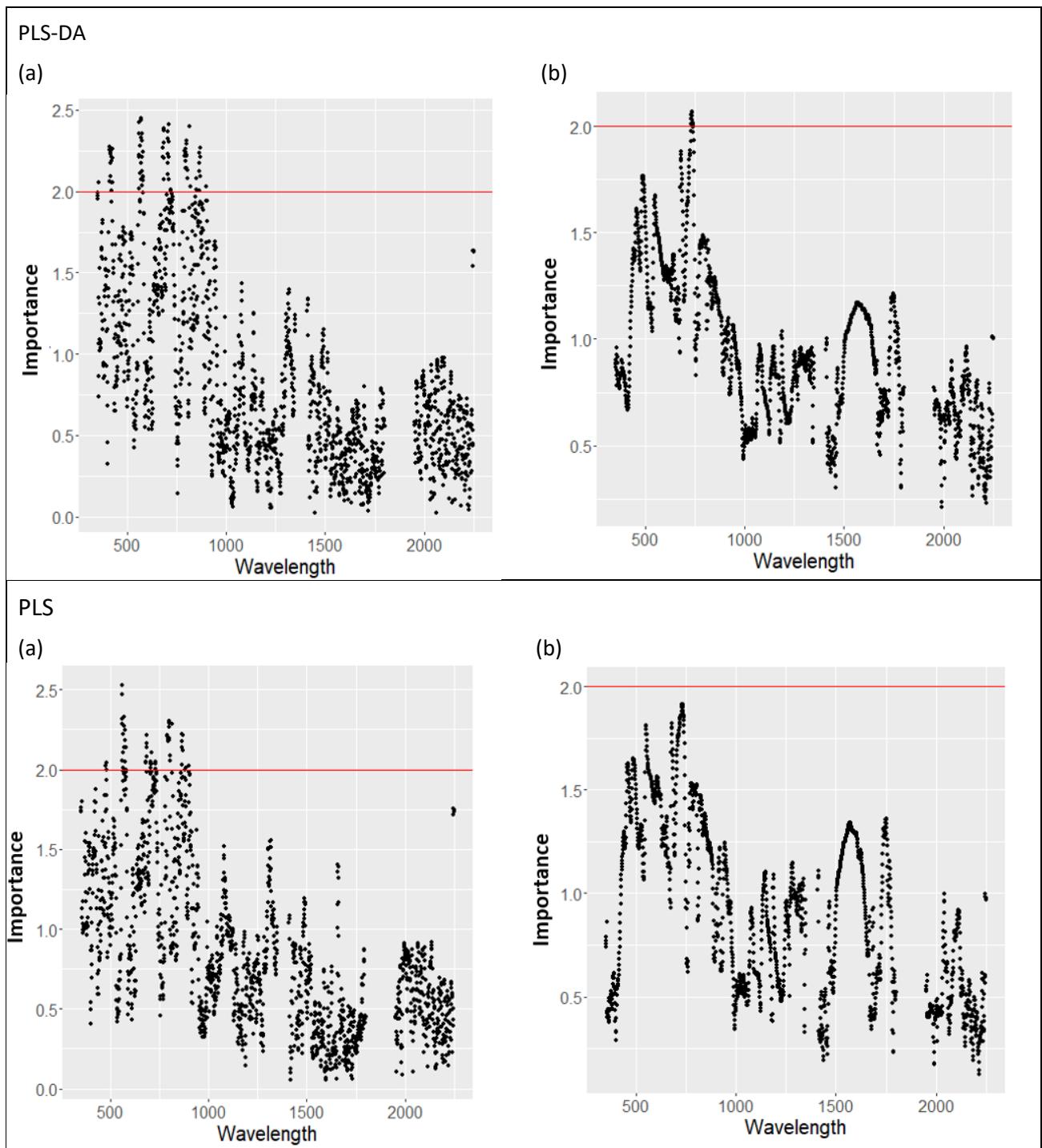
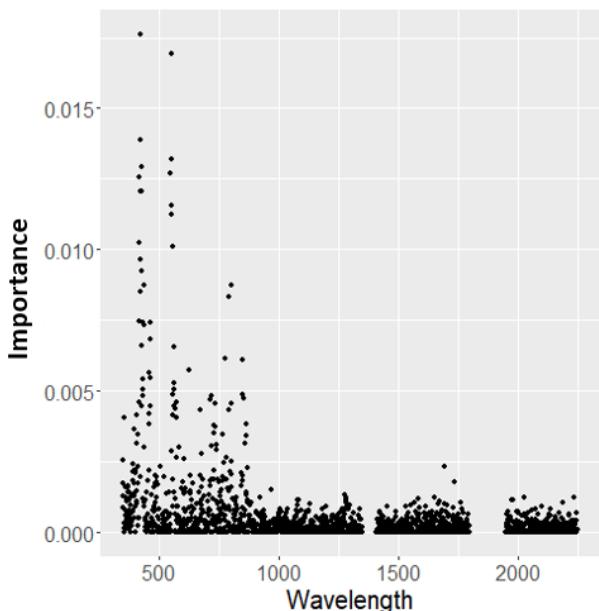


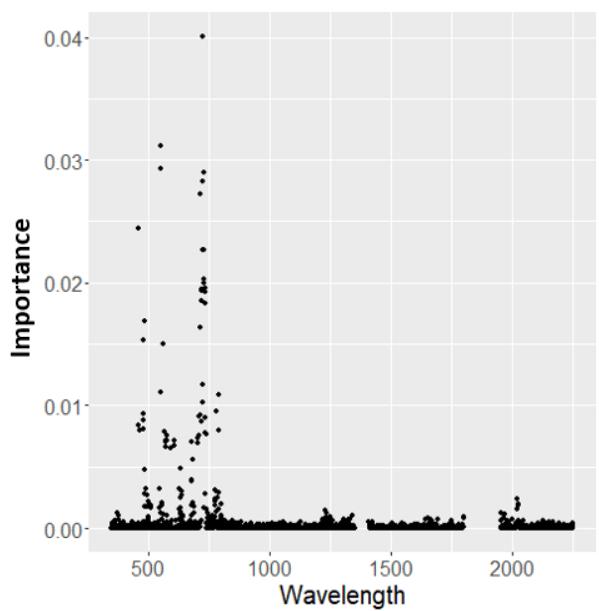
Figure 37: PLS and PLS-DA VIP for corn (a) and sunflower (b) plants.

Random forest classification

(a)

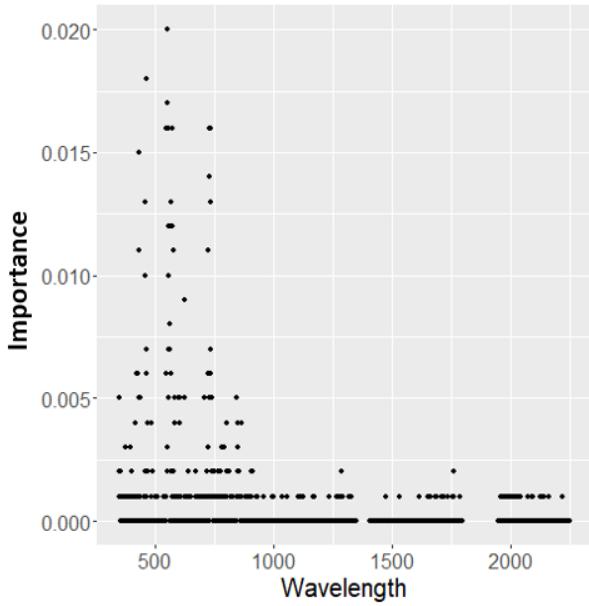


(b)



Random forest regression

(a)



(b)

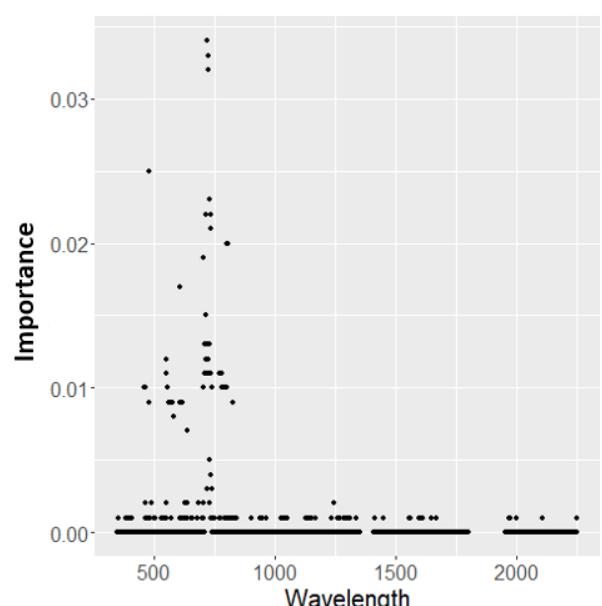


Figure 38: Random forest features importance for corn (a) and sunflower (b) plants.

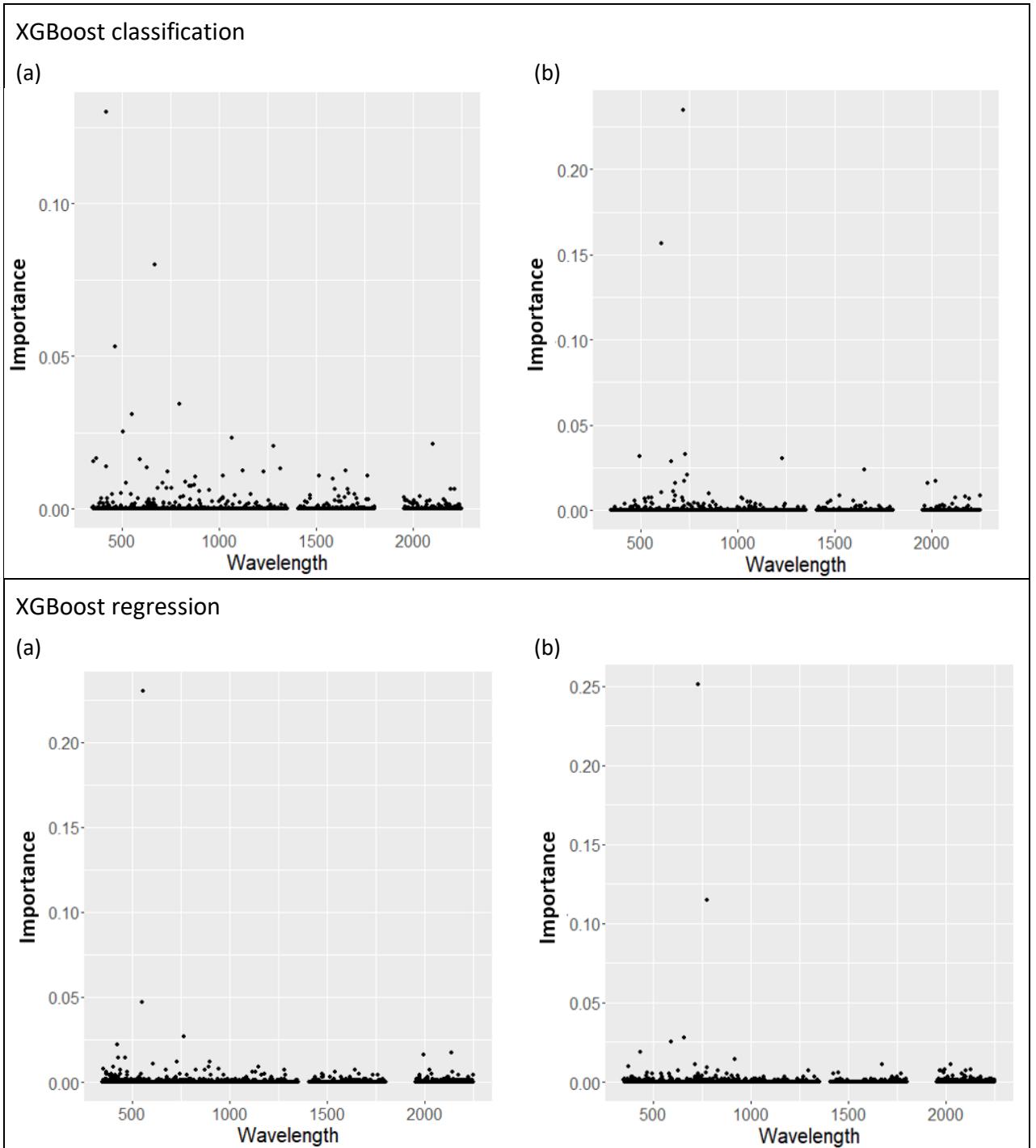


Figure 39: XGBoost features importance for corn (a) and sunflower (b) plants.

The wavelengths' importance of all models combined are presented (Figure 40 and Figure 41). To identify key areas in the spectrum, we merged every 8nm by summing their importance (corresponding to the sensor resolution). This explains why the classification and regression of 7 bands is represented only by 6 bands. Among the decision trees' algorithms, each tree saw a subset of the wavelengths. Thus, different wavelengths that are very close were often chosen. This issue was addressed by merging close areas.

For both plants, the most important variables for classification, as well as regression by PLS, PLS-DA and random forest algorithms, belong to the visible light (red, green, blue) and the NIR field (Figure 40 and Figure 41). The most important variables for classification, as well as regression by XGBoost algorithm, spread throughout all measurement ranges (visible, NIR and SWIR) (Figure 40 and Figure 41).

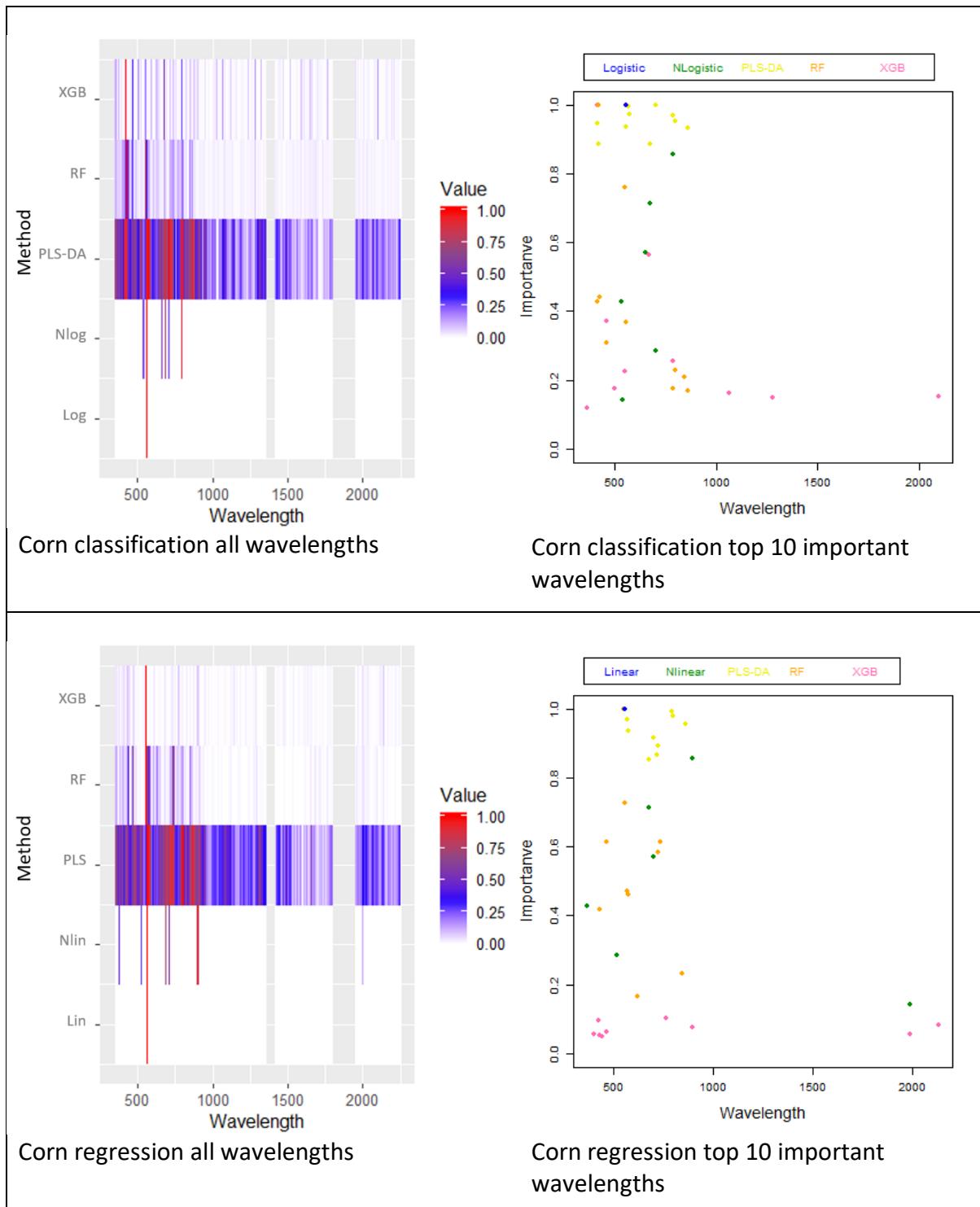


Figure 40: Corn importance wavelengths summary

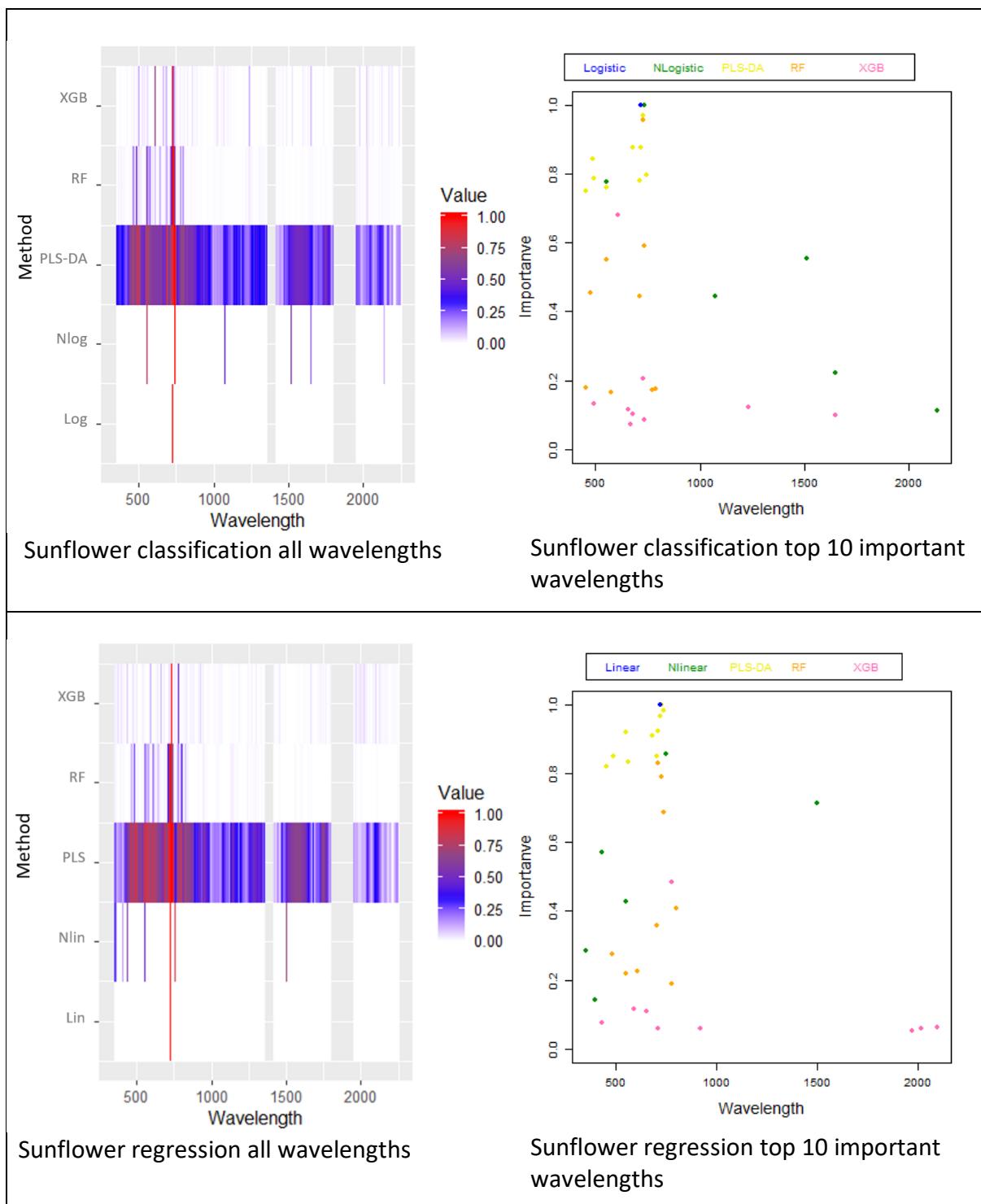


Figure 41: Sunflower importance wavelengths summary

PCA: The wavelengths' importance in the PCA models is attributed to the spectrum variance and not to the *phenotypes' average/status*. The components that explained the most variance in corn (42.1%) given highest weight to 1ST derivative at 1951nm, belongs to the SWIR field. The components that explained the most variance in sunflower (52%) given highest weight to the 1ST derivative at 1800nm, belongs to also the SWIR field (Table 34).

Table 34: The most contributing wavelength in each component (PCA)

Plant	Corn		Sunflower	
Component	Explained variance ratio	Most important wavelength	Explained variance ratio	Most important wavelength
1	0.421	1951	0.520	1800
2	0.130	350	0.146	1410
3	0.092	1410	0.099	350
4	0.048	700	0.056	2250
5	0.033	2000	0.036	1348
6	0.024	1417	0.028	1962
7	0.019	1959	0.016	688
8	0.016	2250		
9	0.014	691		
10	0.010	1419		
11	0.009	1422		
12	0.007	1419		
13	0.006	1421		
14	0.006	2020		
15	0.005	1980		
16	0.005	1583		
17	0.004	2154		
18	0.004	1594		
19	0.004	1955		
20	0.004	1964		
21	0.004	1798		
22	0.004	1425		
23	0.003	533		
24	0.003	1561		
25	0.003	2136		
26	0.003	1602		
27	0.003	2005		
28	0.003	1553		
29	0.003	1602		
30	0.003	2157		
31	0.003	1761		
32	0.003	2157		
33	0.003	2023		

8.2. TOP LEAD WAVELENGTHS

Using the entire spectrum requires expensive resources. In the next section, we recommend a limited number of wavelengths to make models more applicable. The classification and regressions models which achieved the best performance were produced by the random forest and logistic/linear regression algorithms.

8.2.1. RANDOM FOREST

The top 10 1ST derivative of the wavelengths (features) for each plant and target are presented (Figure 42). The most powerful features for corn classification spread around the blue color, then around the green color and the NIR field. Corn regression's most powerful features are around green color, then around NIR field and blue color. The most powerful features among the sunflower classification spread around NIR field, then around the green and the blue color. The sunflower regression's powerful features are spread around NIR field, then around the blue and the red colors.

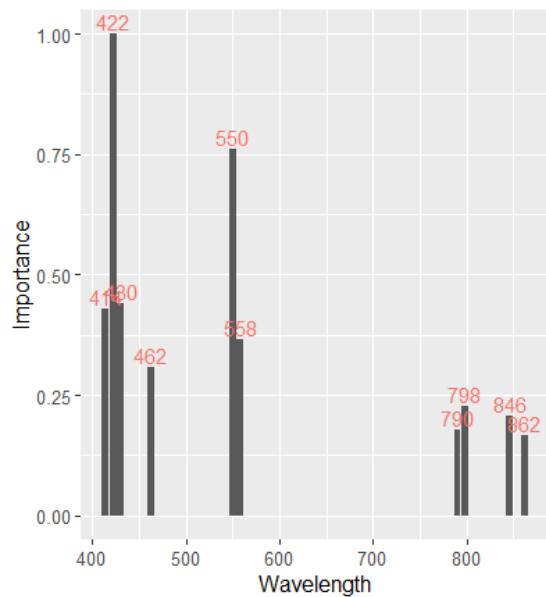
To understand which 1ST derivative of the wavelength is generally fit for abiotic stress detection, all wavelengths importance by random forest model in all plants and all missions were summarized for each wavelength. Additionally, each 8nm were merged together (Table 35).

Table 35: Lead wavelengths in random forest

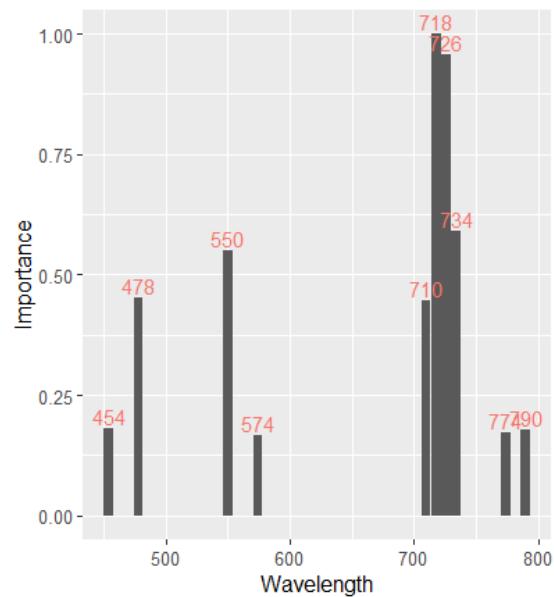
	Wavelength (nm)	Importance sum		Wavelength (nm)	Importance sum
1	550	2.528	12	574	0.627
2	726	2.328	13	566	0.473
3	718	2.000	14	846	0.438
4	734	1.893	15	414	0.429
5	710	1.273	16	774	0.360
6	558	1.092	17	702	0.359
7	422	1.000	18	790	0.353
8	462	0.924	19	606	0.227
9	430	0.857	20	454	0.180
10	478	0.726	21	862	0.167
11	798	0.633	22	622	0.165

The summary of the importance by fields leads to the conclusion that the most powerful field is the NIR, then the green and the blue colors (Table 35).

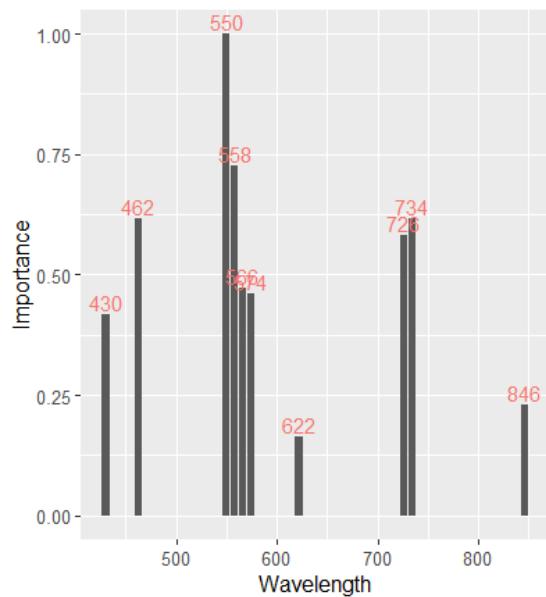
Random forest corn classification



Random forest sunflower classification



Random forest corn regression



Random forest sunflower regression

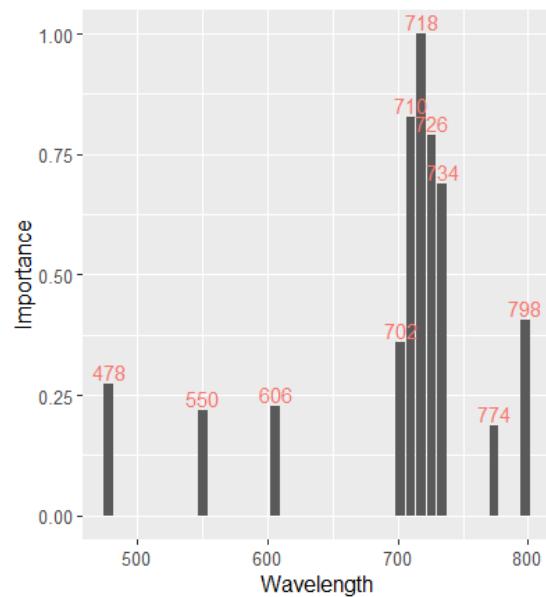


Figure 42: Random forest top 10 important features of the best models

8.2.2. LINEAR AND LOGISTIC REGRESSION

The top 6/7 wavelengths for each plant and target using linear and logistic regression are presented (Figure 43).

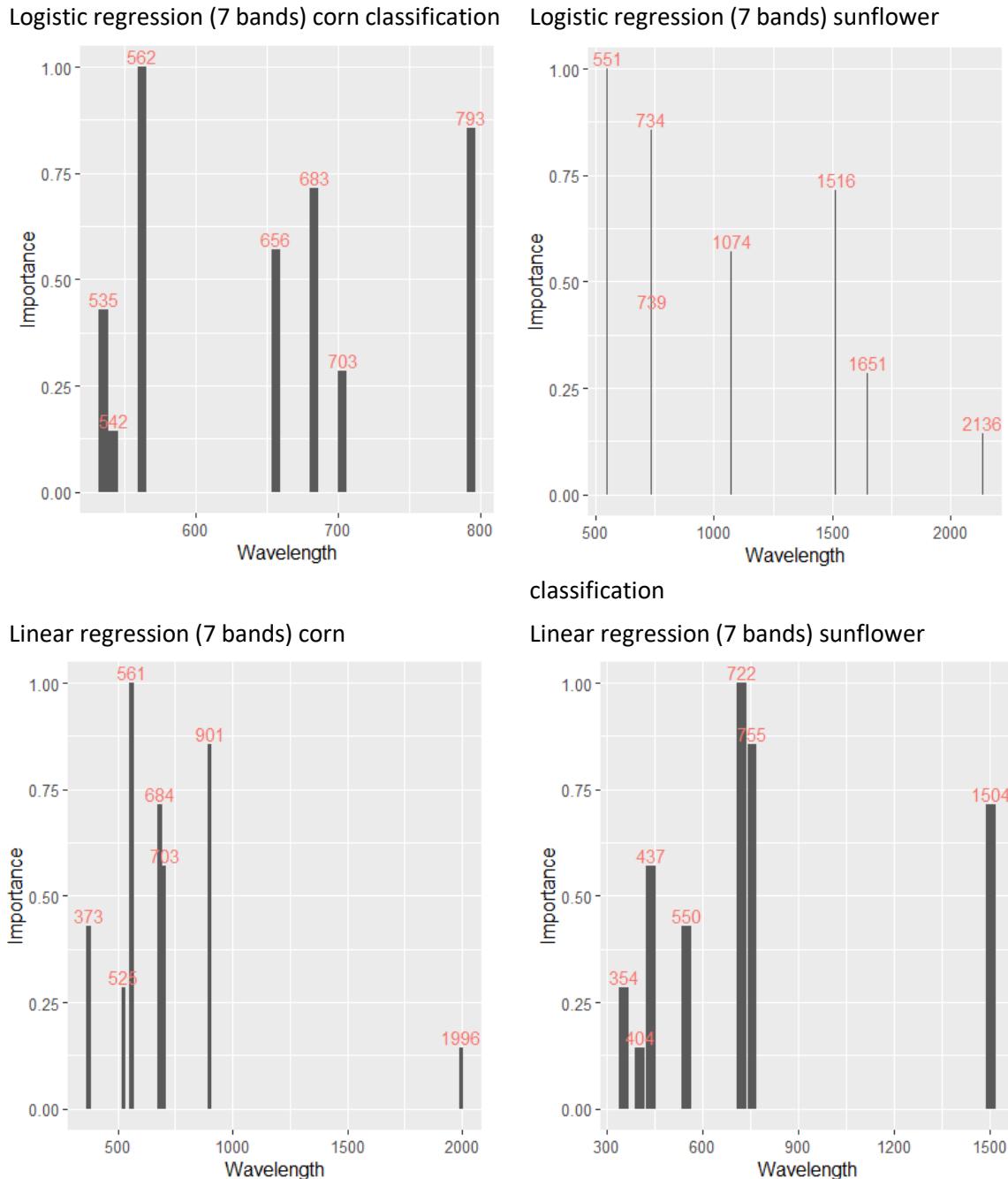


Figure 43: Linear/logistic regression top 10 important wavelengths of the best models

The same procedure to understand which 1ST derivative of the wavelengths points are generally fit for abiotic stress detection was performed (all wavelengths importance by logistic model and linear regression in all plants were summarized for each wavelength. Additionally, each 8nm were merged together) (Table 36).

Table 36: Lead wavelengths in linear and logistic regression.

	Wavelength (nm)	Importance sum		Wavelength (nm)	Importance sum
1	558	2.000	13	1513	0.556
2	678	1.429	14	1070	0.444
3	550	1.206	15	366	0.429
4	718	1.000	16	534	0.429
5	734	1.000	17	350	0.286
6	702	0.857	18	518	0.286
7	750	0.857	19	1649	0.222
8	790	0.857	20	398	0.143
9	894	0.857	21	542	0.143
10	1497	0.714	22	1991	0.143
11	430	0.571	23	2135	0.111
12	654	0.571			

Summarizing the importance by fields leads to the conclusion that the most powerful field is the NIR, then the green and the SWIR field (Table 36).

Comparing the two tables (Table 35, Table 36), several lead notable wavelengths are derived in both the random forest model and logistic regression model-1ST derivative at: 550nm, 718nm, 734nm, 558nm, 430nm, 702nm and 790nm. These are respectively denoted as the most important features for abiotic stress detection.

8.2.3. WITHOUT PRE-PROCESS PROCEDURE

Due to the Savitzky-Golay procedure, all wavelengths in the analysis consist of 11 wavelengths (1ST derivative of 11 wavelengths window). In order to determine specific wavelengths, ignoring the different environmental conditions, logistic and linear regression models were calculated on the raw data. According to this model, the suitable wavelengths were derived (Table 37).

Table 37: Chosen wavelengths in linear and logistic regression on the raw data.

Plant	Classification	Regression
Corn	[684,503,759,688,707,689,981]	[691,525,581,394,678,707,2011]
Sunflower	[691,517,352,758,719,735,693]	[690,745,647,1338,709,412,656]

All wavelengths importance by logistic model and linear regression in all plants were summarized for each wavelength. Additionally, each 8 nm were merged together.

Table 38: Lead wavelengths in linear and logistic regression on the raw data.

	Wavelength (nm)	Importance sum		Wavelength (nm)	Importance sum
1	686	3.857	11	350	0.625
2	678	1.429	12	390	0.571
3	758	1.214	13	1334	0.571
4	702	1.143	14	718	0.375
5	502	0.857	15	406	0.286
6	518	0.857	16	734	0.250
7	742	0.857	17	654	0.143
8	1513	0.750	18	974	0.143
9	574	0.714	19	2007	0.143
10	646	0.714	20	358	0.000

The most powerful wavelengths were in the red color range followed by the NIR and the SWIR ranges (Table 38).

The wavelengths derived by comparing to the linear/logistic powerful features models (Table 36 and Table 38) with Savitzky-Golay are: 350nm, 518nm, 654nm, 678nm, 702nm, 718nm, 734nm and 1513nm.

The wavelengths derived comparing to random forest and linear/logistic models (Table 35, Table 36 and Table 38) with Savitzky-Golay are: 702nm, 718nm and 734nm.

8.2.4. EARLY DETECTION FEATURE IMPORTANCE

The top 10 wavelengths for each plant and target were derived for the random forest algorithms and for the linear/logistic regression models (Figure 44, Figure 45).

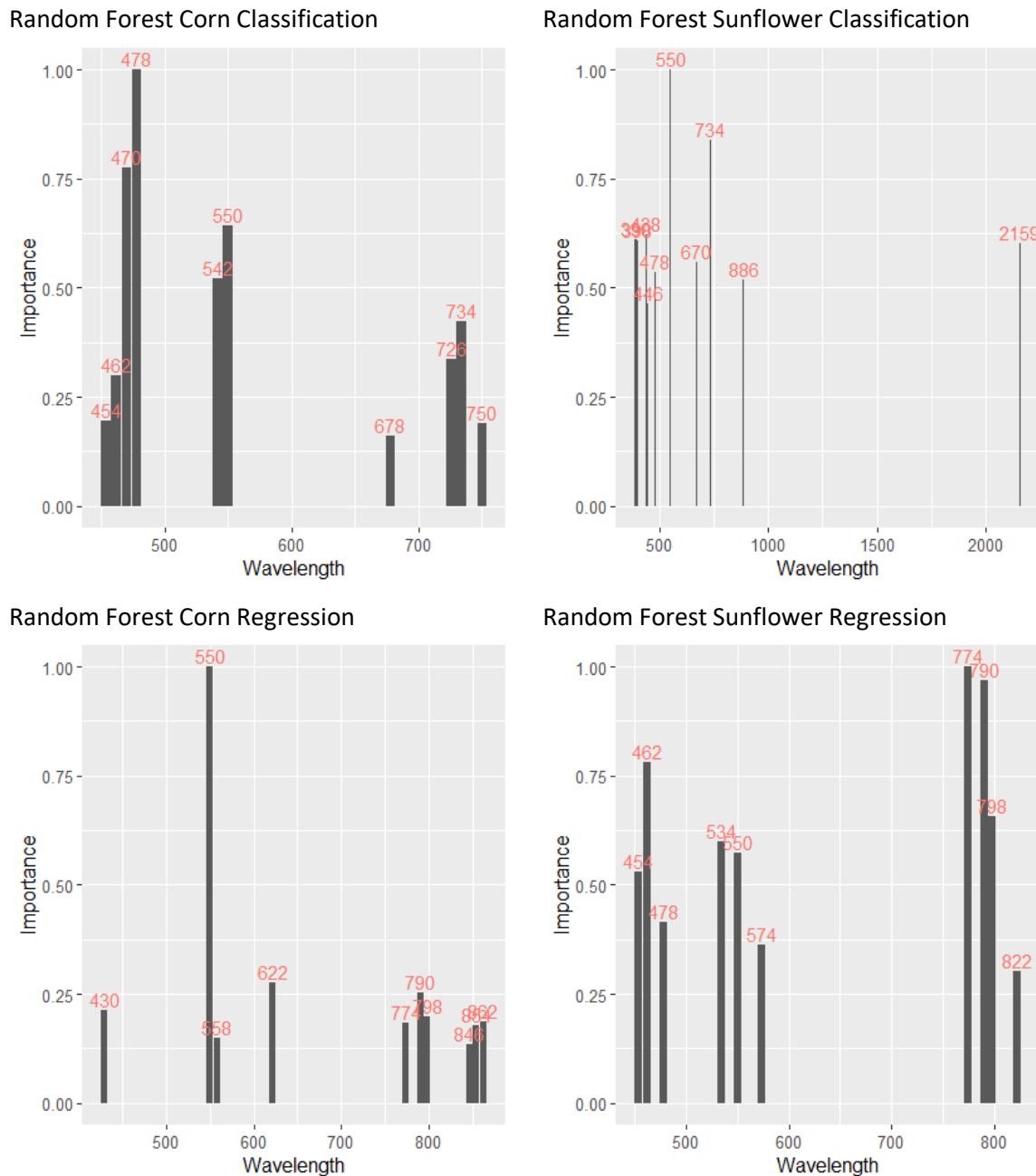


Figure 44: Random forest top 10 important wavelengths of the early detection best models

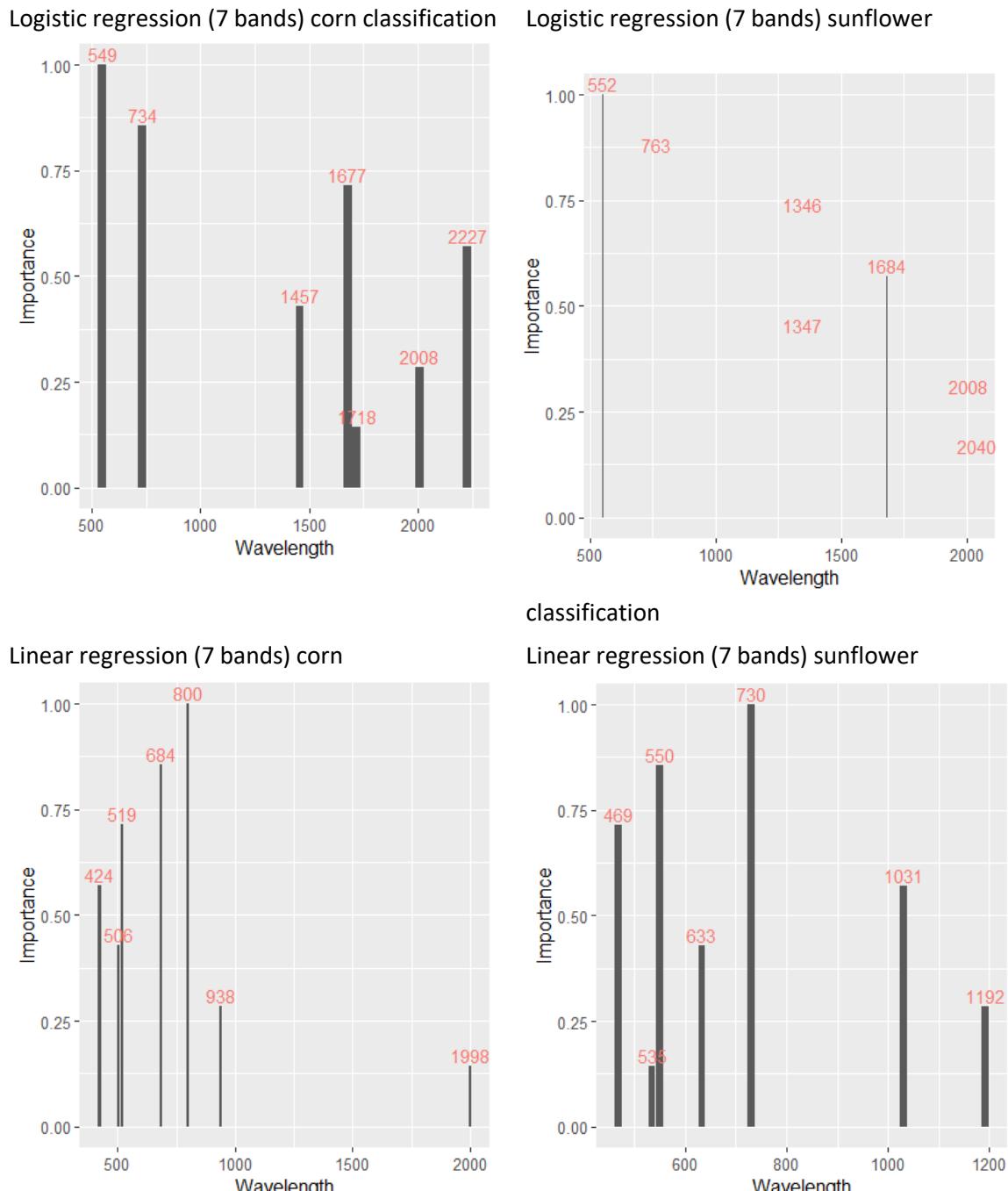


Figure 45: Linear/logistic regression top 10 important wavelengths of the early detection best models

The same procedure to understand which wavelengths are generally fit for early abiotic stress detection was conducted.

Table 39: Lead wavelengths in the random forest for early detection.

	Wavelength (nm)	Importance sum		Wavelength (nm)	Importance sum
1	550	3.215	11	398	0.607
2	734	1.263	12	2159	0.602
3	790	1.222	13	534	0.599
4	774	1.183	14	670	0.558
5	462	1.080	15	454	0.529
6	478	1.000	16	542	0.522
7	798	0.857	17	726	0.337
8	470	0.774	18	622	0.275
9	438	0.622	19	430	0.214
10	390	0.611	20	862	0.187

Linear and Logistic regression:

Table 40: Lead wavelengths in linear/logistic regression for early detection.

	Wavelength (nm)	Importance sum		Wavelength (nm)	Importance sum
1	550	1.732	14	2223	0.571
2	542	1.000	15	2007	0.536
3	726	1.000	16	1681	0.500
4	798	1.000	17	502	0.429
5	1342	1.000	18	630	0.429
6	678	0.857	19	1457	0.429
7	734	0.857	20	934	0.286
8	758	0.750	21	1190	0.286
9	462	0.714	22	534	0.143
10	518	0.714	23	1713	0.143
11	1673	0.714	24	1991	0.143
12	422	0.571	25	2039	0.125
13	1030	0.571	26	350	0.000

Comparing the two tables (Table 39, Table 40), there are several lead notable wavelengths in the random forest model, as well as in the logistic regression model: 462nm, 534nm, 550nm, 734nm and 798nm. Thus, robustly, these wavelengths were derived as the most important features for early abiotic tress detection. In order to test this recommendation, we fitted logistic regression models for each dataset with these 5 wavelengths. The models reached a F1 score of approximately 70%.

8.2.5. TEST RECOMMENDATIONS

The following are the recommended options for analyses based on 7 wavelengths:

1. 7 top 1ST derivative of wavelengths' points of the random forest algorithm (1ST derivative at: 550nm, 726nm, 718nm, 734nm, 710nm, 558nm and 422nm).
2. 7 top 1ST derivative of wavelengths' points of linear and logistic models (1ST derivative at: 558nm, 678nm, 550nm, 718nm, 734nm, 702nm and 750nm).
3. 1ST derivative of wavelengths' points appears also in the random forest, as well as in linear and logistic regression models (1ST derivative at: 550nm, 718nm, 734nm, 558nm, 430nm, 702nm and 790nm).
4. 7 top wavelength reflectance of the linear and logistic regression models (686nm, 678nm, 758nm, 702nm, 502nm, 518nm and 742nm).
5. 1ST derivative of wavelengths' points, that appears in linear and logistic regression, which also appears in linear and logistic regression wavelengths' reflectance (350nm, 518nm, 654nm, 678nm, 702nm, 718nm, 734nm and 1513nm).

Logistic regression models were fitted for each dataset and evaluated by the F1 score. The data sets were: raw data (reflectance) for each plant and each experiment (corn, corn2, sunflower) and the data after the Savitzky-Golay procedure, the 1ST derivative (Dcorn, Dcorn2, Dsunflower).

Option 1- [550, 726, 718, 734, 710, 558, 422]

Option 2- [558, 678, 550, 718, 734, 702, 750]

Option 3- [550, 718, 734, 558, 430, 702, 790]

Option 4- [686, 678, 758, 702, 502, 518, 742]

Option 5- [350, 518, 654, 678, 702, 718, 734, 1513]

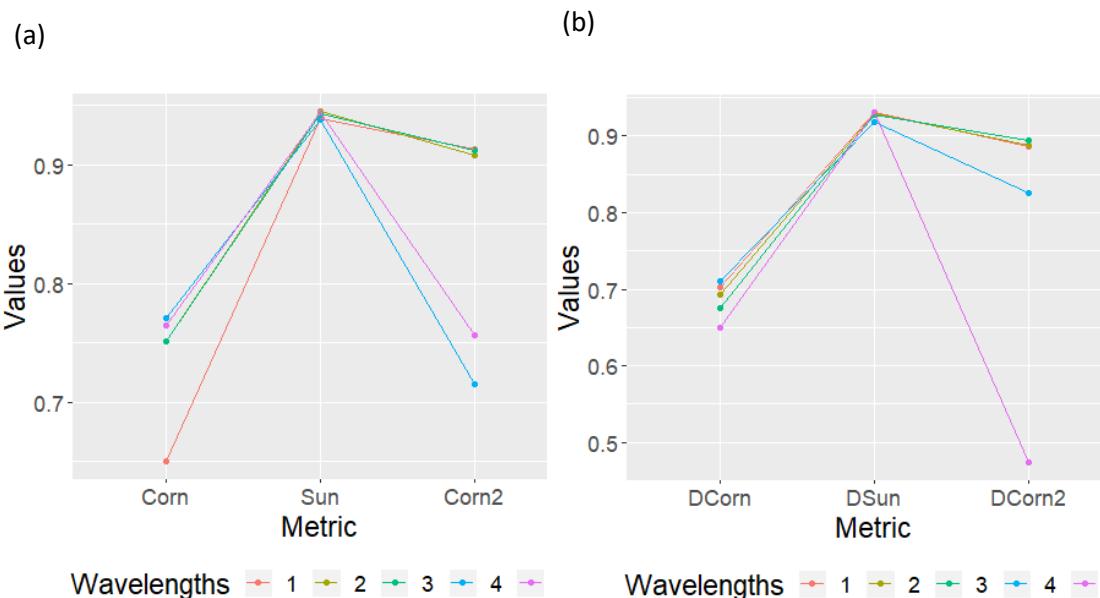


Figure 46: Wavelength recommendations evaluation for the (a) reflectance datasets and (b) first derivative datasets.

All suggestions reached similar results for reflectance datasets of experiment 1; approximately 75% and 94% for corn and sunflower plants respectively. However, the reflectance dataset of experiment 2 (corn2) obtained better results with the first three models (suggestions); approximately 91% for the first three suggestions, versus 71%, 57% for the fourth and fifth suggestions respectively (Figure 46 (a)).

The 1ST derivative sunflower dataset reached similar results for all five suggestions (around 92%) and the 1ST derivative corn experiments 1 reached close results for all five suggestions as well (65%-71%).

For corn experiments 2 datasets reached 10%-40% better results with the first three suggestions (Figure 46 (b)).

Therefore, we recommend to use the wavelengths that were chosen by the 1ST derivative datasets' models with option 3- 550nm, 718nm, 734nm, 558nm, 430nm, 702nm and 790nm which reached the best performance.

9. CONCLUSIONS & FUTURE WORK

9.1 CONCLUSIONS

The random forest algorithms yielded best performance for both classification and regression models with 88% and 92.5% F1 scores and 0.221 and 0.19 RMSE for the corn and sunflower plants respectively. Validation results on new data one year later on corn plants only yielded a F1 score of 79.9% and RMSE of 0.243.

However, the linear regression and the logistic regression models yielded close performance with only 7 wavelengths. Results obtained were 79.9% and 94.7% F1 scores with 0.249 and 0.222 RMSE for the corn and sunflower classification and regression respectively, with an 84.6% F1 and 0.269 RMSE scores for the new corn set classification and regression.

Early prediction models were developed for intervals between 2 and 7 days before appearance for the regression task, and only 2 days before appearance for the classification task. For “two days before” the prediction by the random forest classification yielded a F1 score of 72.9% for corn plants and 85% for sunflower plants. For “seven days before”, the prediction by the random forest regression yielded a RMSE of 0.331 and 0.413 for corn and sunflower plants respectively.

By using linear and logistic regression there will be a loss of about 3%-5% F1 score in classification and an increase of about 0.028 RMSE (error rate of 2%) in regression.

Although the phenotypes (i.e. the ground truth) in this research were visible plant characteristics, results revealed that the information outside the visible spectrum (above 700 nm) is very relevant for abiotic stress detection.

According to lead models in this research, the most powerful range is the NIR range followed by wavelengths in the green color range. With limited resources, several wavelengths recommendations were given. All recommendations were tested on the new dataset (experiment 2). The recommendation that reached the best performance (approximately 90%) used the following wavelengths: 550nm, 718nm, 734nm, 558nm, 430nm, 702nm, 790nm. These wavelengths are important for both the current time point prediction models and the prediction models that used the data from two days before appearance. 550 belongs to the green color range, while 734 belongs to NIR range. Therefore, we can assume these fields are important.

The young leaves contain most of the information for abiotic stress detection, implying that this is the best place to measure at the time of the sampling. The developed models were not able to determine which mechanism was damaged.

9.2. FUTURE WORK

Future work should explore the following:

In this research the models were trained on a set of 875 corn leaves and 840 sunflowers leaves with approximately 2000 measurements (wavelengths). To develop more complex models (like deep learning models), more samples should be measured.

Corn and sunflower plants were measured in this research. Other plants should be measured. Additionally, the abiotic stress, in this research, was induced by herbicides. To have more robust models, the train set should be expanded by more plants and more abiotic stress injuries (like water shortage).

The experiments were conducted in a controlled greenhouse. Additional environmental conditions should be tested (e.g., additional greenhouses, field conditions).

Hyperspectral images were acquired in the second experiment. A segmentation algorithm was developed to separate plants leaves and background (Appendix G). Images were filtered by the most important bands indicated in this thesis. Models for abiotic stress detection using hyperspectral data should be developed (like deep learning convolutional neural network algorithms).

Other analysis for these current datasets:

- Using factor analysis to build new target values.
- Using canonical-correlation analysis for all phenotypes values (as vector).

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APPENDICES

APPENDIX A. MODELS DETAILS

A.1. CLASSIFICATION MODELS

Logistic Regression- the explanatory variable used in logistic regression was 561nm for corn plants and 722nm for sunflower plants.

Logistic Regression with 7 bands- the explanatory variables used in logistic regression for corn plants were: 562nm, 794nm, 683nm, 656nm, 535nm, 703nm and 542nm. The explanatory variables used in logistic regression for sunflower plants were: 551nm, 734nm, 1516nm, 1074nm, 739nm, 1651nm and 2136nm.

Logistic Regression on PCA- the number of components that were chosen by the minimum between: number of components which explain together 90% of the spectrum variance and the 10% from the samples' number as well as 10% from the features numbers.

For corn plants the number of components was between 27-33 and for sunflower was between 7-8. The next plot shows the number of components which were given 90% of the spectrum's variance in the fifth iteration (Figure 47).

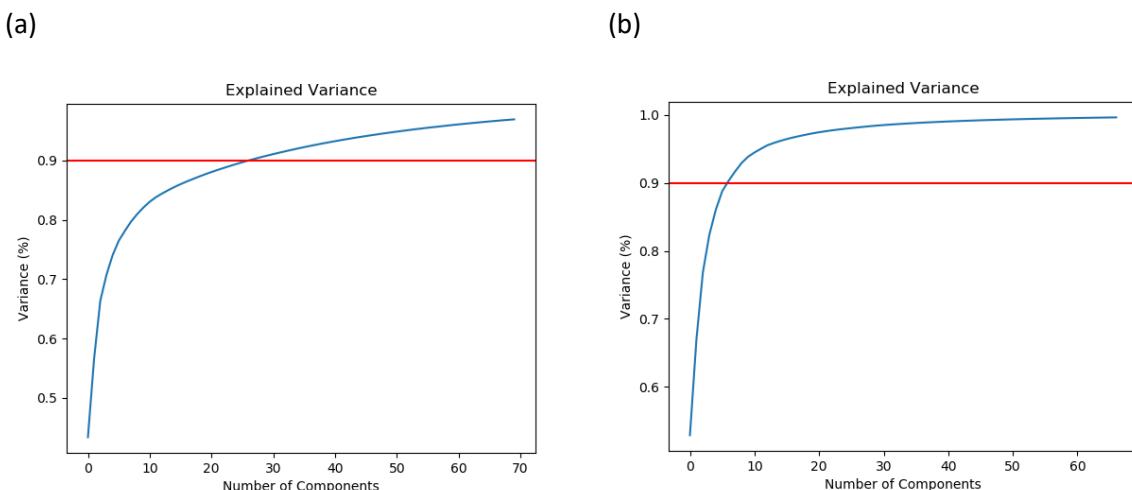


Figure 47: PCA component selection for corn (a) folder: 5, chosen component number: 27 and sunflower (b) folder: 5, , chosen component number: 7

PLS-DA- the number of components was selected as the minimum between the number of components which maximized AUC criterion, 10% from the samples number and 10% from the features' number resulting with 2 and 4-11 components for corn and sunflower respectively. (Figure 48).

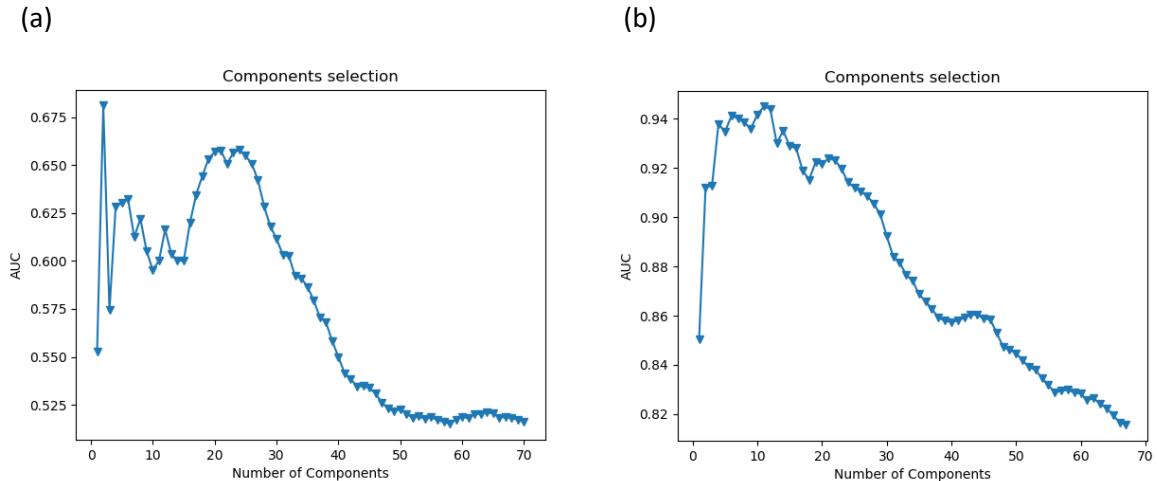


Figure 48: PLS-DA component selection for corn (a) folder: 5, chosen component number: 2 and sunflower (b) folder: 5, , chosen component number: 11

Random forest- models' parameters after training on all corn datasets were: max_depth of 6, max_features of 30 and n_estimators of 80. Sunflower models' parameters after training on all datasets were: max_depth of 6, max_features of 40 and n_estimators of 80.

XGBoost- models' parameters after training on all corn datasets were: colsample_bytree of 0.029, learning_rate of 0.9, max_depth of 8, n_estimators of 70 and subsample of 0.8. Sunflower models' parameters after training on all datasets were: colsample_bytree of 0.023, learning_rate of 0.5, max_depth of 7, n_estimators of 80 and subsample of 0.9.

A.2. LEAVES CLASSIFICATION MODELS

Logistic Regression- the explanatory variable used in logistic regression was 553nm for the first corn leaf, 561 for the second leaf and 731 for the young leaf. 730nm for the mature sunflower leaf and 721 for the young leaf.

Logistic Regression with 7 bands- the explanatory variables used in logistic regression for the first corn leaf was: [552,428,677,612,680,654,1086], for the second corn leaf-[430,684,656,1334,1421,1995,472] and for the young corn leaf- [731,852,855,1420,948].

The explanatory variables used in logistic regression for the mature sunflowerleaf were: [551,745,1283,356,818,2136,2080] and for the young sunflower leaf-[731,801,679,744,1343,357,887].

Logistic Regression on PCA- for the first corn leaf the components' number was between 20-22, for the second leaf 20-24 and for the young leaf 8 components. For sunflower leaves there were 6 components for the mature leaf and 7 components for the young leaf.

PLS-DA- for the first corn leaf the components' number was between 4-12, for the second leaf 1-4 and for the young leaf 1-5 components. For sunflower leaves there were 2-8 components for the mature leaf and 4-5 components for the young leaf.

For machine learning models see appendix B.

A.3. MOA CLASSIFICATION MODELS

Logistic Regression- the explanatory variable used in logistic regression was 466nm for corn IP MOA leaf, 432 for LM MOA and 625 for AAM MOA. 729nm for sunflower IP MOA and 721 for AAM MOA.

Logistic Regression with 7 bands- the explanatory variables used in logistic regression for corn IP MOA were: [728,1662,1608,1619,705,373,1787], for corn LM MOA- [429,558,374,633,409,1680,1249] and for the AAM corn MOA- [429,579,637,1238,1961,408,612].

The explanatory variables used in logistic regression for sunflower IP MOA were: [802,730] and for the AAM sunflower MOA- [551,1036,357,1127,486,763].

Logistic Regression on PCA- for corn IP MOA the components' number was between 17-20, for LM MOA 14-18 and for AAM MOA 15-17 components. 6-7 components for the IP MOA and 6-11 components for the AAM MOA.

PLS-DA- for corn IP MOA the components' number was between 1-2, for LM MOA 2-7 and for AAM MOA, 2-13 components. For sunflower IP, 3-5 components for the AAM MOA and 6-11 components for the young leaf.

For machine learning models see appendix B.

A.4. EARLY CLASSIFICATION MODELS

Logistic Regression- the explanatory variable used in logistic regression was 553nm for corn plants and 552nm for sunflower plants.

Logistic Regression with 7 bands- the explanatory variables used in logistic regression for corn plants were: [552,763,1346,1684,1347,2008,2040]. The explanatory variables used in logistic regression for sunflower plants were: [549,734,1677,2227,1457,2008,1781].

Logistic Regression on PCA- for corn plants the components' number was 5 and for sunflower plants between 6-7.

PLS-DA- 713 and 6-14 components for corn and sunflower respectively.

For machine learning models see appendix B.

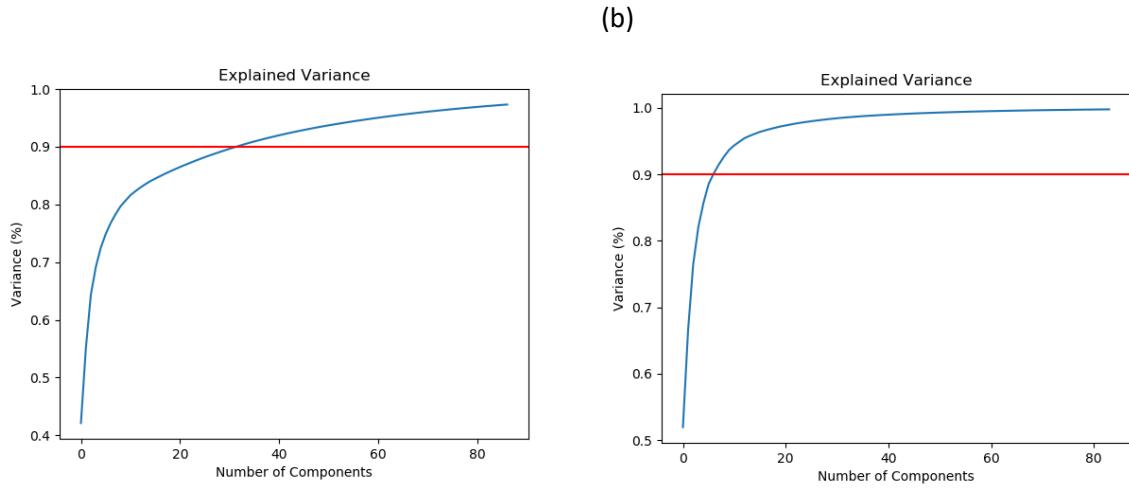
A.5. REGRESSION MODELS

Linear Regression- the explanatory variable used in linear regression was 561nm for corn plants and 722nm for sunflower plants.

Linear Regression with 7 bands- the explanatory variables used in linear regression for corn plants were: 561nm, 901nm, 684nm, 703nm, 373nm, 525nm and 1996nm. The explanatory variables used in linear regression for sunflower plants were: 722nm, 755nm, 1504nm, 437nm, 550nm, 354nm and 404nm.

Linear Regression on PCA- the number of components was chosen by the minimum between: number of components which explain together 90% of the spectrum variance, 10% from the samples' number and 10% from the features' number.

For corn plants the components' number was between 29-32 and for sunflower between 7-8. The number of components which yielded 90% spectrum's variance of the fifth iteration is described in Figure 49.

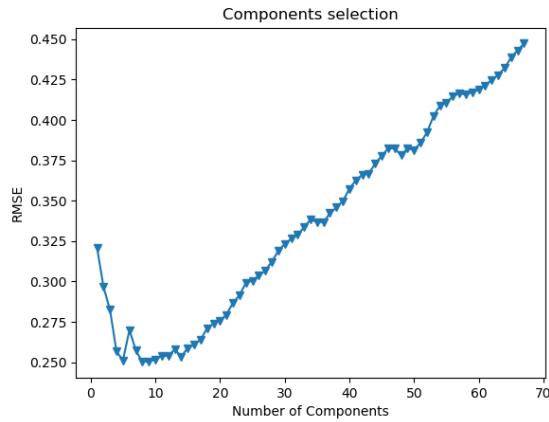


(a)

Figure 49: PCA component selection for corn (a) folder: 5, chosen component number: 31 and sunflower (b) folder: 5, chosen component number: 8.

PLS Regression - the number of components was selected as the minimum between the number of components which minimize RMSE criterion, 10% from the samples' number and 10% from the features' number, resulting with 2-4 and 4-8 components for corn and sunflower respectively. (Figure 50).

(a)



(b)

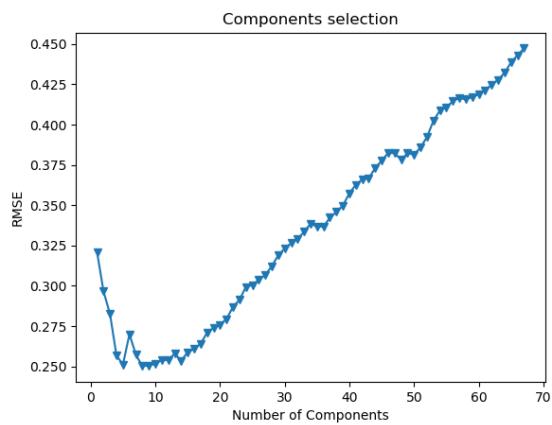


Figure 50: PLS component selection for corn (a) folder: 5, chosen component number: 3 and sunflower (b) folder: 5, chosen component number: 8

Random Rorest- models' parameters after training on all corn datasets were: max_depth of 8, max_features of 35 and n_estimators of 80 with a RMSE validation of 0.218. Sunflower models' parameters after training on all datasets were: max_depth of 8, max_features of 30 and n_estimators of 70 with validation RMSE of 0.188.

XGBoost- models' parameters after training on all corn datasets were: colsample_bytree of 0.035, learning_rate of 0.8, max_depth of 7, n_estimators of 70 and subsample of 0.9 with RMSE validation of 0.257. Sunflower models' parameters after training on all datasets were: colsample_bytree of 0.029, learning_rate of 0.5, max_depth of 7, n_estimators of 80 and subsample of 0.8 with RMSE validation of 0.211.

SMOTE on random forest classification:

Model: Random forest classification for phenotypes' status, using SMOTE, to create synthetic samples among the minority class.

Averaged scores:

Dataset	AUC	Accuracy	f1
DCorn	0.936	0.852	0.871
Dsunflower	0.978	0.934	0.924

Confusion matrix: Figure 51

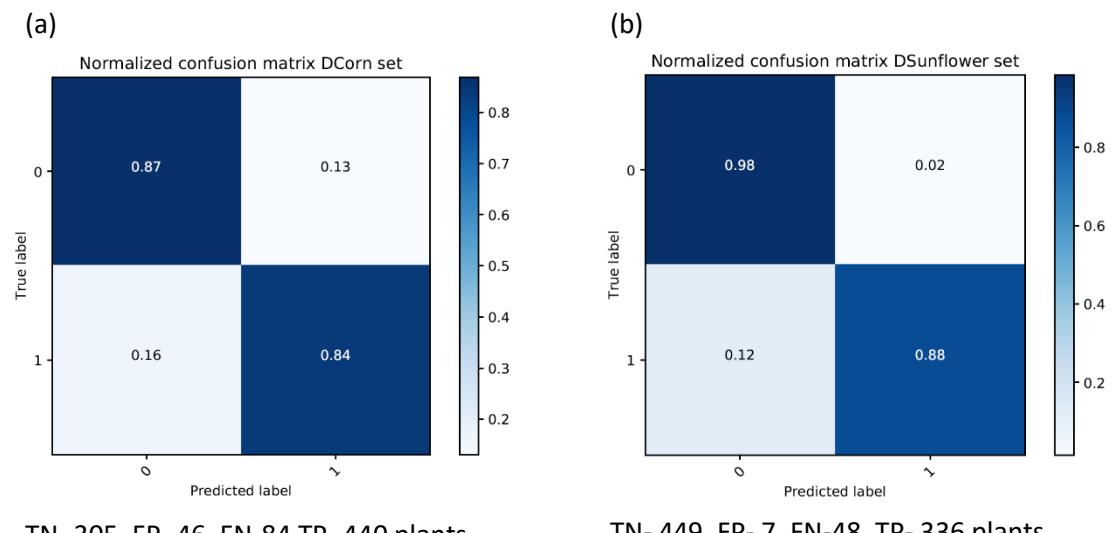


Figure 51: Random forest after SMOTE confusion matrix for corn (a) and sunflower (b).

According to the results, SMOTE algorithm did not improve the scores. However, it improved the performance among healthy corn plants.

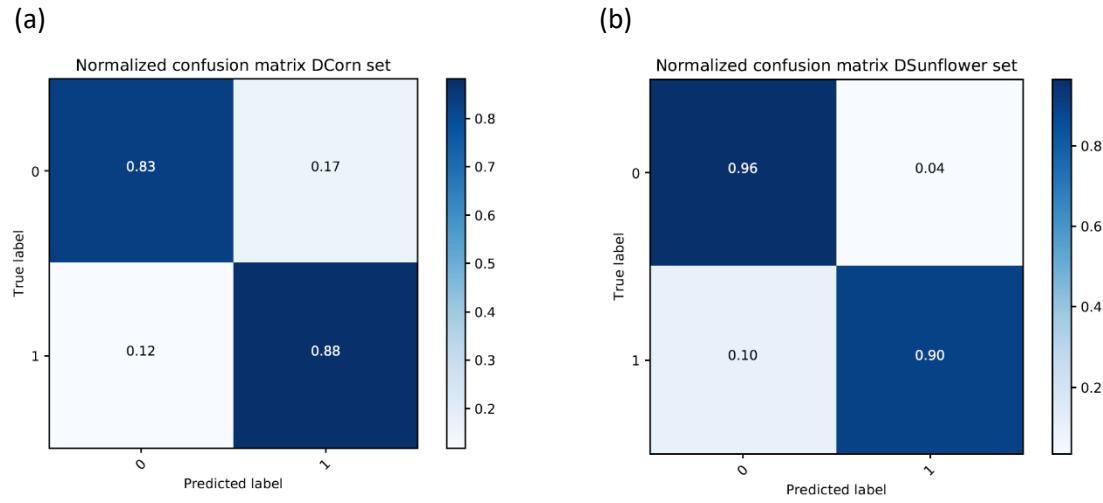
SMOTE on XGBoost classification:

Model: XGBoost classification for phenotypes' status, using SMOTE to create synthetic samples among the minority class.

Averaged scores:

Dataset	AUC	Accuracy	f1
DCorn	0.936	0.863	0.885
Dsunflower	0.979	0.935	0.926

Confusion matrix: Figure 52



TN- 293, FP- 58, FN-62 TP- 462 plants

TN- 440, FP- 16, FN-39 TP- 345 plants

Figure 52: XGBoost after SMOTE confusion matrix for corn (a) and sunflower (b).

According to the results, SMOTE algorithm did not improve the scores.

A.6. LEAVES REGRESSION MODELS

Linear Regression- the explanatory variables used in linear regression were 553nm for the first corn leaf, 561 for the second leaf and 731 for young leaf. 730nm for the mature sunflower leaf and 721 for young leaf.

Linear Regression with 7 bands- the explanatory variables used in logistic regression for the first cornleaf were: [553,391,559,474,466,1005,706], for the second corn leaf-[561,900,685,576,1975,1249,1965] and for the young corn leaf- [731,853,400,628,707,377,715].

The explanatory variables used in logistic regression for the mature sunflower leaf were: [730,543,1015,1632,427,672,604] and for the young sunflower leaf-[721,755,587,555,711,1515,625].

Linear Regression on PCA- for the first corn leaf the components' number was between 18-22, for the second leaf 20-22 and for the young leaf there were 8 components. For the sunflower leaves, there were 6 components for the mature leaf and 7 components for the young leaf.

PLS- for the first corn leaf the components' number was between 3-5, for the second leaf 2 and for the young leaf 1-3 components. For sunflower leaves there were 1-6 components for the mature leaf and 5-11 components for the young leaf.

For machine learning models see appendix B.

A.7. MOA REGRESSION MODELS

Linear Regression- the explanatory variable used in linear regression was 466nm for corn IP MOA leaf, 432 for LM MOA and 625 for AAM MOA. 729nm for sunflower IP MOA and 721 for AAM MOA.

Linear Regression with 7 bands- the explanatory variables used in linear regression for corn IP MOA were: [466,707,682,866,1661,1655,1749], for the corn LM MOA-[432,560,398,542,474,1656,372] and for the AAM corn MOA- [625,579,373,425,2183,1146,1209].

The explanatory variables used in linear regression for sunflower IP MOA were:
[729,678,762,912,1723,360,1439] and for the AAM sunflower MOA-[721,2246,1505,1619,1791,2081,1347].

Linear Regression on PCA- for corn IP MOA the components' number was between 18-20, for LM MOA 13-17 components and for AAM MOA 15-17 components. 6-7 components for the IP MOA and 7 components for the AAM MOA.

PLS- for corn IP MOA the components' number was between 1-4, for LM MOA 3-6 and for AAM MOA 4 components. For sunflower IP 5-7 components for the AAM MOA and 3-8 components for the young leaf.

For machine learning models see appendix B.

A.8. EARLY REGRESSION MODELS

Corn:

Model	2 days before	4 days before	5 days before	7 days before
Logistic regression one bend	Wavelength: 800 nm	Wavelength: 554 nm	Wavelength: 552 nm	Wavelength: 551 nm
Logistic regression several bends	Wavelengths: [800,684,519,424, 506,938,1998]	Wavelengths: [554,629,473,1999,2 096,1680,2132]	Wavelengths: [552,472,441,1988, 779,2182,1418]	Wavelengths: [551,2181,1988,400 ,470,2138,438]
PCA classification	Components number: 37	Components number: 4	Components number: 6-7	Components number: 6-7
PLS classification	Components number: 2-3	Components number: 2-12	Components number: 1-4	Components number: 1-3

Sunflower:

Model	2 days before	4 days before	5 days before	7 days before
Logistic regression one bend	Wavelength: 730 nm	Wavelength: 730 nm	Wavelength: 730 nm	Wavelength: 730 nm
Logistic regression several bends	Wavelengths: [730,550,469,1031, 633,1192,535]	Wavelengths: [730,1140,700,611, 624,2220,628]	Wavelengths: [730,1176,1442,763, 817,888,1448]	Wavelengths: [730,1177,2209,200 3,632,828,764]
PCA classification	Components number: 6	Components number: 6-7	Components number: 5	Components number: 5
PLS classification	Components number: 4-9	Components number: 5	Components number: 1-7	Components number: 1-7

APPENDIX B. MODELS SCORES BY ITERATION

B.1. CLASSIFICATION

Data set	Max correlation	Ind ex	logistic AUC	logisti c Acc	logisti c F1	7 indices	logistic 7w Acc	logistic 3w AUC	logistic 7w F1	PCA number of comp	PCA AUC	PCA Acc	PCA F1	PLS number of comp	PLS AUC	PLS Acc	PLS F1
DCor n_1	0.554	56 1	0.771	0.693	0.675	[562,794,683,656, 535,703,542]	0.841	0.932	0.806	31	0.77 2	0.65 9	0.6 39	2	0.84 9	0.7 7	0.7 81
DCor n_2	0.554	56 1	0.761	0.623	0.593	[562,794,683,656, 535,703,542]	0.817	0.901	0.792	31	0.71 1	0.65 1	0.6 47	2	0.85 9	0.8 8	0.8 19
DCor n_3	0.554	56 1	0.777	0.714	0.713	[562,794,683,656, 535,703,542]	0.863	0.938	0.833	31	0.71 7	0.61 7	0.6 04	2	0.85 8	0.7 4	0.7 75
DCor n_4	0.554	56 1	0.801	0.657	0.639	[562,794,683,656, 535,703,542]	0.817	0.926	0.784	33	0.80 8	0.68 63	0.6 63	2	0.81 4	0.7 2	0.7 35
DCor n_5	0.554	56 1	0.847	0.753	0.765	[562,794,683,656, 535,703,542]	0.839	0.941	0.781	27	0.79 1	0.71 3	0.7 19	2	0.86 5	0.78 2	0.8 02
mean	0.554	56 1	0.792	0.688	0.677	[562,794,683,656, 535,703,542]	0.835	0.927	0.799	27-33	0.76	0.66 4	0.6 54	2	0.84 9	0.76 5	0.7 82
std			0.034	0.05	0.066		0.019	0.016	0.021		0.04 4	0.03 5	0.0 42		0.02	0.03	0.0 32

Datase t	Max correlati on	Ind ex	logistic AUC	logisti c Acc	logist ic F1	7 indices	logistic 7w Acc	logistic 3w AUC	logistic 7w F1	PCA number of comp	PCA AUC	PCA Acc	PCA F1	PLS number of comp	PLS AUC	PLS Acc	PLS F1
DCorn L1_1	0.634	55 3	0.728	0.635	0.508	[552,428,677,612,6 80,654,1086]	0.847	0.909	0.843	20	0.59 8	0.57 6	0.5 38	4	0.73 7	0.6 1	0.6 74
DCorn L1_2	0.634	55 3	0.876	0.741	0.711	[552,428,677,612,6 80,654,1086]	0.882	0.963	0.865	20	0.66 6	0.57 6	0.5 38	12	0.80 5	0.76 5	0.7 56
DCorn L1_3	0.634	55 3	0.931	0.738	0.694	[552,428,677,612,6 80,654,1086]	0.845	0.944	0.831	22	0.74 3	0.66 7	0.6 22	9	0.87 8	0.76 2	0.7 62
DCorn L1_4	0.634	55 3	0.849	0.711	0.657	[552,428,677,612,6 80,654,1086]	0.880	0.947	0.865	20	0.77 1	0.65 1	0.6 42	9	0.85 6	0.74 7	0.7 27
DCorn L1_5	0.634	55 3	0.826	0.687	0.606	[552,428,677,612,6 80,654,1086]	0.892	0.938	0.892	20	0.78 4	0.66 3	0.6 32	8	0.86 5	0.74 7	0.7 53
mean	0.634	55 3	0.842	0.702	0.635	[552,428,677,612,6 80,654,1086]	0.869	0.940	0.859	20-22	0.71 2	0.62 7	0.5 94	4-12	0.82 8	0.73 8	0.7 35
std			0.075	0.044	0.082		0.021	0.020	0.023		0.07 9	0.04 6	0.0 52		0.05 8	0.03 9	0.0 36

Dataset	Max correlation	Index	logistic AUC	logistic Acc	logistic F1	7 indices	logistic 7w Acc	logistic 3w AUC	logistic 7w F1	PCA number of comp	PCA AUC	PCA Acc	PCA F1	PLS number of comp	PLS AUC	PLS Acc	PLS F1	
DCorn_L2_1	0.613	561	0.766	0.686	0.703	[430,684,656,1334,1,421,1995,472]	0.886	0.939	0.840	24	0.778	0.7	0.7	3	0.851	0.786	0.839	
DCorn_L2_2	0.613	561	0.768	0.629	0.618	[430,684,656,1334,1,421,1995,472]	0.843	0.943	0.776	20	0.74	0.7	0.7	1	0.832	0.729	0.816	
DCorn_L2_3	0.613	561	0.742	0.671	0.701	[430,684,656,1334,1,421,1995,472]	0.914	0.973	0.875	21	0.764	0.743	0.7	1	0.814	0.671	0.768	
DCorn_L2_4	0.613	561	0.831	0.71	0.714	[430,684,656,1334,1,421,1995,472]	0.899	0.960	0.851	21	0.728	0.623	0.6	4	0.779	0.717	0.767	
DCorn_L2_5	0.613	561	0.725	0.594	0.611	[430,684,656,1334,1,421,1995,472]	0.739	0.866	0.640	22	0.726	0.652	0.6	3	0.851	0.754	0.8	
mean	0.613	561	0.767	0.658	0.669	[430,684,656,1334,1,421,1995,472]	0.856	0.936	0.796	20-24	0.747	0.684	0.7	1-4	0.825	0.735	0.798	
std			0.04	0.046	0.051		0.071	0.042	0.095		0.023	0.047	0.0	6		0.03	0.043	0.031

Dataset	Max correlation	Index	logistic AUC	logistic Acc	logistic F1	7 indices	logistic 7w Acc	logistic 3w AUC	logistic 7w F1	PCA number of comp	PCA AUC	PCA Acc	PCA F1	PLS number of comp	PLS AUC	PLS Acc	PLS F1	
DCorn_L3_1	0.770	731	0.982	0.955	0.966	[731,852,855,1420,948]	1.000	1.000	1.000	8	0.839	0.773	0.8	2	1	0.909	0.933	
DCorn_L3_2	0.770	731	0.955	0.864	0.88	[731,852,855,1420,948]	1.000	1.000	1.000	8	0.705	0.773	0.8	1	0.884	0.682	0.8	
DCorn_L3_3	0.770	731	0.982	0.909	0.923	[731,852,855,1420,948]	0.955	0.960	0.941	8	0.813	0.682	0.6	2	1	0.955	0.966	
DCorn_L3_4	0.770	731	1	0.81	0.818	[731,852,855,1420,948]	1.000	1.000	1.000	8	0.894	0.714	0.7	5	0.971	0.857	0.87	
DCorn_L3_5	0.770	731	0.978	0.9	0.917	[731,852,855,1420,948]	0.950	0.956	0.933	8	0.857	0.7	0.7	3	0.923	0.857	0.87	
mean	0.770	731	0.98	0.887	0.901	[731,852,855,1420,948]	0.981	0.983	0.975	8	0.822	0.728	0.7	1-5	0.956	0.851	0.888	
std			0.016	0.054	0.055		0.026	0.023	0.034		0.071	0.042	0.0	6		0.051	0.103	0.064

Dataset	Max correlation	Index	logistic AUC	logistic Acc	logistic F1	7 indices	logistic 7w Acc	logistic 3w AUC	logistic 7w F1	PCA number of comp	PCA AUC	PCA Acc	PCA F1	PLS number of comp	PLS AUC	PLS Acc	PLS F1
DCorn_IP_1	0.789	46	0.887	0.774	0.76	[728,1662,1608,1619,705,373,1787]	0.906	0.963	0.894	19	0.872	0.83	0.842	1	0.893	0.83	0.836
DCorn_IP_2	0.789	46	0.818	0.692	0.652	[728,1662,1608,1619,705,373,1787]	0.788	0.920	0.744	19	0.735	0.673	0.679	2	0.783	0.712	0.737
DCorn_IP_3	0.789	46	0.817	0.769	0.75	[728,1662,1608,1619,705,373,1787]	0.827	0.920	0.800	17	0.864	0.808	0.821	2	0.842	0.782	0.807
DCorn_IP_4	0.789	46	0.785	0.731	0.696	[728,1662,1608,1619,705,373,1787]	0.846	0.933	0.818	20	0.867	0.731	0.741	1	0.881	0.731	0.731
DCorn_IP_5	0.789	46	0.932	0.745	0.723	[728,1662,1608,1619,705,373,1787]	0.922	0.981	0.905	19	0.846	0.745	0.764	1	0.934	0.824	0.83
mean	0.789	46	0.848	0.742	0.716	[728,1662,1608,1619,705,373,1787]	0.858	0.943	0.832	17-20	0.837	0.757	0.769	1-2	0.866	0.777	0.788
std			0.06	0.033	0.044		0.055	0.028	0.067		0.058	0.063	0.065		0.056	0.054	0.051

Dataset	Max correlation	Index	logistic AUC	logistic Acc	logistic F1	7 indices	logistic 7w Acc	logistic 3w AUC	logistic 7w F1	PCA number of comp	PCA AUC	PCA Acc	PCA F1	PLS number of comp	PLS AUC	PLS Acc	PLS F1
DCorn_LM_1	0.679	43	0.9	0.816	0.757	[429,558,374,633,409,1680,1249]	0.939	0.991	0.947	15	0.692	0.592	0.375	4	0.941	0.816	0.757
DCorn_LM_2	0.679	43	0.843	0.735	0.629	[429,558,374,633,409,1680,1249]	0.918	0.990	0.933	16	0.722	0.633	0.438	2	0.853	0.776	0.645
DCorn_LM_3	0.679	43	0.938	0.813	0.743	[429,558,374,633,409,1680,1249]	0.958	0.996	0.964	13	0.821	0.813	0.821	2	0.946	0.896	0.857
DCorn_LM_4	0.679	43	0.885	0.809	0.743	[429,558,374,633,409,1680,1249]	0.915	0.985	0.929	18	0.759	0.723	0.629	2	0.850	0.830	0.75
DCorn_LM_5	0.679	43	0.955	0.809	0.69	[429,558,374,633,409,1680,1249]	0.830	0.964	0.862	14	0.626	0.596	0.345	7	0.909	0.851	0.774
mean	0.679	43	0.904	0.796	0.712	[429,558,374,633,409,1680,1249]	0.912	0.985	0.927	14-18	0.724	0.671	0.517	2-7	0.898	0.834	0.757
std			0.044	0.034	0.053		0.049	0.012	0.039		0.073	0.095	0.193		0.046	0.044	0.076

Dataset	Max correlation	Index	logistic AUC	logistic Acc	logistic F1	7 indices	logistic 7w Acc	logistic 3w AUC	logistic 7w F1	PCA number of comp	PCA AUC	PCA Acc	PCA F1	PLS number of comp	PLS AUC	PLS Acc	PLS F1
DCorn_AAM_1	0.729	625	0.81	0.673	0.6	[429,579,637,1238, 1961,408,612]	0.980	1.000	0.980	17	0.653	0.592	0.524	3	0.897	0.857	0.851
DCorn_AAM_2	0.729	625	0.678	0.592	0.444	[429,579,637,1238, 1961,408,612]	0.939	0.997	0.941	15	0.727	0.592	0.412	2	0.877	0.796	0.792
DCorn_AAM_3	0.729	625	0.816	0.667	0.529	[429,579,637,1238, 1961,408,612]	0.875	0.979	0.875	16	0.394	0.417	0.391	3	0.878	0.833	0.801
DCorn_AAM_4	0.729	625	0.701	0.625	0.55	[429,579,637,1238, 1961,408,612]	0.938	0.990	0.933	17	0.592	0.542	0.522	13	0.858	0.833	0.804
DCorn_AAM_5	0.729	625	0.7	0.604	0.537	[429,579,637,1238, 1961,408,612]	0.917	0.988	0.920	17	0.552	0.5	0.4	2	0.832	0.708	0.722
mean	0.729	625	0.741	0.632	0.532	[429,579,637,1238, 1961,408,612]	0.930	0.991	0.930	15-17	0.584	0.528	0.45	2-13	0.867	0.806	0.802
std			0.066	0.037	0.056		0.038	0.008	0.038		0.125	0.073	0.067		0.023	0.059	0.052

Dataset	Max correlation	Index	logistic AUC	logistic Acc	logistic F1	7 indices	logistic 7w Acc	logistic 3w AUC	logistic 7w F1	PCA number of comp	PCA AUC	PCA Acc	PCA F1	PLS number of comp	PLS AUC	PLS Acc	PLS F1
DSunflower_1	0.801	722	0.933	0.893	0.875	[551,734,1516,1074, 739,1651,2136]	0.911	0.971	0.918	7	0.896	0.882	0.853	10	0.967	0.941	0.931
DSunflower_2	0.801	722	0.922	0.875	0.851	[551,734,1516,1074, 739,1651,2136]	0.946	0.995	0.953	8	0.889	0.851	0.812	4	0.974	0.881	0.851
DSunflower_3	0.801	722	0.892	0.869	0.847	[551,734,1516,1074, 739,1651,2136]	0.958	0.992	0.963	7	0.863	0.857	0.821	6	0.963	0.944	0.931
DSunflower_4	0.801	722	0.896	0.857	0.829	[551,734,1516,1074, 739,1651,2136]	0.940	0.980	0.946	7	0.862	0.815	0.75	4	0.972	0.905	0.884
DSunflower_5	0.801	722	0.883	0.886	0.869	[551,734,1516,1074, 739,1651,2136]	0.952	0.991	0.956	7	0.852	0.832	0.791	11	0.971	0.944	0.931
mean	0.801	722	0.905	0.876	0.854	[551,734,1516,1074, 739,1651,2136]	0.942	0.986	0.947	7-8	0.872	0.846	0.805	4-11	0.969	0.921	0.905
std			0.021	0.014	0.018		0.018	0.010	0.017		0.019	0.027	0.038		0.004	0.027	0.037

Dataset	Max correlation	Ind ex	logistic AUC	logistic Acc	logistic F1	7 indices	logistic 7w Acc	logistic 3w AUC	logistic 7w F1	PCA number of comp	PCA AUC	PCA Acc	PCA F1	PLS number of comp	PLS AUC	PLS Acc	PLS F1
DSunflower_L_1	0.827	730	0.884	0.835	0.806	[551,745,1283,356,8 18,2136,2080]	0.918	0.968	0.923	6	0.819	0.835	0.788	8	0.916	0.906	0.895
DSunflower_L_2	0.827	730	0.893	0.847	0.817	[551,745,1283,356,8 18,2136,2080]	0.871	0.965	0.882	6	0.854	0.871	0.836	6	0.961	0.871	0.841
DSunflower_L_3	0.827	730	0.844	0.845	0.806	[551,745,1283,356,8 18,2136,2080]	0.929	0.974	0.936	6	0.779	0.817	0.778	8	0.942	0.917	0.901
DSunflower_L_4	0.827	730	0.921	0.88	0.857	[551,745,1283,356,8 18,2136,2080]	0.940	0.986	0.946	6	0.901	0.855	0.818	8	0.981	0.916	0.901
DSunflower_L_5	0.827	730	0.855	0.855	0.818	[551,745,1283,356,8 18,2136,2080]	0.928	0.990	0.933	6	0.781	0.819	0.769	2	0.906	0.831	0.774
mean	0.827	730	0.879	0.853	0.821	[551,745,1283,356,8 18,2136,2080]	0.917	0.976	0.924	6	0.827	0.838	0.798	2-8	0.941	0.888	0.862
std			0.031	0.017	0.021		0.027	0.011	0.025		0.052	0.025	0.028		0.031	0.037	0.056

Dataset	Max correlation	Ind ex	logistic AUC	logistic Acc	logistic F1	7 indices	logistic 7w Acc	logistic 3w AUC	logistic 7w F1	PCA number of comp	PCA AUC	PCA Acc	PCA F1	PLS number of comp	PLS AUC	PLS Acc	PLS F1
DSunflower_C_1	0.836	721	0.983	0.976	0.974	[731,801,679,744,1 343,357,887]	0.988	0.991	0.989	7	0.969	0.918	0.907	4	0.977	0.965	0.966
DSunflower_C_2	0.836	721	0.983	0.929	0.917	[731,801,679,744,1 343,357,887]	0.976	0.999	0.978	7	0.866	0.788	0.735	5	0.997	0.965	0.966
DSunflower_C_3	0.836	721	0.969	0.929	0.914	[731,801,679,744,1 343,357,887]	0.976	0.998	0.978	7	0.936	0.869	0.841	4	0.987	0.952	0.944
DSunflower_C_4	0.836	721	0.945	0.928	0.914	[731,801,679,744,1 343,357,887]	0.988	1.000	0.989	7	0.871	0.807	0.75	4	0.999	0.964	0.959
DSunflower_C_5	0.836	721	0.97	0.916	0.899	[731,801,679,744,1 343,357,887]	0.988	0.998	0.989	7	0.876	0.831	0.774	4	0.994	0.964	0.959
mean	0.836	721	0.97	0.936	0.923	[731,801,679,744,1 343,357,887]	0.983	0.997	0.985	7	0.904	0.843	0.801	4-5	0.991	0.962	0.956
std			0.016	0.024	0.029		0.006	0.004	0.006		0.046	0.052	0.071		0.009	0.005	0.070

Dataset	Max correlation	Ind ex	logistic AUC	logistic Acc	logisti c F1	7 indices	logistic 7w Acc	logistic 3w AUC	logistic 7w F1	PCA number of comp	PCA AUC	PCA Acc	PCA F1	PLS number of comp	PLS AUC	PLS Acc	PLS F1
DSunflower_IP_1	0.895	729	0.964	0.896	0.906	[802, 730]	1	1	1	7	0.871	0.771	0.784	4	0.996	0.917	0.923
DSunflower_IP_2	0.895	729	0.98	0.917	0.923	[802, 730]	1	1	1	6	0.991	0.896	0.902	5	0.989	0.938	0.943
DSunflower_IP_3	0.895	729	0.998	0.979	0.982	[802, 730]	1	1	1	7	0.904	0.813	0.816	4	1	0.979	0.982
DSunflower_IP_4	0.895	729	1	0.979	0.982	[802, 730]	1	1	1	6	0.938	0.833	0.867	5	1	0.979	0.982
DSunflower_IP_5	0.895	729	0.989	0.958	0.964	[802, 730]	0.979	1	0.976	7	0.939	0.896	0.902	3	0.993	0.938	0.945
mean	0.895	729	0.986	0.946	0.951	[802, 730]	0.996	1	0.995	6-7	0.929	0.842	0.854	3-5	0.996	0.956	0.955
std			0.015	0.038	0.035	[802, 730]	0.009	0	0.011		0.045	0.054	0.053		0.005	0.028	0.026

Dataset	Max correlation	Ind ex	logisti c AUC	logisti c Acc	logist ic F1	7 indices	logistic 7w Acc	logistic 3w AUC	logistic 7w F1	PCA number of comp	PCA AUC	PCA Acc	PCA F1	PLS number of comp	PLS AUC	PLS Acc	PLS F1
DSunflower_AAM_1	0.840	721	0.906	0.833	0.818	[551,1036,357,1 127,486,763]	0.979	1.000	0.979	7	0.859	0.875	0.857	6	0.991	0.938	0.936
DSunflower_AAM_2	0.840	721	0.873	0.854	0.837	[551,1036,357,1 127,486,763]	0.938	0.979	0.933	7	0.872	0.833	0.818	6	0.997	0.958	0.958
DSunflower_AAM_3	0.840	721	0.877	0.917	0.909	[551,1036,357,1 127,486,763]	1.000	1.000	1.000	7	0.873	0.875	0.864	11	1	1	1
DSunflower_AAM_4	0.840	721	0.962	0.875	0.87	[551,1036,357,1 127,486,763]	0.938	0.972	0.936	6	0.875	0.771	0.744	11	0.981	0.917	0.913
DSunflower_AAM_5	0.840	721	0.823	0.875	0.864	[551,1036,357,1 127,486,763]	1.000	1.000	1.000	7	0.707	0.771	0.703	6	0.964	0.855	0.857
mean	0.840	721	0.888	0.871	0.86	[551,1036,357,1 127,486,763]	0.971	0.990	0.970	6-7	0.837	0.825	0.797	6-11	0.986	0.933	0.933
std			0.051	0.031	0.035		0.032	0.014	0.033		0.073	0.052	0.071		0.016	0.054	0.0253

B.2. REGRESSION

Datas et	correlat ion	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DCorn _1	0.554	561	0.306	0.26	[561,901,684,703,373,5 25,1996]	0.241	0.195	29	0.267	0.22	2	0.262	0.214
DCorn _2	0.554	561	0.312	0.261	[561,901,684,703,373,5 25,1996]	0.239	0.190	32	0.261	0.21	2	0.267	0.218
DCorn _3	0.554	561	0.309	0.263	[561,901,684,703,373,5 25,1996]	0.246	0.190	31	0.269	0.215	4	0.242	0.185
DCorn _4	0.554	561	0.372	0.289	[561,901,684,703,373,5 25,1996]	0.267	0.215	30	0.324	0.26	4	0.294	0.227
DCorn _5	0.554	561	0.325	0.271	[561,901,684,703,373,5 25,1996]	0.251	0.200	31	0.287	0.241	3	0.270	0.217
mean			0.325	0.269	[561,901,684,703,373,5 25,1996]	0.249	0.198	29-32	0.282	0.229	2-4	0.267	0.212
std			0.027	0.012		0.011	0.010		0.026	0.021		0.019	0.016

Dataset	correlat ion	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DCorn_L 1_1	0.634	553	0.315	0.264	[553,391,559,474,466, 1005,706]	0.272	0.212	22	0.320	0.247	3	0.302	0.220
DCorn_L 1_2	0.634	553	0.327	0.256	[553,391,559,474,466, 1005,706]	0.256	0.197	21	0.336	0.262	5	0.312	0.206
DCorn_L 1_3	0.634	553	0.303	0.257	[553,391,559,474,466, 1005,706]	0.238	0.181	21	0.291	0.241	3	0.281	0.201
DCorn_L 1_4	0.634	553	0.303	0.242	[553,391,559,474,466, 1005,706]	0.237	0.174	20	0.279	0.219	5	0.247	0.174
DCorn_L 1_5	0.634	553	0.260	0.224	[553,391,559,474,466, 1005,706]	0.238	0.185	18	0.265	0.214	3	0.241	0.193
mean	0.634	553	0.302	0.249	[553,391,559,474,466, 1005,706]	0.248	0.190	18-22	0.298	0.237	3-5	0.277	0.199
std			0.025	0.016		0.016	0.015		0.029	0.020		0.032	0.017

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DCorn_L_2_1	0.613	561	0.309	0.263	[561,900,685,576,1975,1 249,1965]	0.231	0.186	22	0.291	0.239	2	0.278	0.222
DCorn_L_2_2	0.613	561	0.370	0.247	[561,900,685,576,1975,1 249,1965]	0.255	0.194	22	0.271	0.211	2	0.279	0.218
DCorn_L_2_3	0.613	561	0.315	0.265	[561,900,685,576,1975,1 249,1965]	0.212	0.176	20	0.265	0.222	2	0.313	0.250
DCorn_L_2_4	0.613	561	0.286	0.245	[561,900,685,576,1975,1 249,1965]	0.218	0.182	22	0.243	0.206	2	0.240	0.204
DCorn_L_2_5	0.613	561	0.278	0.228	[561,900,685,576,1975,1 249,1965]	0.245	0.203	21	0.246	0.201	2	0.243	0.206
mean	0.613	561	0.311	0.250	[561,900,685,576,1975,1 249,1965]	0.232	0.188	20-22	0.263	0.216	2	0.271	0.220
std			0.036	0.015		0.018	0.011		0.020	0.015		0.030	0.018

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DCorn_L_3_1	0.770	731	0.229	0.185	[731,853,400,628,707, 377,715]	0.141	0.120	8	0.273	0.237	1	0.309	0.276
DCorn_L_3_2	0.770	731	0.253	0.204	[731,853,400,628,707, 377,715]	0.145	0.107	8	0.273	0.219	2	0.252	0.206
DCorn_L_3_3	0.770	731	0.280	0.218	[731,853,400,628,707, 377,715]	0.172	0.133	8	0.311	0.254	2	0.213	0.176
DCorn_L_3_4	0.770	731	0.176	0.139	[731,853,400,628,707, 377,715]	0.179	0.154	8	0.263	0.229	3	0.261	0.226
DCorn_L_3_5	0.770	731	0.235	0.211	[731,853,400,628,707, 377,715]	0.174	0.149	8	0.267	0.229	1	0.270	0.233
mean	0.770	731	0.235	0.192	[731,853,400,628,707, 377,715]	0.162	0.133	8	0.277	0.233	1-3	0.261	0.223
std			0.038	0.032		0.018	0.020		0.019	0.013		0.034	0.037

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DCorn_I_P_1	0.789	466	0.249	0.206	[466,707,682,866,1661,1,655,1749]	0.184	0.139	19	0.221	0.172	1	0.232	0.180
DCorn_I_P_2	0.789	466	0.212	0.184	[466,707,682,866,1661,1,655,1749]	0.160	0.131	20	0.169	0.141	1	0.161	0.137
DCorn_I_P_3	0.789	466	0.239	0.204	[466,707,682,866,1661,1,655,1749]	0.179	0.144	18	0.208	0.174	4	0.241	0.191
DCorn_I_P_4	0.789	466	0.293	0.245	[466,707,682,866,1661,1,655,1749]	0.223	0.175	18	0.257	0.217	2	0.265	0.216
DCorn_I_P_5	0.789	466	0.227	0.207	[466,707,682,866,1661,1,655,1749]	0.158	0.135	19	0.218	0.180	1	0.215	0.186
mean	0.789	466	0.244	0.209	[466,707,682,866,1661,1,655,1749]	0.181	0.145	18-20	0.215	0.177	1-4	0.223	0.182
std			0.031	0.022		0.026	0.018		0.032	0.027		0.039	0.029

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DCorn_L_M_1	0.679	432	0.304	0.219	[432,560,398,542,474,1656,372]	0.234	0.167	13	0.339	0.272	6	0.322	0.222
DCorn_L_M_2	0.679	432	0.306	0.224	[432,560,398,542,474,1656,372]	0.213	0.160	16	0.304	0.255	6	0.246	0.172
DCorn_L_M_3	0.679	432	0.323	0.248	[432,560,398,542,474,1656,372]	0.164	0.123	15	0.316	0.235	3	0.305	0.181
DCorn_L_M_4	0.679	432	0.383	0.287	[432,560,398,542,474,1656,372]	0.277	0.202	15	0.327	0.250	6	0.403	0.232
DCorn_L_M_5	0.679	432	0.245	0.202	[432,560,398,542,474,1656,372]	0.208	0.156	17	0.248	0.203	6	0.199	0.136
mean	0.679	432	0.312	0.236	[432,560,398,542,474,1656,372]	0.219	0.162	13-17	0.307	0.243	3-6	0.295	0.189
std			0.049	0.033		0.041	0.028		0.035	0.026		0.078	0.039

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DCorn_AA_M_1	0.729	625	0.230	0.175	[625,579,373,425,2183, 1146,1209]	0.156	0.111	15	0.184	0.148	4	0.187	0.112
DCorn_AA_M_2	0.729	625	0.172	0.138	[625,579,373,425,2183, 1146,1209]	0.143	0.107	16	0.199	0.160	4	0.150	0.113
DCorn_AA_M_3	0.729	625	0.174	0.154	[625,579,373,425,2183, 1146,1209]	0.135	0.099	17	0.191	0.145	4	0.149	0.116
DCorn_AA_M_4	0.729	625	0.210	0.182	[625,579,373,425,2183, 1146,1209]	0.152	0.115	15	0.247	0.199	4	0.195	0.133
DCorn_AA_M_5	0.729	625	0.163	0.143	[625,579,373,425,2183, 1146,1209]	0.132	0.100	17	0.146	0.119	4	0.134	0.102
mean	0.729	625	0.190	0.159	[625,579,373,425,2183, 1146,1209]	0.143	0.107	15-17	0.194	0.154	4	0.163	0.115
std			0.029	0.019		0.010	0.007		0.036	0.029		0.027	0.011

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DSunflower_1	0.801	722	0.273	0.201	[722,755,1504,437,550 ,354,404]	0.214	0.157	7	0.270	0.179	5	0.248	0.175
DSunflower_2	0.801	722	0.247	0.194	[722,755,1504,437,550 ,354,404]	0.204	0.158	8	0.201	0.156	4	0.192	0.146
DSunflower_3	0.801	722	0.268	0.210	[722,755,1504,437,550 ,354,404]	0.197	0.144	7	0.238	0.177	8	0.207	0.154
DSunflower_4	0.801	722	0.328	0.236	[722,755,1504,437,550 ,354,404]	0.255	0.182	7	0.306	0.211	5	0.275	0.181
DSunflower_5	0.801	722	0.290	0.223	[722,755,1504,437,550 ,354,404]	0.238	0.169	7	0.251	0.177	8	0.232	0.161
mean	0.801	722	0.281	0.213	[722,755,1504,437,550 ,354,404]	0.222	0.162	7-8	0.253	0.180	4-8	0.231	0.163
std			0.030	0.017		0.024	0.014		0.039	0.020		0.033	0.014

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DSunflower_L_1	0.827	730	0.285	0.206	[730,543,1015,1632,427,6 72,604]	0.216	0.163	6	0.296	0.227	5	0.226	0.169
DSunflower_L_2	0.827	730	0.257	0.197	[730,543,1015,1632,427,6 72,604]	0.202	0.152	6	0.282	0.222	5	0.223	0.164
DSunflower_L_3	0.827	730	0.310	0.227	[730,543,1015,1632,427,6 72,604]	0.270	0.192	6	0.346	0.250	6	0.284	0.201
DSunflower_L_4	0.827	730	0.230	0.180	[730,543,1015,1632,427,6 72,604]	0.188	0.147	6	0.255	0.193	1	0.249	0.177
DSunflower_L_5	0.827	730	0.233	0.171	[730,543,1015,1632,427,6 72,604]	0.196	0.146	6	0.252	0.189	5	0.196	0.144
mean	0.827	730	0.263	0.196	[730,543,1015,1632,427,6 72,604]	0.215	0.160	6	0.286	0.216	1-6	0.236	0.171
std			0.035	0.022		0.033	0.019		0.038	0.026		0.033	0.021

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DSunflower_C_1	0.836	721	0.277	0.213	[721,755,587,555,711,15 15,625]	0.219	0.147	7	0.274	0.185	5	0.227	0.160
DSunflower_C_2	0.836	721	0.267	0.192	[721,755,587,555,711,15 15,625]	0.181	0.122	7	0.232	0.165	11	0.225	0.147
DSunflower_C_3	0.836	721	0.243	0.191	[721,755,587,555,711,15 15,625]	0.184	0.134	7	0.230	0.165	4	0.199	0.146
DSunflower_C_4	0.836	721	0.255	0.195	[721,755,587,555,711,15 15,625]	0.168	0.125	7	0.217	0.160	6	0.170	0.133
DSunflower_C_5	0.836	721	0.245	0.189	[721,755,587,555,711,15 15,625]	0.169	0.121	7	0.196	0.148	5	0.195	0.143
mean			0.257	0.196	[721,755,587,555,711,15 15,625]	0.184	0.130	7	0.230	0.165	5-11	0.203	0.146
std			0.014	0.009		0.021	0.011		0.028	0.013		0.024	0.010

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DSunflower_IP_1	0.895	729	0.176	0.128	[729,678,762,912,1723,360,1439]	0.134	0.096	7	0.208	0.144	5	0.160	0.118
DSunflower_IP_2	0.895	729	0.204	0.163	[729,678,762,912,1723,360,1439]	0.166	0.131	6	0.274	0.201	5	0.167	0.125
DSunflower_IP_3	0.895	729	0.220	0.175	[729,678,762,912,1723,360,1439]	0.177	0.135	7	0.264	0.179	5	0.209	0.169
DSunflower_IP_4	0.895	729	0.183	0.142	[729,678,762,912,1723,360,1439]	0.152	0.118	6	0.175	0.142	5	0.148	0.116
DSunflower_IP_5	0.895	729	0.190	0.138	[729,678,762,912,1723,360,1439]	0.129	0.100	7	0.249	0.181	7	0.178	0.132
mean	0.895	729	0.195	0.149	[729,678,762,912,1723,360,1439]	0.152	0.116	6-7	0.234	0.170	5-7	0.172	0.132
std			0.018	0.019		0.020	0.018		0.042	0.026		0.023	0.021

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DSunflower_AAM_1	0.840	721	0.306	0.260	[721,2246,1505,1619,179,1,2081,1347]	0.244	0.182	7	0.352	0.275	3	0.290	0.216
DSunflower_AAM_2	0.840	721	0.301	0.226	[721,2246,1505,1619,179,1,2081,1347]	0.254	0.193	7	0.277	0.197	8	0.293	0.222
DSunflower_AAM_3	0.840	721	0.283	0.231	[721,2246,1505,1619,179,1,2081,1347]	0.221	0.176	7	0.238	0.190	4	0.215	0.156
DSunflower_AAM_4	0.840	721	0.236	0.170	[721,2246,1505,1619,179,1,2081,1347]	0.196	0.129	7	0.260	0.171	4	0.241	0.148
DSunflower_AAM_5	0.840	721	0.299	0.242	[721,2246,1505,1619,179,1,2081,1347]	0.219	0.178	7	0.256	0.202	4	0.236	0.192
mean	0.840	721	0.285	0.226	[721,2246,1505,1619,179,1,2081,1347]	0.227	0.171	7	0.277	0.207	3-8	0.255	0.187
std			0.029	0.034		0.023	0.024		0.044	0.040		0.035	0.034

B.3. ML CLASSIFICATION

Random forest

Dataset	AUC	Accuracy	f1	max_depth	max_features	n_estimators
DCorn_1	0.922	0.83	0.854	8	35	70
DCorn_2	0.934	0.874	0.891	8	35	60
DCorn_3	0.936	0.857	0.882	8	35	80
DCorn_4	0.947	0.857	0.876	7	30	60
DCorn_5	0.955	0.879	0.9	7	40	60
mean	0.939	0.859	0.88			
std	0.013	0.019	0.017			

Dataset	AUC	Accuracy	f1	max_depth	max_features	n_estimators
DCorn_L1_1	0.855	0.776	0.8	8	30	60
DCorn_L1_2	0.915	0.847	0.869	6	35	70
DCorn_L1_3	0.922	0.81	0.822	7	40	60
DCorn_L1_4	0.921	0.819	0.831	8	40	70
DCorn_L1_5	0.947	0.855	0.867	7	30	80
mean	0.912	0.822	0.838			
std	0.034	0.032	0.03			

Dataset	AUC	Accuracy	f1	max_depth	max_features	n_estimators
DCorn_L2_1	0.92	0.8	0.844	7	40	70
DCorn_L2_2	0.948	0.843	0.884	6	30	60
DCorn_L2_3	0.96	0.886	0.913	6	40	70
DCorn_L2_4	0.851	0.797	0.854	8	40	80
DCorn_L2_5	0.833	0.812	0.866	6	30	80
mean	0.903	0.827	0.872			
std	0.057	0.037	0.027			

Dataset	AUC	Accuracy	f1	max_depth	max_features	n_estimators
DCorn_L3_1	0.982	0.955	0.966	6	30	60
DCorn_L3_2	0.96	0.909	0.929	6	35	60
DCorn_L3_3	0.973	0.864	0.897	6	35	60
DCorn_L3_4	0.971	0.857	0.87	6	30	60
DCorn_L3_5	0.945	0.9	0.917	6	35	60
mean	0.966	0.897	0.915			
std	0.014	0.039	0.036			

Dataset	AUC	Accuracy	f1	max_depth	max_features	n_estimators
DCorn_IP_1	0.957	0.887	0.897	8	30	70
DCorn_IP_2	0.842	0.788	0.814	8	40	60
DCorn_IP_3	0.933	0.827	0.847	8	40	80
DCorn_IP_4	0.917	0.865	0.881	7	40	80
DCorn_IP_5	0.956	0.863	0.877	8	30	80
mean	0.921	0.846	0.863			
std	0.047	0.039	0.033			

Dataset	AUC	Accuracy	f1	max_depth	max_features	n_estimators
DCorn_LM_1	0.974	0.898	0.878	8	30	80
DCorn_LM_2	0.953	0.857	0.821	8	40	80
DCorn_LM_3	0.973	0.958	0.947	7	35	80
DCorn_LM_4	0.949	0.851	0.8	6	35	80
DCorn_LM_5	0.944	0.83	0.75	6	40	70
mean	0.959	0.879	0.839			
std	0.014	0.051	0.076			

Dataset	AUC	Accuracy	f1	max_depth	max_features	n_estimators
DCorn_AAM_1	0.976	0.918	0.92	8	40	80
DCorn_AAM_2	0.943	0.878	0.875	6	35	70
DCorn_AAM_3	0.97	0.917	0.913	6	35	60
DCorn_AAM_4	0.938	0.875	0.88	6	35	60
DCorn_AAM_5	0.927	0.792	0.792	8	30	80
mean	0.951	0.876	0.876			
std	0.021	0.051	0.051			

Dataset	AUC	Accuracy	f1	max_depth	max_features	n_estimators
DSunflower_1	0.967	0.947	0.939	8	35	60
DSunflower_2	0.987	0.94	0.931	7	35	80
DSunflower_3	0.985	0.946	0.938	6	40	80
DSunflower_4	0.958	0.923	0.909	8	30	80
DSunflower_5	0.991	0.922	0.91	6	40	80
mean	0.978	0.936	0.925			
std	0.014	0.012	0.015			

Dataset	AUC	Accuracy	f1	max_depth	max_features	n_estimators
DSunflower_L_1	0.95	0.906	0.892	6	30	80
DSunflower_L_2	0.962	0.871	0.849	6	40	80
DSunflower_L_3	0.931	0.893	0.873	6	40	60
DSunflower_L_4	0.957	0.928	0.914	6	30	80
DSunflower_L_5	0.963	0.892	0.87	8	40	80
mean	0.953	0.898	0.88			
std	0.013	0.021	0.025			

Dataset	AUC	Accuracy	f1	max_depth	max_features	n_estimators
DSunflower_C_1	0.982	0.976	0.974	6	40	80
DSunflower_C_2	1	1	1	7	40	80
DSunflower_C_3	0.977	0.976	0.973	8	35	80
DSunflower_C_4	1	0.988	0.987	6	30	80
DSunflower_C_5	0.995	0.976	0.973	7	35	60
mean	0.991	0.983	0.981			
std	0.011	0.011	0.012			

Dataset	AUC	Accuracy	f1	max_depth	max_features	n_estimators
DSunflower_IP_1	1	1	1	6	30	60
DSunflower_IP_2	0.996	0.979	0.982	6	30	60
DSunflower_IP_3	1	1	1	6	30	60
DSunflower_IP_4	1	0.979	0.982	6	40	80
DSunflower_IP_5	1	0.979	0.982	6	30	60
mean	0.999	0.988	0.989			
std	0.002	0.011	0.01			

Dataset	AUC	Accuracy	f1	max_depth	max_features	n_estimators
DSunflower_AAM_1	0.978	0.958	0.958	6	40	70
DSunflower_AAM_2	0.979	0.917	0.917	7	30	70
DSunflower_AAM_3	1	0.979	0.98	7	40	70
DSunflower_AAM_4	0.981	0.917	0.913	6	35	70
DSunflower_AAM_5	0.974	0.896	0.894	6	30	60
mean	0.982	0.933	0.932			
std	0.01	0.034	0.035			

XGboost

Dataset	AUC	Accuracy	f1	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DCorn_1	0.847	0.852	0.876	0.029	0.5	6	80	0.6
DCorn_2	0.881	0.874	0.890	0.035	0.5	8	80	0.8
DCorn_3	0.862	0.874	0.898	0.035	0.5	6	70	0.9
DCorn_4	0.798	0.800	0.829	0.023	0.5	6	80	0.6
DCorn_5	0.907	0.914	0.929	0.029	0.5	6	60	0.9
mean	0.859	0.863	0.885					
std	0.041	0.042	0.036					

Dataset	AUC	Accuracy	f1	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DCorn_L1_1	0.847	0.765	0.792	0.023	0.5	6	80	0.6
DCorn_L1_2	0.93	0.847	0.866	0.023	0.8	7	80	0.6
DCorn_L1_3	0.922	0.821	0.831	0.023	0.5	6	70	0.8
DCorn_L1_4	0.885	0.795	0.795	0.035	0.8	6	60	0.8
DCorn_L1_5	0.935	0.867	0.882	0.035	0.5	7	60	0.8
mean	0.904	0.819	0.833					
std	0.037	0.041	0.041					

Dataset	AUC	Accuracy	f1	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DCorn_L2_1	0.91	0.843	0.884	0.035	0.5	6	70	0.9
DCorn_L2_2	0.947	0.871	0.901	0.035	0.9	6	70	0.9
DCorn_L2_3	0.939	0.886	0.917	0.023	0.8	6	70	0.9
DCorn_L2_4	0.87	0.768	0.833	0.029	0.9	6	70	0.9
DCorn_L2_5	0.868	0.783	0.839	0.023	0.5	7	70	0.9
mean	0.907	0.83	0.875					
std	0.037	0.053	0.037					

Dataset	AUC	Accuracy	f1	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DCorn_L3_1	1.000	0.955	0.966	0.035	0.5	6	80	0.6
DCorn_L3_2	0.964	0.864	0.897	0.029	0.9	6	80	0.6
DCorn_L3_3	0.982	0.864	0.897	0.035	0.5	6	60	0.9
DCorn_L3_4	0.990	0.905	0.917	0.023	0.5	6	60	0.9
DCorn_L3_5	0.923	0.850	0.880	0.023	0.5	6	60	0.9
mean	0.972	0.887	0.911					
std	0.030	0.043	0.033					

Dataset	AUC	Accuracy	f1	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DCorn_IP_1	0.946	0.849	0.867	0.035	0.9	7	60	0.9
DCorn_IP_2	0.836	0.75	0.772	0.035	0.5	6	70	0.6
DCorn_IP_3	0.93	0.865	0.873	0.029	0.5	8	60	0.9
DCorn_IP_4	0.953	0.904	0.921	0.023	0.8	7	60	0.9
DCorn_IP_5	0.96	0.902	0.915	0.035	0.5	6	60	0.6
mean	0.925	0.854	0.869					
std	0.051	0.063	0.06					

Dataset	AUC	Accuracy	f1	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DCorn_LM_1	0.966	0.878	0.857	0.029	0.5	6	60	0.8
DCorn_LM_2	0.931	0.857	0.821	0.023	0.5	6	80	0.9
DCorn_LM_3	0.973	0.917	0.889	0.035	0.5	6	70	0.8
DCorn_LM_4	0.91	0.872	0.833	0.035	0.8	6	80	0.6
DCorn_LM_5	0.945	0.809	0.71	0.023	0.5	6	70	0.8
mean	0.945	0.866	0.822					
std	0.026	0.039	0.068					

Dataset	AUC	Accuracy	f1	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DCorn_AAM_1	0.957	0.918	0.917	0.035	0.9	6	80	0.8
DCorn_AAM_2	0.972	0.857	0.851	0.029	0.8	6	70	0.9
DCorn_AAM_3	0.967	0.917	0.92	0.023	0.8	6	70	0.6
DCorn_AAM_4	0.92	0.875	0.875	0.035	0.5	6	60	0.8
DCorn_AAM_5	0.885	0.833	0.84	0.035	0.9	6	60	0.8
mean	0.94	0.88	0.881					
std	0.037	0.037	0.037					

Dataset	AUC	Accuracy	f1	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DSunflower_1	0.938	0.941	0.933	0.029	0.5	7	80	0.8
DSunflower_2	0.933	0.935	0.927	0.035	0.5	7	60	0.9
DSunflower_3	0.942	0.946	0.938	0.035	0.5	7	80	0.6
DSunflower_4	0.922	0.923	0.915	0.035	0.5	7	60	0.9
DSunflower_5	0.955	0.958	0.952	0.023	0.5	7	80	0.8
mean	0.938	0.940	0.933					
std	0.012	0.013	0.014					

Dataset	AUC	Accuracy	f1	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DSunflower_L_1	0.950	0.871	0.861	0.035	0.5	6	70	0.8
DSunflower_L_2	0.960	0.847	0.827	0.023	0.5	6	80	0.9
DSunflower_L_3	0.931	0.905	0.892	0.035	0.5	6	60	0.6
DSunflower_L_4	0.967	0.904	0.886	0.035	0.5	6	70	0.8
DSunflower_L_5	0.963	0.892	0.870	0.035	0.5	7	80	0.9
mean	0.955	0.884	0.867					
std	0.014	0.025	0.026					

Dataset	AUC	Accuracy	f1	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DSunflower_C_1	0.974	0.976	0.974	0.029	0.8	6	60	0.8
DSunflower_C_2	0.999	0.988	0.987	0.023	0.5	6	60	0.9
DSunflower_C_3	0.978	0.964	0.959	0.029	0.5	6	60	0.9
DSunflower_C_4	1.000	1.000	1.000	0.023	0.5	6	60	0.9
DSunflower_C_5	0.975	0.964	0.960	0.029	0.8	6	60	0.6
mean	0.986	0.979	0.976					
std	0.013	0.016	0.018					

Dataset	AUC	Accuracy	f1	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DSunflower_IP_1	1	1	1	0.023	0.5	6	60	0.6
DSunflower_IP_2	0.996	0.958	0.964	0.023	0.5	6	60	0.6
DSunflower_IP_3	1	1	1	0.035	0.8	6	60	0.9
DSunflower_IP_4	1	1	1	0.023	0.8	6	60	0.8
DSunflower_IP_5	1	0.979	0.982	0.023	0.8	6	60	0.6
mean	0.999	0.988	0.989					
std	0.002	0.019	0.016					

Dataset	AUC	Accuracy	f1	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DSunflower_AAM_1	0.969	0.979	0.979	0.023	0.8	6	60	0.9
DSunflower_AAM_2	0.986	0.896	0.894	0.035	0.8	6	80	0.8
DSunflower_AAM_3	1	1	1	0.035	0.5	6	60	0.9
DSunflower_AAM_4	0.972	0.896	0.889	0.023	0.8	6	60	0.9
DSunflower_AAM_5	0.948	0.896	0.894	0.029	0.5	6	60	0.6
mean	0.975	0.933	0.931					
std	0.02	0.052	0.054					

Random forest with SMOTE

Dataset	AUC	Accuracy	f1	max_depth	max_features	n_estimators
DCorn_1	0.918	0.818	0.842	8	40	60
DCorn_2	0.936	0.857	0.873	8	40	70
DCorn_3	0.943	0.857	0.877	8	40	80
DCorn_4	0.936	0.84	0.861	8	35	60
DCorn_5	0.947	0.885	0.903	8	30	70
mean	0.936	0.852	0.871			
std	0.011	0.025	0.022			

Dataset	AUC	Accuracy	f1	max_depth	max_features	n_estimators
DSunflower_1	0.961	0.953	0.946	8	40	80
DSunflower_2	0.985	0.935	0.924	8	30	80
DSunflower_3	0.991	0.94	0.931	8	40	70
DSunflower_4	0.963	0.917	0.903	6	40	80
DSunflower_5	0.99	0.928	0.918	8	35	60
mean	0.978	0.934	0.924			
std	0.015	0.013	0.016			

XGboost with SMOTE

Dataset	AUC	Accuracy	f1	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DCorn_1	0.937	0.835	0.861	0.023	0.5	7	80	0.9
DCorn_2	0.949	0.880	0.894	0.023	0.5	8	80	0.9
DCorn_3	0.942	0.869	0.893	0.023	0.5	6	60	0.9
DCorn_4	0.902	0.846	0.872	0.023	0.9	7	60	0.8
DCorn_5	0.951	0.885	0.905	0.023	0.5	7	80	0.9
mean	0.936	0.863	0.885					
std	0.020	0.022	0.018					

Dataset	AUC	Accuracy	f1	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DSunflower_1	0.967	0.935	0.928	0.023	0.5	6	80	0.6
DSunflower_2	0.990	0.946	0.938	0.029	0.5	8	70	0.9
DSunflower_3	0.991	0.935	0.926	0.035	0.5	6	80	0.8
DSunflower_4	0.961	0.923	0.912	0.029	0.8	6	60	0.9
DSunflower_5	0.988	0.934	0.927	0.029	0.5	6	80	0.9
mean	0.979	0.935	0.926					
std	0.014	0.008	0.009					

B.4. ML REGRESSION

Random Forest

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
Dcorn_1	0.177	0.234	8	40	60
Dcorn_2	0.156	0.204	8	35	80
Dcorn_3	0.146	0.204	8	40	70
Dcorn_4	0.183	0.254	8	40	80
Dcorn_5	0.157	0.209	8	40	70
mean	0.164	0.221			
std	0.015	0.022			

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
Dcorn_L1_1	0.181	0.251	6	35	80
Dcorn_L1_2	0.201	0.274	8	40	80
Dcorn_L1_3	0.171	0.232	8	40	80
Dcorn_L1_4	0.154	0.213	8	40	60
Dcorn_L1_5	0.158	0.226	8	35	80
mean	0.173	0.239			
std	0.019	0.024			

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
Dcorn_L2_1	0.149	0.199	8	35	60
Dcorn_L2_2	0.164	0.230	8	30	60
Dcorn_L2_3	0.169	0.223	8	40	60
Dcorn_L2_4	0.154	0.203	7	35	60
Dcorn_L2_5	0.166	0.214	8	35	70
mean	0.161	0.214			
std	0.009	0.013			

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
Dcorn_L3_1	0.179	0.221	8	35	60
Dcorn_L3_2	0.161	0.209	8	40	60
Dcorn_L3_3	0.166	0.210	8	35	70
Dcorn_L3_4	0.136	0.174	7	40	70
Dcorn_L3_5	0.173	0.203	7	35	80
mean	0.163	0.203			
std	0.017	0.018			

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
Dcorn_IP_1	0.124	0.172	7	30	80
Dcorn_IP_2	0.123	0.155	7	30	70
Dcorn_IP_3	0.117	0.159	8	30	60
Dcorn_IP_4	0.181	0.255	8	40	70
Dcorn_IP_5	0.135	0.181	7	30	80
mean	0.136	0.184			
std	0.026	0.041			

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
Dcorn_LM_1	0.161	0.224	6	40	60
Dcorn_LM_2	0.157	0.214	7	40	80
Dcorn_LM_3	0.155	0.231	8	40	80
Dcorn_LM_4	0.205	0.307	7	35	80
Dcorn_LM_5	0.139	0.188	7	35	70
mean	0.164	0.233			
std	0.025	0.045			

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
Dcorn_AAM_1	0.102	0.140	8	30	80
Dcorn_AAM_2	0.101	0.146	7	35	80
Dcorn_AAM_3	0.072	0.098	8	40	80
Dcorn_AAM_4	0.121	0.178	8	35	80
Dcorn_AAM_5	0.091	0.137	8	30	70
mean	0.097	0.140			
std	0.018	0.028			

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
DSunflower_1	0.106	0.172	7	40	70
DSunflower_2	0.100	0.153	8	40	70
DSunflower_3	0.113	0.183	8	40	70
DSunflower_4	0.130	0.243	8	35	70
DSunflower_5	0.119	0.201	8	35	60
mean	0.114	0.190			
std	0.012	0.034			

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
DSunflower_L_1	0.126	0.193	7	40	60
DSunflower_L_2	0.132	0.199	7	40	60
DSunflower_L_3	0.148	0.256	6	35	80
DSunflower_L_4	0.121	0.194	6	40	80
DSunflower_L_5	0.099	0.150	6	35	80
mean	0.125	0.198			
std	0.018	0.038			

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
DSunflower_C_1	0.107	0.180	7	40	80
DSunflower_C_2	0.086	0.156	7	40	70
DSunflower_C_3	0.079	0.138	8	40	60
DSunflower_C_4	0.093	0.172	8	35	60
DSunflower_C_5	0.070	0.135	8	40	60
mean	0.087	0.156			
std	0.014	0.020			

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
DSunflower_IP_1	0.041	0.087	8	35	60
DSunflower_IP_2	0.072	0.145	7	35	60
DSunflower_IP_3	0.079	0.147	6	40	70
DSunflower_IP_4	0.046	0.100	6	35	60
DSunflower_IP_5	0.058	0.098	6	35	60
mean	0.059	0.115			
std	0.016	0.028			

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
DSunflower_AAM_1	0.126	0.181	6	35	80
DSunflower_AAM_2	0.110	0.230	8	40	80
DSunflower_AAM_3	0.121	0.224	8	40	80
DSunflower_AAM_4	0.083	0.135	7	30	70
DSunflower_AAM_5	0.127	0.184	7	40	80
mean	0.113	0.191			
std	0.019	0.039			

XGBoost

	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
Dcorn_1	0.189	0.312	0.035	0.5	6	70	0.6
Dcorn_2	0.117	0.248	0.035	0.5	8	70	0.6
Dcorn_3	0.135	0.251	0.029	0.9	8	70	0.9
Dcorn_4	0.167	0.323	0.035	0.5	6	80	0.9
Dcorn_5	0.127	0.250	0.035	0.5	6	80	0.6
mean	0.147	0.277					
std	0.030	0.037					

	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
Dcorn_L1_1	0.208	0.374	0.035	0.5	6	80	0.9
Dcorn_L1_2	0.216	0.374	0.035	0.9	8	70	0.8
Dcorn_L1_3	0.140	0.276	0.035	0.9	7	70	0.9
Dcorn_L1_4	0.130	0.252	0.023	0.8	8	70	0.6
Dcorn_L1_5	0.157	0.276	0.035	0.9	6	80	0.9
mean	0.170	0.310					
std	0.040	0.059					

	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
Dcorn_L2_1	0.139	0.244	0.023	0.5	8	80	0.6
Dcorn_L2_2	0.174	0.308	0.035	0.9	7	80	0.8
Dcorn_L2_3	0.135	0.252	0.035	0.5	8	80	0.6
Dcorn_L2_4	0.141	0.243	0.029	0.8	7	80	0.9
Dcorn_L2_5	0.155	0.248	0.035	0.5	6	70	0.8
mean	0.149	0.259					
std	0.016	0.028					

	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
Dcorn_L3_1	0.211	0.325	0.023	0.8	6	70	0.8
Dcorn_L3_2	0.186	0.302	0.029	0.9	6	70	0.6
Dcorn_L3_3	0.190	0.300	0.035	0.8	6	80	0.6
Dcorn_L3_4	0.177	0.288	0.035	0.5	6	80	0.6
Dcorn_L3_5	0.165	0.283	0.035	0.8	6	60	0.6
mean	0.186	0.300					
std	0.017	0.016					

	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
Dcorn_IP_1	0.094	0.200	0.023	0.8	8	80	0.9
Dcorn_IP_2	0.070	0.157	0.035	0.5	8	60	0.9
Dcorn_IP_3	0.094	0.224	0.035	0.5	6	60	0.8
Dcorn_IP_4	0.121	0.256	0.035	0.5	8	70	0.8
Dcorn_IP_5	0.107	0.221	0.023	0.8	8	60	0.8
mean	0.097	0.212					
std	0.019	0.036					

	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
Dcorn_LM_1	0.191	0.379	0.029	0.8	7	60	0.8
Dcorn_LM_2	0.159	0.349	0.035	0.8	7	70	0.9
Dcorn_LM_3	0.106	0.252	0.029	0.9	6	60	0.6
Dcorn_LM_4	0.174	0.336	0.035	0.8	6	70	0.8
Dcorn_LM_5	0.097	0.207	0.029	0.5	6	60	0.8
mean	0.145	0.305					
std	0.042	0.072					

	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
Dcorn_AMM_1	0.102	0.222	0.029	0.5	8	80	0.9
Dcorn_AMM_2	0.052	0.135	0.035	0.9	7	60	0.9
Dcorn_AMM_3	0.042	0.105	0.035	0.5	7	80	0.9
Dcorn_AMM_4	0.083	0.188	0.035	0.8	8	80	0.9
Dcorn_AMM_5	0.081	0.175	0.035	0.5	6	80	0.9
mean	0.072	0.165					
std	0.025	0.046					

	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
Dsunflower_1	0.075	0.187	0.023	0.5	7	80	0.6
Dsunflower_2	0.064	0.171	0.035	0.5	8	80	0.8
Dsunflower_3	0.074	0.195	0.029	0.5	6	80	0.6
Dsunflower_4	0.131	0.321	0.029	0.9	7	80	0.8
Dsunflower_5	0.104	0.248	0.023	0.5	7	60	0.8
mean	0.090	0.224					
std	0.028	0.061					

	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
Dsunflower_L_1	0.111	0.220	0.023	0.5	6	70	0.6
Dsunflower_L_2	0.094	0.238	0.029	0.5	6	80	0.9
Dsunflower_L_3	0.131	0.320	0.035	0.5	6	60	0.9
Dsunflower_L_4	0.105	0.235	0.035	0.8	7	70	0.6
Dsunflower_L_5	0.079	0.191	0.035	0.5	7	60	0.9
mean	0.104	0.241					
std	0.019	0.048					

	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
Dsunflower_C_1	0.091	0.223	0.035	0.8	6	60	0.6
Dsunflower_C_2	0.082	0.190	0.029	0.5	6	60	0.6
Dsunflower_C_3	0.078	0.226	0.029	0.9	6	70	0.8
Dsunflower_C_4	0.091	0.247	0.029	0.9	6	70	0.9
Dsunflower_C_5	0.061	0.176	0.035	0.5	7	80	0.8
mean	0.081	0.212					
std	0.012	0.029					

	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
Dsunflower_IP_1	0.011	0.067	0.029	0.9	6	70	0.9
Dsunflower_IP_2	0.087	0.239	0.035	0.5	6	60	0.9
Dsunflower_IP_3	0.059	0.193	0.035	0.5	6	60	0.6
Dsunflower_IP_4	0.025	0.107	0.035	0.8	6	80	0.8
Dsunflower_IP_5	0.028	0.120	0.035	0.9	6	60	0.9
mean	0.042	0.145					
std	0.031	0.070					

	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
Dsunflower_AAM_1	0.078	0.188	0.035	0.8	6	60	0.8
Dsunflower_AAM_2	0.108	0.295	0.029	0.9	6	70	0.6
Dsunflower_AAM_3	0.108	0.278	0.029	0.9	7	80	0.8
Dsunflower_AAM_4	0.036	0.111	0.035	0.5	6	70	0.6
Dsunflower_AAM_5	0.057	0.143	0.029	0.5	6	70	0.9
mean	0.077	0.203					
std	0.032	0.081					

B.5. EARLY PREDICTION

Classification 2 days before

Dataset	Max correlation	Ind ex	logistic AUC	logistic c Acc	logistic c F1	7 indices	logistic 7w Acc	logistic 7w AUC	logistic 7w F1	PCA number of comp	PCA AUC	PCA Acc	PCA F1	PLS number of comp	PLS AUC	PLS Acc	PLS F1
DCorn_2 Days_1	0.839	553	0.679	0.714	0.714	[552,763,1346,1684,1 347,2008,2040]	0.786	0.904	0.750	5	0.444	0.607	0.703	13	0.722	0.679	0.743
DCorn_2 Days_2	0.839	553	0.559	0.481	0.462	[552,763,1346,1684,1 347,2008,2040]	0.852	0.888	0.800	5	0.559	0.519	0.581	7	0.806	0.704	0.733
DCorn_2 Days_3	0.839	553	0.594	0.593	0.560	[552,763,1346,1684,1 347,2008,2040]	0.741	0.759	0.667	5	0.712	0.667	0.667	7	0.759	0.593	0.593
DCorn_2 Days_4	0.839	553	0.729	0.593	0.522	[552,763,1346,1684,1 347,2008,2040]	0.741	0.829	0.696	5	0.453	0.519	0.581	7	0.606	0.556	0.647
DCorn_2 Days_5	0.839	553	0.635	0.630	0.615	[552,763,1346,1684,1 347,2008,2040]	0.815	0.876	0.737	5	0.612	0.704	0.789	12	0.876	0.815	0.865
mean	0.839	553	0.639	0.602	0.575	[552,763,1346,1684,1 347,2008,2040]	0.787	0.851	0.730	5	0.556	0.603	0.664	7-13	0.754	0.669	0.716
std			0.068	0.084	0.096		0.048	0.059	0.051		0.112	0.084	0.088		0.101	0.102	0.104

Dataset	Max correlation	Ind ex	logistic AUC	logistic c Acc	logistic c F1	7 indices	logistic 7w Acc	logistic 7w AUC	logistic 7w F1	PCA number of comp	PCA AUC	PCA Acc	PCA F1	PLS number of comp	PLS AUC	PLS Acc	PLS F1
DSunflower _2Days_1	0.678	552	0.800	0.679	0.690	[549,734,1677,2227,1 457,2008,1781]	0.821	0.967	0.737	7	0.594	0.500	0.533	14	0.861	0.750	0.811
DSunflower _2Days_2	0.678	552	0.583	0.464	0.483	[549,734,1677,2227,1 457,2008,1781]	0.821	0.922	0.762	6	0.478	0.393	0.452	10	0.700	0.607	0.667
DSunflower _2Days_3	0.678	552	0.756	0.714	0.733	[549,734,1677,2227,1 457,2008,1781]	0.857	0.950	0.800	6	0.572	0.536	0.629	6	0.650	0.643	0.722
DSunflower _2Days_4	0.678	552	0.644	0.643	0.667	[549,734,1677,2227,1 457,2008,1781]	0.964	1.000	0.952	6	0.411	0.464	0.483	9	0.717	0.679	0.727
DSunflower _2Days_5	0.678	552	0.706	0.643	0.722	[549,734,1677,2227,1 457,2008,1781]	0.857	0.950	0.800	6	0.467	0.571	0.684	14	0.744	0.750	0.811
mean	0.678	552	0.698	0.629	0.659	[549,734,1677,2227,1 457,2008,1781]	0.864	0.958	0.810	6-7	0.504	0.493	0.556	6-14	0.734	0.686	0.748
std			0.086	0.096	0.102		0.059	0.028	0.084		0.077	0.069	0.098		0.079	0.064	0.062

Random forest

Dataset	AUC	Accuracy	f1	max_depth	max_features	n_estimators
DCorn_2Days_1	0.861	0.821	0.865	8	35	80
DCorn_2Days_2	0.641	0.593	0.667	8	30	60
DCorn_2Days_3	0.624	0.556	0.625	8	30	60
DCorn_2Days_4	0.735	0.704	0.733	7	30	80
DCorn_2Days_5	0.759	0.667	0.757	6	30	70
mean	0.724	0.668	0.729			
std	0.096	0.104	0.092			

Dataset	AUC	Accuracy	f1	max_depth	max_features	n_estimators
DSunflower_2Days_1	0.883	0.786	0.813	6	35	70
DSunflower_2Days_2	0.872	0.786	0.833	6	30	80
DSunflower_2Days_3	0.850	0.821	0.872	6	40	70
DSunflower_2Days_4	0.969	0.857	0.882	8	35	80
DSunflower_2Days_5	0.906	0.786	0.850	7	30	70
mean	0.896	0.807	0.850			
std	0.046	0.032	0.028			

XGboost

Dataset	AUC	Accuracy	f1	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DCorn_2Days_1	0.668	0.607	0.703	0.029	0.5	6	60	0.9
DCorn_2Days_2	0.676	0.593	0.667	0.029	0.8	6	60	0.9
DCorn_2Days_3	0.600	0.630	0.667	0.029	0.5	6	70	0.9
DCorn_2Days_4	0.641	0.630	0.688	0.023	0.8	8	60	0.9
DCorn_2Days_5	0.741	0.630	0.706	0.029	0.9	6	60	0.6
mean	0.665	0.618	0.686					
std	0.052	0.017	0.019					

Dataset	AUC	Accuracy	f1	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DSunflower_2Days_1	0.833	0.821	0.857	0.029	0.5	6	60	0.8
DSunflower_2Days_2	0.956	0.893	0.919	0.029	0.5	7	70	0.8
DSunflower_2Days_3	0.850	0.714	0.800	0.023	0.5	6	60	0.9
DSunflower_2Days_4	0.928	0.786	0.813	0.035	0.5	7	60	0.8
DSunflower_2Days_5	0.861	0.714	0.789	0.023	0.5	6	70	0.8
mean	0.886	0.786	0.836					
std	0.053	0.076	0.053					

Regression 2 days before

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DCorn_2Days_1	0.457	800	0.364	0.324	[800,684,519,424,506, 938,1998]	0.297	0.253	37	0.313	0.267	3	0.292	0.233
DCorn_2Days_2	0.457	800	0.366	0.318	[800,684,519,424,506, 938,1998]	0.312	0.268	37	0.343	0.296	3	0.342	0.295
DCorn_2Days_3	0.457	800	0.356	0.304	[800,684,519,424,506, 938,1998]	0.311	0.259	37	0.345	0.280	2	0.346	0.289
DCorn_2Days_4	0.457	800	0.336	0.289	[800,684,519,424,506, 938,1998]	0.311	0.266	37	0.330	0.274	3	0.321	0.267
DCorn_2Days_5	0.457	800	0.364	0.322	[800,684,519,424,506, 938,1998]	0.301	0.254	37	0.342	0.291	2	0.332	0.289
mean	0.457	800	0.357	0.311	[800,684,519,424,506, 938,1998]	0.306	0.260	37	0.334	0.282	2-3	0.327	0.275
std			0.012	0.015		0.007	0.007		0.013	0.012		0.021	0.026

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DSunflower_2 Days_1	0.793	730	0.286	0.218	[730,550,469,1031,633 ,1192,535]	0.215	0.158	6	0.308	0.237	4	0.270	0.204
DSunflower_2 Days_2	0.793	730	0.286	0.227	[730,550,469,1031,633 ,1192,535]	0.185	0.151	6	0.283	0.238	5	0.217	0.176
DSunflower_2 Days_3	0.793	730	0.315	0.250	[730,550,469,1031,633 ,1192,535]	0.279	0.204	6	0.347	0.277	8	0.305	0.226
DSunflower_2 Days_4	0.793	730	0.269	0.209	[730,550,469,1031,633 ,1192,535]	0.211	0.162	6	0.391	0.304	5	0.243	0.185
DSunflower_2 Days_5	0.793	730	0.327	0.244	[730,550,469,1031,633 ,1192,535]	0.247	0.180	6	0.294	0.223	9	0.308	0.230
mean	0.793	730	0.297	0.230	[730,550,469,1031,633 ,1192,535]	0.228	0.171	6	0.324	0.256	4-9	0.268	0.204
std			0.024	0.017		0.036	0.021		0.044	0.033		0.039	0.024

Random forest

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
DCorn_2Days_1	0.189	0.238	7	40	80
DCorn_2Days_2	0.211	0.261	7	30	80
DCorn_2Days_3	0.184	0.255	6	35	70
DCorn_2Days_4	0.186	0.233	7	35	70
DCorn_2Days_5	0.211	0.267	6	40	80
mean	0.196	0.251			
std	0.014	0.015			

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
DSunflower_2Days_1	0.153	0.216	7	40	80
DSunflower_2Days_2	0.125	0.175	7	30	70
DSunflower_2Days_3	0.197	0.293	8	30	80
DSunflower_2Days_4	0.168	0.227	6	35	60
DSunflower_2Days_5	0.170	0.237	7	30	80
mean	0.163	0.229			
std	0.026	0.043			

XGboost

Dataset	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DCorn_2Days_1	0.173	0.328	0.029	0.5	6	60	0.9
DCorn_2Days_2	0.180	0.290	0.029	0.8	6	80	0.8
DCorn_2Days_3	0.184	0.319	0.035	0.5	7	80	0.9
DCorn_2Days_4	0.193	0.347	0.023	0.5	7	60	0.9
DCorn_2Days_5	0.199	0.338	0.029	0.5	7	60	0.6
mean	0.186	0.325					
std	0.010	0.022					

Dataset	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DSunflower_2Days_1	0.098	0.237	0.029	0.5	6	60	0.8
DSunflower_2Days_2	0.069	0.169	0.029	0.5	6	80	0.6
DSunflower_2Days_3	0.132	0.318	0.035	0.5	8	70	0.8
DSunflower_2Days_4	0.108	0.254	0.029	0.5	6	70	0.9
DSunflower_2Days_5	0.116	0.262	0.035	0.5	6	60	0.8
mean	0.105	0.248					
std	0.023	0.054					

Regression 4 days before

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DCorn_4Days_1	0.482	554	0.332	0.289	[554,629,473,1999,2096, 1680,2132]	0.283	0.238	4	0.344	0.304	4	0.336	0.296
DCorn_4Days_2	0.482	554	0.310	0.273	[554,629,473,1999,2096, 1680,2132]	0.226	0.188	4	0.304	0.262	12	0.332	0.289
DCorn_4Days_3	0.482	554	0.301	0.260	[554,629,473,1999,2096, 1680,2132]	0.259	0.206	4	0.342	0.288	3	0.308	0.258
DCorn_4Days_4	0.482	554	0.336	0.282	[554,629,473,1999,2096, 1680,2132]	0.280	0.227	4	0.343	0.296	2	0.346	0.300
DCorn_4Days_5	0.482	554	0.272	0.234	[554,629,473,1999,2096, 1680,2132]	0.237	0.180	4	0.290	0.252	10	0.302	0.225
mean	0.482	554	0.310	0.268	[554,629,473,1999,2096, 1680,2132]	0.257	0.208	4	0.325	0.280	2-12	0.325	0.274
std			0.026	0.022		0.025	0.025		0.026	0.022		0.019	0.032

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DSunflower_4 Days_1	0.724	730	0.324	0.262	[730,1140,700,611,624 ,2220,628]	0.173	0.135	6	0.359	0.299	5	0.292	0.223
DSunflower_4 Days_2	0.724	730	0.365	0.299	[730,1140,700,611,624 ,2220,628]	0.234	0.171	6	0.366	0.282	5	0.338	0.255
DSunflower_4 Days_3	0.724	730	0.402	0.316	[730,1140,700,611,624 ,2220,628]	0.224	0.164	7	0.377	0.307	5	0.327	0.237
DSunflower_4 Days_4	0.724	730	0.362	0.305	[730,1140,700,611,624 ,2220,628]	0.221	0.167	6	0.357	0.305	5	0.319	0.254
DSunflower_4 Days_5	0.724	730	0.295	0.230	[730,1140,700,611,624 ,2220,628]	0.152	0.118	6	0.320	0.258	5	0.232	0.186
mean	0.724	730	0.350	0.283	[730,1140,700,611,624 ,2220,628]	0.201	0.151	6-7	0.356	0.290	5	0.302	0.231
std			0.041	0.036		0.036	0.023		0.021	0.021		0.043	0.029

Random forest

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
DCorn_4Days_1	0.288	0.344	8	30	80
DCorn_4Days_2	0.243	0.288	6	40	60
DCorn_4Days_3	0.211	0.251	6	30	80
DCorn_4Days_4	0.293	0.348	8	40	60
DCorn_4Days_5	0.210	0.259	6	30	60
mean	0.249	0.298			
std	0.040	0.046			

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
DSunflower_4Days_1	0.212	0.305	7	40	60
DSunflower_4Days_2	0.210	0.305	6	30	80
DSunflower_4Days_3	0.194	0.245	6	35	70
DSunflower_4Days_4	0.236	0.288	6	30	60
DSunflower_4Days_5	0.175	0.233	6	40	60
mean	0.205	0.275			
std	0.022	0.034			

XGBoost

Dataset	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DCorn_4Days_1	0.173	0.328	0.029	0.5	6	60	0.9
DCorn_4Days_2	0.180	0.290	0.029	0.8	6	80	0.8
DCorn_4Days_3	0.184	0.319	0.035	0.5	7	80	0.9
DCorn_4Days_4	0.193	0.347	0.023	0.5	7	60	0.9
DCorn_4Days_5	0.199	0.338	0.029	0.5	7	60	0.6
mean	0.186	0.325					
std	0.010	0.022					

Dataset	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DSunflower_4Days_1	0.227	0.433	0.023	0.5	6	60	0.9
DSunflower_4Days_2	0.185	0.359	0.029	0.9	6	70	0.8
DSunflower_4Days_3	0.153	0.296	0.029	0.5	6	70	0.8
DSunflower_4Days_4	0.198	0.349	0.029	0.9	6	60	0.8
DSunflower_4Days_5	0.078	0.216	0.029	0.8	6	60	0.8
mean	0.168	0.331					
std	0.057	0.080					

Regression 5 days before

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DCorn_5Days_1	0.476	552	0.351	0.292	[552,472,441,1988,779, 2182,1418]	0.289	0.240	7	0.386	0.319	4	0.363	0.300
DCorn_5Days_2	0.476	552	0.296	0.234	[552,472,441,1988,779, 2182,1418]	0.253	0.203	6	0.293	0.235	4	0.302	0.254
DCorn_5Days_3	0.476	552	0.285	0.228	[552,472,441,1988,779, 2182,1418]	0.236	0.199	7	0.319	0.254	1	0.305	0.246
DCorn_5Days_4	0.476	552	0.302	0.262	[552,472,441,1988,779, 2182,1418]	0.209	0.174	6	0.331	0.281	4	0.327	0.284
DCorn_5Days_5	0.476	552	0.321	0.274	[552,472,441,1988,779, 2182,1418]	0.260	0.214	7	0.352	0.292	1	0.353	0.294
mean	0.476	552	0.311	0.258	[552,472,441,1988,779, 2182,1418]	0.250	0.206	6-7	0.336	0.277	1-4	0.330	0.275
std			0.026	0.027		0.030	0.024		0.035	0.033		0.028	0.024

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7 indices	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DSunflower_5Days_1	0.373	730	0.466	0.406	[730,1176,1442,763,81 7,888,1448]	0.386	0.322	5	0.492	0.445	1	0.484	0.428
DSunflower_5Days_2	0.373	730	0.470	0.428	[730,1176,1442,763,81 7,888,1448]	0.431	0.371	5	0.517	0.481	1	0.500	0.468
DSunflower_5Days_3	0.373	730	0.468	0.411	[730,1176,1442,763,81 7,888,1448]	0.401	0.347	5	0.484	0.443	7	0.432	0.360
DSunflower_5Days_4	0.373	730	0.444	0.388	[730,1176,1442,763,81 7,888,1448]	0.414	0.356	5	0.458	0.405	7	0.466	0.394
DSunflower_5Days_5	0.373	730	0.479	0.399	[730,1176,1442,763,81 7,888,1448]	0.450	0.381	5	0.497	0.441	4	0.497	0.424
mean	0.373	730	0.465	0.406	[730,1176,1442,763,81 7,888,1448]	0.416	0.355	5	0.490	0.443	1-7	0.476	0.415
std			0.013	0.015		0.025	0.023		0.035	0.033		0.028	0.024

Random forest

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
DCorn_5Days_1	0.256	0.313	7	40	80
DCorn_5Days_2	0.205	0.262	7	40	80
DCorn_5Days_3	0.182	0.233	8	40	80
DCorn_5Days_4	0.254	0.297	8	40	60
DCorn_5Days_5	0.222	0.264	8	40	80
mean	0.224	0.274			
std	0.032	0.032			

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
DSunflower_5Days_1	0.351	0.424	8	35	80
DSunflower_5Days_2	0.398	0.447	7	30	80
DSunflower_5Days_3	0.341	0.400	8	40	80
DSunflower_5Days_4	0.312	0.384	7	35	60
DSunflower_5Days_5	0.362	0.448	7	30	60
mean	0.353	0.421			
std	0.031	0.028			

XGBoost

Dataset	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DCorn_5Days_1	0.290	0.415	0.023	0.8	6	70	0.6
DCorn_5Days_2	0.254	0.359	0.029	0.5	6	60	0.9
DCorn_5Days_3	0.210	0.326	0.035	0.9	8	60	0.8
DCorn_5Days_4	0.290	0.398	0.035	0.5	6	60	0.9
DCorn_5Days_5	0.262	0.381	0.023	0.9	6	70	0.8
mean	0.261	0.376					
std	0.033	0.035					

Dataset	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DSunflower_5Days_1	0.383	0.605	0.029	0.5	7	70	0.8
DSunflower_5Days_2	0.323	0.532	0.023	0.5	8	60	0.9
DSunflower_5Days_3	0.244	0.460	0.023	0.5	8	60	0.9
DSunflower_5Days_4	0.278	0.484	0.029	0.5	6	80	0.6
DSunflower_5Days_5	0.362	0.600	0.035	0.9	6	70	0.9
mean	0.318	0.536					
std	0.058	0.066					

Regression 7 days before

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7 indicies	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DCorn_7Days_1	0.306	551	0.340	0.289	[551,2181,1988,400,470 ,2138,438]	0.307	0.248	7	0.342	0.300	3	0.339	0.291
DCorn_7Days_2	0.306	551	0.273	0.219	[551,2181,1988,400,470 ,2138,438]	0.262	0.206	7	0.301	0.248	1	0.285	0.231
DCorn_7Days_3	0.306	551	0.369	0.308	[551,2181,1988,400,470 ,2138,438]	0.331	0.284	6	0.388	0.332	1	0.377	0.321
DCorn_7Days_4	0.306	551	0.377	0.318	[551,2181,1988,400,470 ,2138,438]	0.339	0.281	7	0.375	0.309	1	0.381	0.320
DCorn_7Days_5	0.306	551	0.366	0.303	[551,2181,1988,400,470 ,2138,438]	0.348	0.292	7	0.367	0.318	3	0.371	0.323
mean	0.306	551	0.345	0.287	[551,2181,1988,400,470 ,2138,438]	0.317	0.262	6-7	0.355	0.301	1-3	0.351	0.297
std			0.043	0.039		0.034	0.036		0.034	0.032		0.040	0.039

Dataset	correlation	Ind ex	linear RMSE	linear MAE	7indicies	linear 7w RMSE	linear 7w MAE	PCA number of comp	PCA linear RMSE	PCA linear MAE	PLS number of comp	PLS RMSE	PLS MAE
DSunflower_7 Days_1	0.381	730	0.433	0.364	[730,1177,2209,2003,6 32,828,764]	0.395	0.325	5	0.449	0.399	1	0.441	0.387
DSunflower_7 Days_2	0.381	730	0.461	0.406	[730,1177,2209,2003,6 32,828,764]	0.410	0.363	5	0.505	0.458	6	0.518	0.452
DSunflower_7 Days_3	0.381	730	0.488	0.418	[730,1177,2209,2003,6 32,828,764]	0.428	0.370	5	0.496	0.447	7	0.503	0.410
DSunflower_7 Days_4	0.381	730	0.462	0.394	[730,1177,2209,2003,6 32,828,764]	0.434	0.371	5	0.495	0.441	7	0.449	0.383
DSunflower_7 Days_5	0.381	730	0.485	0.437	[730,1177,2209,2003,6 32,828,764]	0.399	0.343	5	0.522	0.481	1	0.514	0.467
mean	0.381	730	0.466	0.404	[730,1177,2209,2003,6 32,828,764]	0.413	0.354	5	0.494	0.445	1-7	0.485	0.420
std			0.022	0.027		0.017	0.020		0.027	0.030		0.037	0.038

Random forest

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
DCorn_7Days_1	0.275	0.319	8	40	60
DCorn_7Days_2	0.212	0.255	8	30	80
DCorn_7Days_3	0.304	0.360	7	30	60
DCorn_7Days_4	0.298	0.356	8	40	80
DCorn_7Days_5	0.306	0.366	7	30	80
mean	0.279	0.331			
std	0.040	0.046			

Dataset	MAE	RMSE	max_depth	max_features	n_estimators
DSunflower_7Days_1	0.318	0.383	6	35	70
DSunflower_7Days_2	0.388	0.447	7	30	80
DSunflower_7Days_3	0.357	0.416	6	35	70
DSunflower_7Days_4	0.351	0.421	8	40	60
DSunflower_7Days_5	0.367	0.425	8	30	60
mean	0.356	0.418			
std	0.026	0.023			

XGBoost

Dataset	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DCorn_7Days_1	0.305	0.470	0.029	0.8	7	70	0.9
DCorn_7Days_2	0.284	0.405	0.023	0.9	7	70	0.6
DCorn_7Days_3	0.281	0.430	0.029	0.5	8	70	0.9
DCorn_7Days_4	0.332	0.490	0.029	0.8	6	80	0.8
DCorn_7Days_5	0.296	0.461	0.023	0.5	7	70	0.9
mean	0.300	0.451					
std	0.021	0.034					

Dataset	MAE	RMSE	colsample_bytree	learning_rate	max_depth	n_estimators	subsample
DSunflower_7Days_1	0.365	0.579	0.029	0.5	7	80	0.8
DSunflower_7Days_2	0.307	0.525	0.035	0.5	6	60	0.9
DSunflower_7Days_3	0.308	0.523	0.035	0.5	6	70	0.9
DSunflower_7Days_4	0.390	0.609	0.023	0.8	7	80	0.8
DSunflower_7Days_5	0.287	0.507	0.029	0.5	8	60	0.8
mean	0.331	0.548					
std	0.044	0.043					

APPENDIX C. MOA CLASSIFICATION:

Dataset	Accuracy	max_depth	max_features	n_estimators
DCornMOA_1	0.638	8	40	80
DCornMOA_2	0.686	8	30	70
DCornMOA_3	0.718	7	30	70
DCornMOA_4	0.631	7	35	70
DCornMOA_5	0.621	8	35	60
mean	0.659			
std	0.041			

APPENDIX D. ECPA ARTICLE

Early detection of corn and sunflower stress induced by chemical spraying

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Abstract

Herbicides inhibit plant growth by affecting different bio-chemical pathways or bio-physical states. Stress, that was induced by inhibiting lipid metabolism or photosynthesis on corn and sunflower, was detected using leaf spectral reflectance. Leaves' spectral signatures were measured at six time points along two weeks by a spectro-radiometer. Phenotypes were evaluated by an expert at the same time points. Spectral processing models were used to compare the spectral response of a control group to treated plants using statistical T-tests. Results revealed that spectral reflectance can be used to detect the stress induced by inhibiting photosynthesis on corn and sunflower at the same time when the first visual symptoms appeared. Also, early detection can be accomplished with a lower confidence two days before visual symptoms appear.

Introduction

Different organisms reflect or absorb the sun's electromagnetic radiation in different ways. By analyzing the spectral reflectance at suitable wavelengths, changes in the plant mechanisms can be derived. Multispectral and hyper spectral sensors are commonly used for early disease detection and zones delineation for site specific treatment of the disease. Spectral data analyses derive vegetation parameters and diseases using indices like Normalized Difference Vegetation Index (NDVI) and the Red Inflection Point (REIP) which are based on selected wavelengths (Lowe et al. 2017).

Application examples include detection of: 1) Zn stress in Bahia grass using NDVI and Ratio Vegetation Index (RVI) indices (Schuerger et al. 2003), 2) Sunn pest/cereal pest stress in wheat (Genc et al. 2008) using NDVI and 3) leaf rust (*Puccinia triticina*) in wheat using a Leaf Rust Disease Severity Index (LRDSI) (Ashourloo et al. 2014). Moreover, a relationship was discovered between the concentration of a pollutant named Phenanthrene, to several plant characteristics such as chlorophyll density and live stem density, by comparing the red edge area and their first derivative of the reflectance

spectra (Zhu et al. 2014). In another work, NDVI was used to estimate biomass index, and resulted in improved vineyard management (Drissi et al. 2009).

The objective of this work was to estimate the potential of using leaf spectral reflectance to detect inhibition of two leaf mechanisms: lipid metabolism and photosynthesis. This article presents results of the analysis that aimed to detect the above plant stresses at an early stage, using spectral sensing. Successful completion of this task can lead to delineation of management zones to be treated with variable rate application systems.

Materials and methods

Experimental design: Corn (cultivar VIVANI 700) and sunflower plants (cultivar Jerusalem Dwarf Yellow Spray) were grown in pots in a controlled greenhouse ($25\pm2^{\circ}\text{C}$ day $20\pm2^{\circ}\text{C}$ night, flood irrigation of tap water + fertilizer NPK 5:3:8 + 6, 2ml/l at 50% water content) for a period of one month from the seeding time (sunflower-15.10.18 and corn-25.10.18). The plots were arranged on two tables, one for each crop (Figure 1). Every plot received a number and a bar code for sampling management.

Three seeds were planted in each pot, which were thinned out into one plant. Three days after emergence, the plants were sprayed with different herbicides. Twenty-five different chemical applications were applied to 250 plots/pots which comprised of five repetitions for each herbicide type, in a randomized design. Spectral measurements were conducted on 14 treatments (different chemical applications), 140 plants, due to sampling time constraints. A plant physiologist selected these treatments, to reflect a variety of modes/mechanism of action (MOA) of the herbicides (the primary biochemical or biophysical interference imposed by an herbicide that leads to lethality).

This paper focuses on analysis of ten treatments belonging to three modes of action: ‘lipid metabolism’ (treatments T_9 , T_{11} and T_{12}), ‘Inhibition of photosynthesis’ (treatments T_{14} , T_{15} and T_{16}) and ‘amino acid metabolism’ (treatments T_{20} , T_{22} and T_{24}). These treatments were compared to the control group (treatment T_1).

Spectral acquisition system: Spectral reflectance of each leaf was recorded by a spectroradiometer (ASD FieldSpec 4 hi-res, ASD Inc. Malvern Panalytical, Boulder, Colorado, USA) in the range of 350 nm – 2500 nm, with an optical spectral resolution of 3 nm in the VNIR range and 8 nm in the SWIR range.

Data acquisition: Spectral measurements were conducted between 09:30 to 15:30 local time (UTC+2) through autumn 2018, at six time points (TP): TP1-04.11.18, TP2-06.11.18, TP3-08.11.18, TP4-11.11.18, TP5-13.11.18 and TP6-15.11.18.

Each plant was placed on the greenhouse table under direct sunlight, with the ASD fiber probe aimed at a leaf from a distance of a few centimeters without shading it. White reference was sampled whenever a change in illumination conditions occurred or every fifteen minutes. Four consecutive series of 10 spectra were acquired for each leaf, and the average was saved for later analysis.

Since the sprayed chemicals affect differently mature or young leaves, both young and mature leaves were sampled from each plant. Figure 2 shows the leaves that were sampled and Figure 3 shows the spectral signatures of leaves L1, L2 and L3 at the same time point. In corn plants, three leaves were sampled starting with one leaf at the first time point, two at the second time point and three leaves from the third time point and on (in some treatments, a third leaf did not grow due to the chemical effect). In sunflower plants, one mature leaf and one young leaf were measured at every time point (Figure 2).



Figure 53: Experimental layout

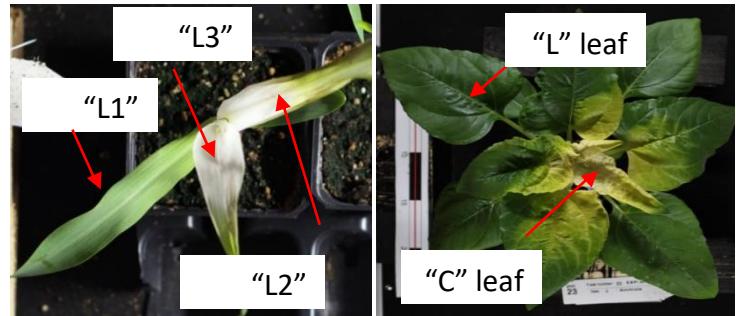


Figure 54: Sampling points of corn and sunflower leaves. The stress effect on the leaf growth and the sampled leaves is visible on the leaves.

Eleven phenotypes were visually evaluated on a 1-6 scale by an expert agronomist at each time point: Pheno 1- Necrosis (spots), Pheno 2- Burning, Pheno 3- Bleaching, Pheno 4- Chlorosis, Pheno 5- Epinasty (curling), Pheno 6- Inhibited growth, Pheno 7- Wilting, Pheno 8- Disturbed apical bud, Pheno 9- Abnormal pigmentation (dark leaf), Pheno 10- Abnormal pigmentation (anathocyanins) and Pheno 11- Disturbed gravitropism.

Analysis of spectral data: Water vapor atmospheric absorbtion windows (1350nm-1410nm, 1800nm-1950nm and 2250nm-2500nm) were removed from the spectral data. The correlations between every wavelength reflectance to every phenotype were calculated for each treatment and leaf during all time points. T test was performed to determine significant differences between the groups, to select the most significant wavelength.

All possible combinations of normalized difference indices, NDI, were calculated (Eq. 1) for each pair of wavelengths (W_i, W_j) for each treatment, leaf and time point:

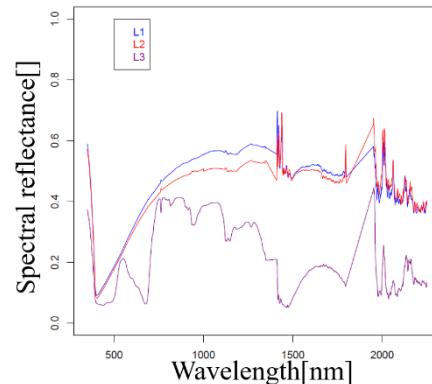


Figure 55: Spectral signature of three corn leaves at the same time point.

$$NDI_{ij} = \frac{R_i - R_j}{R_i + R_j} \quad (1)$$

where R_i and R_j are reflectance values at wavelengths W_i and W_j respectively.

In order to find an indicator of stress in the plant for every treatment, each index was compared to its corresponding index in the control group using the statistical T test with a Bonferroni correction. All analysis was conducted using RStudio software version 1.0.153 (www.rstudio.com).

Results and discussion

Pre-processing of the reflectance data: Qualitative analysis revealed that the variance of different plants belonging to the same group was large, and that it would be difficult to attribute the changes in the spectral reflectance to the chemical treatments only. Therefore, a first derivative and smoothing was performed on the data using a procedure defined by Savitzky-Golay with a filter order of 2 and a filter length of 11 wavelengths (Savitzky and Golay 1964).

Phenotyping: Time point 1 (TP1) was a baseline measurement, before chemicals spraying, resulting in a scale of 1 for all the phenotypes and implying no visual effect. The first phenotypes to arise (at time point 2) were (1) *Necrosis* and (2) *Burning* among a few plants from treatments T_{14} and T_{16} both in corn and sunflower (Table 1).

Phenotypes: (5) *Epinasty (curling)*, (9) *Abnormal pigmentation (dark leaf)* and (11) *Disturbed gravitropism* did not change throughout the experiment period, therefore, they were not included in the analysis. Table 1 shows the time-points when the expert noticed visual changes for each treatment. For treatments T_{11} , T_{14} , T_{15} and T_{16} the first visual changes were noticed at TP4, TP2, TP3, TP2 respectively for both crops. For corn plants, in T_9 , the first-time phenotype appeared at TP3 and for T_2 it appeared at TP4. These treatments had no effect on the sunflower plants. Table 41 also shows that phenotypes appeared earlier for the MOA of inhibition of photosynthesis.

Table 41: Appearance of plant phenotypes. T_x is the treatment number. The phenotype number written in brackets.

MOA	Plant	TP1	TP2	TP3	TP4	TP5	TP6
Inhibition of photosynthesis	Sunflower		$T_{14}(2)$	$T_{14}(2,6)$	$T_{14}(2,6)$	$T_{14}(2,6)$	$T_{14}(2,6)$
				$T_{15}(2,6)$	$T_{15}(2,6)$	$T_{15}(2,6)$	$T_{15}(2,6)$
			$T_{16}(1,2)$	$T_{16}(2,6)$	$T_{16}(2,6)$	$T_{16}(2,6)$	$T_{16}(2,6)$
	Corn		$T_{14}(2)$	$T_{14}(6,7)$	$T_{14}(2,6)$	$T_{14}(2,6)$	$T_{14}(6,7)$
				$T_{15}(1,6)$	$T_{15}(2,6)$	$T_{15}(2,6)$	$T_{15}(3,6)$

				T _{16(2,6)}	T _{16(2,6)}	T _{16(2,6)}	T _{16 (6,7)}
MOA	Plant	TP1	TP2	TP3	TP4	TP5	TP6
Lipid metabolism	Sunflower				T ₁₁₍₄₎	T ₁₁₍₇₎	
	Corn			T _{9(1,6)}	T _{9(1,4,6)}	T _{9(4,6,7)}	T _{9(6,7)}
					T _{11(1,6)}	T _{11(4,6,7)}	T _{11(6,7)}
					T _{12 (6)}	T _{12(6,10)}	T _{12 (6,8)}

To determine the wavelength that is best correlated with each phenotype, the correlation coefficient (in absolute value) between the smoothed derivative of the reflectance spectra and the phenotype score was calculated. Figures 4 and 5 show an example and Table 2 summarizes all phenotypes.

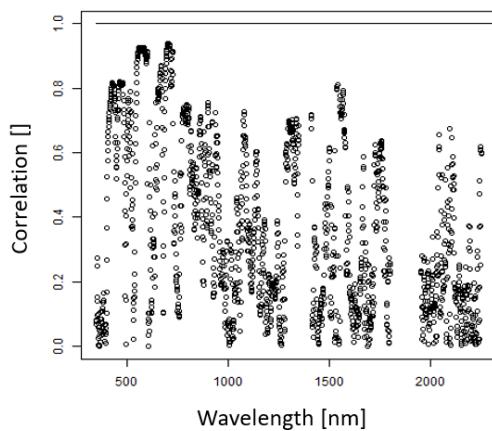


Figure 56: Single wavelength correlation between L1 first derivative of reflectance to Pheno6 for T₁₄

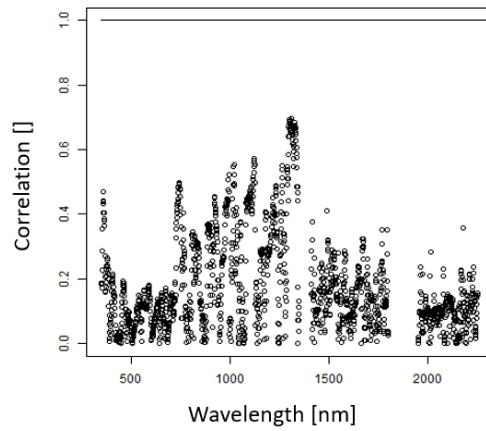


Figure 57: Single wavelength correlation between L1 first derivative of reflectance to Pheno1 for T₉

Table 42: Highest correlations received for corn using the derivative at a single wavelength.

Phenotype	MOA 1- Lipid metabolism			MOA 2- Inhibition of photosynthesis		
	Wavelength [nm]	Correlation [%]	Leaf	Wavelength [nm]	Correlation [%]	Leaf
Necrosis	1303	34	L1	356	32.2	L1
Burning			L1	801	53.8	L1
Bleaching			L1	1994	56.9	L1

Chlorosis	548	59	L1			L1
Epinasty			L1			L1
Inhibited growth	553	68.1	L1	569	85.9	L1
Wilting	553	78.9	L1	587	46.1	L1
Disturbed apical bud	1969	55.8	L1			L1
Abnormal pigmentation (dark leaf)			L1			L1
Abnormal pigmentation (anthocyanins)	1558	69.9	L1			L1
Disturbed gravitropism.			L1			L1
Average all phenotypes	553	69.7	L1	569	88.2	L1

The last row in table 2, indicates the correlation when every visual change was considered. Using the wavelength with the highest correlation with phenotype's average, a linear regression prediction model for corn was built. The data were divided into training and test groups (80% and 20% accordingly). The accuracy of the Lipid metabolism prediction model was 0.64 and for Inhibition of photosynthesis, the accuracy was 0.79. Using the same wavelength, additional linear prediction models were built, were the data from TP(i) were used to predict the average phenotype score at TP(i+1). The prediction accuracy was 0.26 for lipid metabolism and 0.67 for Inhibition of photosynthesis

The mean and standard deviation of the spectra first derivative of each treatment was plotted against the control group for all time points. Due to multiple comparisons, a Bonferroni repair was conducted applying the P value compared to 5% divided by the number of comparisons (1692). For instance, Figure 6 shows the comparison in the mature leaf of T16 at TP2 and TP3.

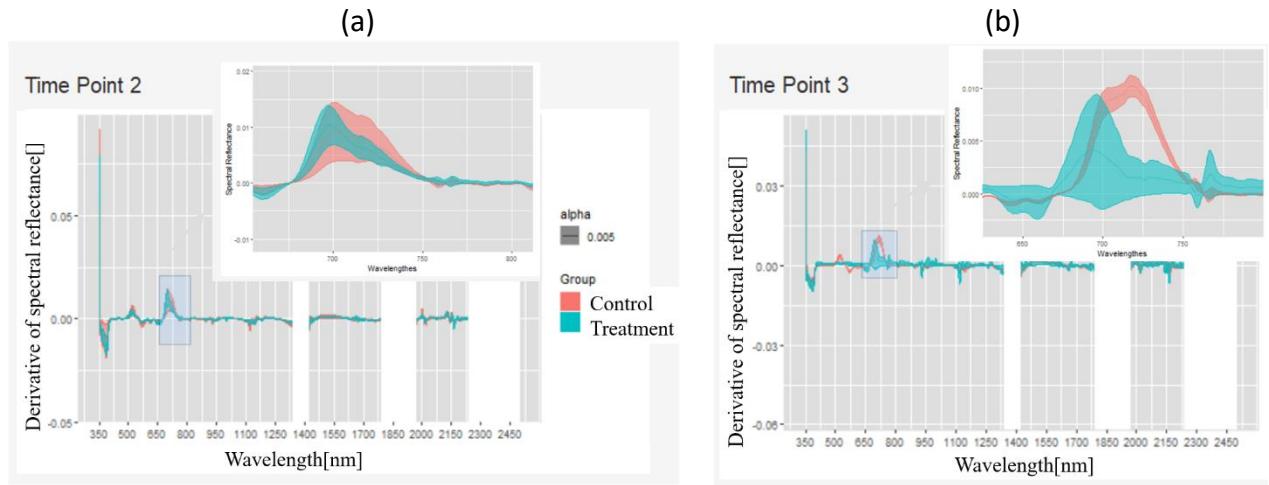


Figure 58: First Derivative spectral data of T_{16} and control plants at (a) TP2 and (b) TP3.

Table 3: Earliest detection of stress using single wavelength first derivative of spectral reflectance

Crop	MOA	Leaf	TP	Wavelength
corn	lipid metabolism	L2	TP5	552-558
	Inhibition of photosynthesis	L1/L2	TP3	460-715
sunflower	lipid metabolism	-	-	-
	Inhibition of photosynthesis	C	TP2	557-804

Figure 6a shows that in TP2 there was no significant difference (at a significance level of 95%) between treated and control plants. Figure 58b shows that in TP3, there was a difference between the groups at a significance level of 95% with P value of $2.914383e-07$ for wavelength 531nm. From this time point onward, the differences remained significant. At TP4, TP5, TP6 the biggest difference was obtained for bands 568nm, 648nm and 582nm respectively. The same procedure (visualization and T test) was performed for all sampled plants and the results are summarized in Table 3. Table 3 shows that the MOA of inhibition of photosynthesis was detected earlier than lipid metabolism.

NDI indices: NDI indices were constructed and compared to the control group. Figure 7 shows a comparison of the mature leaf of treatment 14 through all NDI combinations during all time points. In this sequence, the gap between the groups was observed at time point 3 (the time when significant difference appeared). This example resulted in 1131 significant indices that were able to separate treatment 14 leaf L1 from the control

leaf L1. These indices include combinations of wavelengths 692nm-750nm that belong to the red edge.

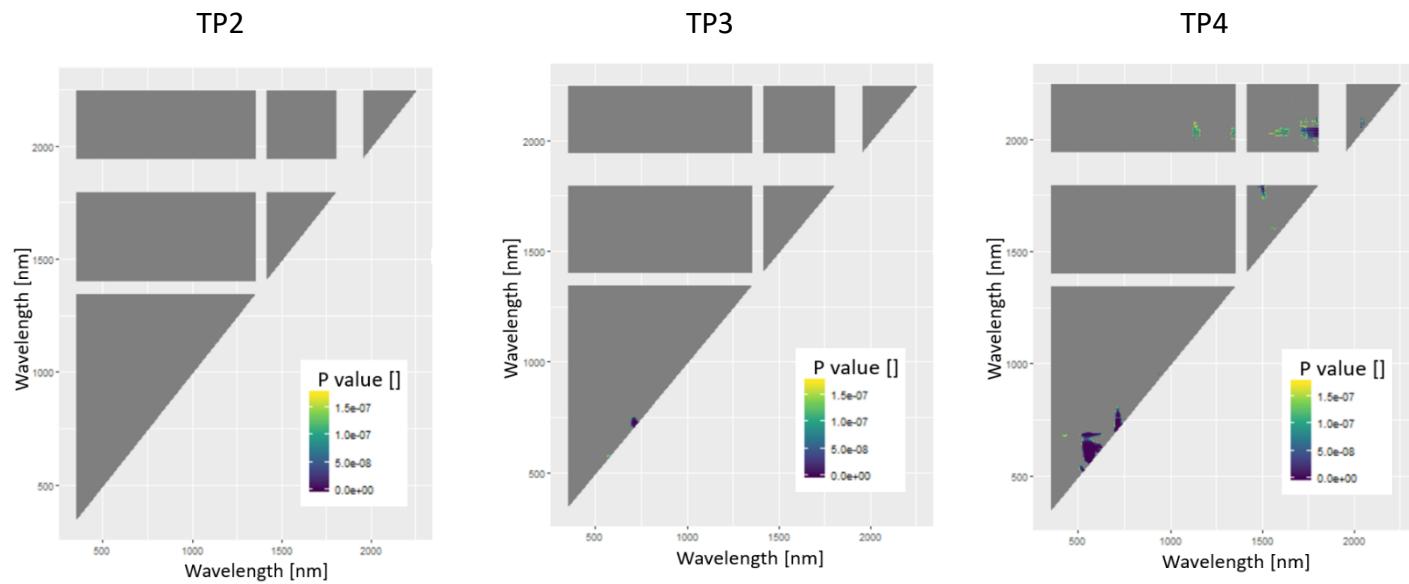


Figure 59: NDI maps demonstrate the difference between treatment 14, leaf “L1” in corn plants to control “L1” corn plants through three time points

Conclusion

Inhibition of photosynthesis was successfully detected using leaf spectral reflectance at the same time when visual phenotypes appeared. The change was detected using the first derivative of a single wavelength and by NDI indices. The first NDI indices which detected the effect of the stress, consisted of pairs of close wavelengths. Linear regression predicting visual changes in corn revealed prediction accuracy of 0.64 and 0.79 for lipid metabolism and photosynthesis inhibition respectively. Moreover, linear regression for predicting the visual changes two days after the spectral measurement resulted to accuracies of 0.26 and 0.67 for lipid metabolism and photosynthesis inhibition respectively. Inhibition of lipid metabolism was detected using spectral reflectance in corn plants after visual symptoms were present. In sunflower, visual symptoms appeared only at the end of the sampling period, and they were not expressed in leaf spectral reflectance. The effect of both MOAs on leaf spectral reflectance included the spectral signature at the red edge area, as well as wavelengths in the SWIR range. This was a preliminary analysis to determine significant areas of the spectrum which can be used to detect specific plant stress. However, sampling frequency should be increased near the sensitive time (time point 3); this may enable earlier detection. Future work will aim to improve stress detection to support farm management.

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APPENDIX E. WAVELENGTH IMPORTANCE:

E.1. CORRELATION: THE PHENOTYPES' AVERAGE CORRELATIVE WAVELENGTHS

Corn							
wavelength	correlation	wavelength	correlation	wavelength	correlation	wavelength	correlation
561	0.554307	903	0.459798	734	0.434873	912	0.403205
562	0.542648	904	0.459132	884	0.434753	871	0.40276
800	0.535679	729	0.458877	735	0.433884	780	0.40272
569	0.531791	564	0.456639	720	0.433815	558	0.401877
817	0.53169	566	0.456088	881	0.433204	482	0.399884
801	0.530557	709	0.455836	425	0.432831	585	0.399803
799	0.525886	728	0.455805	424	0.431505	886	0.398351
570	0.517071	707	0.455178	731	0.429879	906	0.398347
867	0.514953	581	0.452543	732	0.429613	422	0.397048
563	0.514629	559	0.45181	719	0.429257	880	0.395307
868	0.513617	901	0.451559	733	0.428563	847	0.394332
798	0.510406	883	0.450637	850	0.426877	805	0.393483
794	0.509788	863	0.45037	725	0.426485	701	0.390281
795	0.509775	582	0.450336	860	0.425644	858	0.384725
568	0.509461	859	0.450262	862	0.425037	815	0.37909
792	0.509354	706	0.449618	718	0.424672	480	0.378809
796	0.507647	572	0.448894	573	0.424451	483	0.376732
791	0.50733	882	0.448877	818	0.422151	911	0.375636
797	0.506689	580	0.448761	711	0.421843	427	0.375257
578	0.505409	730	0.448687	717	0.421753	782	0.375165
793	0.504395	870	0.447944	726	0.420693	846	0.374593
866	0.503821	710	0.446275	861	0.420429	474	0.372763
560	0.502163	704	0.445551	574	0.416628	2247	0.371415
802	0.502033	721	0.445351	426	0.415673	851	0.37133
865	0.494805	722	0.443438	848	0.414728	913	0.370829
577	0.491593	905	0.443372	885	0.414303	462	0.370477
869	0.489652	565	0.442103	423	0.411909	463	0.369937
571	0.486014	705	0.441251	712	0.410875	2248	0.369425
567	0.483708	575	0.441155	714	0.409724	700	0.369323
579	0.481889	849	0.440648	900	0.409181	2250	0.367935
803	0.477461	790	0.439714	713	0.407006	2249	0.36745
864	0.469596	781	0.439405	584	0.405601	872	0.366935
804	0.467267	727	0.43769	702	0.405184	789	0.366354
902	0.467185	703	0.437446	736	0.4047	907	0.365793
708	0.466102	583	0.436804	481	0.404287	887	0.364555
576	0.466034	724	0.435512	716	0.403616	879	0.362226
816	0.462921	723	0.435162	715	0.403481	421	0.360527

Sunflower							
wavelength	correlation	wavelength	correlation	wavelength	correlation	wavelength	correlation
722	0.801428	561	0.752058	611	0.713725	826	0.685564
723	0.801091	551	0.749261	582	0.713345	818	0.685223
721	0.800152	737	0.748952	603	0.712715	626	0.685141
724	0.798985	562	0.746587	780	0.710407	825	0.684783
720	0.798099	563	0.742018	803	0.709481	586	0.683771
729	0.797649	704	0.740571	702	0.709175	799	0.68326
728	0.797538	564	0.738715	804	0.708949	621	0.682884
725	0.79609	738	0.738485	612	0.70889	827	0.681882
719	0.79576	565	0.736672	802	0.708733	617	0.681838
727	0.795523	570	0.736023	583	0.707681	599	0.68153
730	0.794978	571	0.735954	793	0.706234	620	0.680161
726	0.794412	569	0.735948	602	0.706191	824	0.679497
554	0.793314	568	0.735753	801	0.705051	618	0.679302
718	0.79309	566	0.735717	794	0.704582	619	0.67874
555	0.79132	572	0.735609	792	0.704566	587	0.677031
731	0.790674	567	0.735575	781	0.703482	806	0.676748
553	0.789748	573	0.734869	613	0.703478	797	0.676538
717	0.789535	574	0.733691	550	0.703271	741	0.676454
711	0.789042	575	0.73226	740	0.703253	789	0.67594
712	0.788752	576	0.730446	805	0.702527	627	0.675893
710	0.787039	577	0.728328	584	0.700208	798	0.674733
713	0.78667	578	0.726131	791	0.700026	828	0.674533
556	0.786352	703	0.726042	795	0.698152	598	0.674179
716	0.786017	739	0.723773	772	0.697991	783	0.67414
732	0.785272	579	0.72349	601	0.697975	588	0.671874
714	0.784412	607	0.723253	614	0.697614	819	0.671511
715	0.783886	606	0.722763	800	0.695831	597	0.668932
709	0.783164	608	0.72253	585	0.691811	593	0.668544
557	0.779779	605	0.720922	782	0.691609	823	0.668503
733	0.778813	609	0.720664	615	0.691571	589	0.668182
708	0.777804	580	0.720528	790	0.690957	592	0.667778
552	0.776724	775	0.719173	701	0.689538	594	0.667622
558	0.772467	774	0.719125	600	0.689233	591	0.666584
734	0.771632	776	0.718279	624	0.688975	596	0.66648
707	0.771091	610	0.717773	625	0.688936	590	0.666456
559	0.76513	604	0.717608	623	0.687696	595	0.666144
735	0.764294	777	0.717451	796	0.686958	700	0.665969
706	0.762835	581	0.717354	616	0.686087	829	0.663455
560	0.758265	778	0.716319	622	0.685726	460	0.663111
736	0.757017	773	0.714771	603	0.712715	482	0.662524
705	0.752779	779	0.714211	780	0.710407	459	0.662114

E.2. PLS VIP

Classification

The most important features are the wavelengths with VIP score above 2 (the rest in appendix):

Corn:

Wavelength	VIP	Wavelength	VIP	Wavelength	VIP	Wavelength	VIP
569	2.447	682	2.266	869	2.210	580	2.083
570	2.437	424	2.260	576	2.210	804	2.076
561	2.421	794	2.260	681	2.209	849	2.076
708	2.413	414	2.259	425	2.204	687	2.075
817	2.401	410	2.255	686	2.203	573	2.073
684	2.389	411	2.254	422	2.187	711	2.070
683	2.372	792	2.246	796	2.183	582	2.067
707	2.366	579	2.245	572	2.174	409	2.061
578	2.356	793	2.241	866	2.174	426	2.057
562	2.354	415	2.239	417	2.173	421	2.051
571	2.333	867	2.238	704	2.171	354	2.051
706	2.324	795	2.230	797	2.144	574	2.037
577	2.314	416	2.228	798	2.141	818	2.030
801	2.308	705	2.227	803	2.129	902	2.028
709	2.307	802	2.221	865	2.123	559	2.015
685	2.298	560	2.221	575	2.120	848	2.012
800	2.292	799	2.218	567	2.108	722	2.011
568	2.279	791	2.216	703	2.103	721	2.007
412	2.274	563	2.213	418	2.094	864	2.005
413	2.273	710	2.211	870	2.094	419	2.005
868	2.268	423	2.211	581	2.089		

Sunflower:

Wavelength	VIP
734	2.067
735	2.063
733	2.063
732	2.052
736	2.050
731	2.036
737	2.031
738	2.014
730	2.012
739	2.006
740	2.004

All wavelengths:

Corn:

XAxis	vips
350	1.953
351	1.973
352	1.974
353	1.992
354	2.051
355	0.740
356	0.865
357	1.065
358	1.344
359	1.525
360	1.308
361	1.090
362	1.021
363	1.091
364	1.061
365	1.030
366	1.039
367	1.037
368	1.076
369	1.244
370	1.599
371	1.653
372	1.638
373	1.745
374	1.805
375	1.819
376	1.581
377	1.204
378	1.149
379	0.942
380	0.938
381	0.923
382	0.941
383	0.853
384	0.863
385	0.938
386	1.206
387	1.388
388	1.354
389	1.423
390	1.394
391	1.582
392	1.524
393	1.514
394	1.476
395	1.404
396	1.295
397	1.139
398	0.925
399	0.681
400	0.326
401	0.455
402	0.826
403	1.149
404	1.352
405	1.401
406	1.509
407	1.506
408	1.747
409	2.061
410	2.255
411	2.254
412	2.274
413	2.273
414	2.259
415	2.239
416	2.228
417	2.173
418	2.094
419	2.005
420	1.933
421	2.051
422	2.187
423	2.211
424	2.260
425	2.204
426	2.057
427	1.818
428	1.669
429	1.569
430	1.529
431	1.499
432	1.322
433	1.237
434	1.096
435	0.977
436	0.796
437	0.696
438	0.649
439	0.649
440	0.809
441	1.122
442	1.351
443	1.673
444	1.173
445	0.864
446	0.801
447	0.805
448	0.829
449	0.845
450	0.894
451	0.918
452	0.981
453	1.069
454	1.101
455	1.320
456	1.356
457	1.082
458	1.106
459	1.192
460	1.385
461	1.587
462	1.717
463	1.721
464	1.608
465	1.329
466	1.168
467	1.064
468	1.053
469	1.003
470	1.052
471	1.167
472	1.325
473	1.570
474	1.720
475	1.468
476	1.270
477	1.145
478	1.294
479	1.489
480	1.669
481	1.776
482	1.755
483	1.704
484	1.389
485	1.081
486	0.833
487	0.887
488	1.189
489	1.543
490	1.743
491	1.691
492	1.385
493	1.082
494	1.000
495	1.051
496	1.181
497	1.322
498	1.242
499	1.014
500	0.723
501	0.676
502	0.720
503	0.718
504	0.843
505	0.937
506	0.958
507	0.894
508	0.863
509	0.893
510	0.975
511	1.177
512	1.262
513	1.326
514	1.432
515	1.489
516	1.532
517	1.623
518	1.734
519	1.750
520	1.735
521	1.707
522	1.705
523	1.729
524	1.706
525	1.723
526	1.590
527	1.537
528	1.519
529	1.486
530	1.304
531	1.051
532	0.721
533	0.664
534	0.628
535	0.576
536	0.422
537	0.468
538	0.557
539	0.586
540	0.586
541	0.544
542	0.561
543	0.546
544	0.537
545	0.618
546	0.693
547	0.752
548	0.751
549	0.768
550	0.835
551	0.945
552	0.914
553	0.908
554	0.928
555	1.083
556	1.321
557	1.551
558	1.791
559	2.015
560	2.221
561	2.421
562	2.354
563	2.213
564	1.933
565	1.873
566	1.949
567	2.108
568	2.279

569	2.447
570	2.437
571	2.333
572	2.174
573	2.073
574	2.037
575	2.120
576	2.210
577	2.314
578	2.356
579	2.245
580	2.083
581	2.089
582	2.067
583	1.991
584	1.859
585	1.864
586	1.675
587	1.425
588	1.127
589	0.945
590	0.782
591	0.694
592	0.611
593	0.548
594	0.618
595	0.737
596	0.705
597	0.731
598	0.805
599	0.948
600	0.925
601	0.904
602	0.892
603	0.918
604	0.880
605	0.907
606	0.896
607	0.835
608	0.712
609	0.609
610	0.537
611	0.652
612	0.846
613	1.086
614	1.240
615	1.336
616	1.269
617	1.197
618	1.162
619	1.133
620	1.086
621	0.976
622	0.909
623	0.768
624	0.697
625	0.628
626	0.561
627	0.539
628	0.560
629	0.580
630	0.660
631	0.855
632	1.075
633	1.259
634	1.416
635	1.427
636	1.388
637	1.299
638	1.322
639	1.385
640	1.482
641	1.589
642	1.649
643	1.656
644	1.580
645	1.498
646	1.469
647	1.422
648	1.394
649	1.367
650	1.329
651	1.396
652	1.421
653	1.423
654	1.363
655	1.398
656	1.356
657	1.286
658	1.237
659	1.254
660	1.413
661	1.554
662	1.705
663	1.790
664	1.770
665	1.687
666	1.643
667	1.508
668	1.642
669	1.799
670	1.851
671	1.770
672	1.652
673	1.466
674	1.348
675	1.375
676	1.411
677	1.387
678	1.267
679	1.357
680	1.807
681	2.209
682	2.266
683	2.372
684	2.389
685	2.298
686	2.203
687	2.075
688	1.887
689	1.760
690	1.618
691	1.520
692	1.426
693	1.388
694	1.392
695	1.406
696	1.493
697	1.584
698	1.657
699	1.762
700	1.827
701	1.897
702	1.977
703	2.103
704	2.171
705	2.227
706	2.324
707	2.366
708	2.413
709	2.307
710	2.211
711	2.070
712	1.948
713	1.930
714	1.886
715	1.817
716	1.804
717	1.863
718	1.879
719	1.928
720	1.950
721	2.007
722	2.011
723	1.954
724	1.986
725	1.943
726	1.906
727	1.936
728	1.969
729	1.945
730	1.867
731	1.778
732	1.766
733	1.752
734	1.800
735	1.798
736	1.673
737	1.484
738	1.420
739	1.355
740	1.296
741	1.301
742	1.215
743	1.029
744	0.895
745	0.803
746	0.732
747	0.677
748	0.673
749	0.631
750	0.654
751	0.568
752	0.450
753	0.466
754	0.484
755	0.349
756	0.141
757	0.309
758	0.452
759	0.571
760	0.708
761	0.882
762	1.207
763	1.673
764	1.105
765	0.697
766	0.625
767	0.614
768	0.620
769	0.675
770	0.811
771	0.949
772	1.017
773	0.972
774	0.900
775	0.853
776	0.842
777	0.910
778	1.063
779	1.325
780	1.744
781	1.878
782	1.582
783	1.377
784	1.256
785	1.193
786	1.184
787	1.244
788	1.342
789	1.532
790	1.877
791	2.216
792	2.246
793	2.241
794	2.260
795	2.230
796	2.183
797	2.144
798	2.141

799	2.218
800	2.292
801	2.308
802	2.221
803	2.129
804	2.076
805	1.707
806	1.194
807	0.881
808	0.715
809	0.635
810	0.611
811	0.630
812	0.694
813	0.812
814	1.036
815	1.397
816	1.895
817	2.401
818	2.030
819	1.491
820	1.211
821	1.089
822	1.038
823	1.033
824	1.074
825	1.156
826	1.338
827	1.651
828	1.918
829	1.845
830	1.751
831	1.632
832	1.512
833	1.369
834	1.247
835	1.175
836	1.143
837	1.144
838	1.159
839	1.205
840	1.293
841	1.415
842	1.549
843	1.725
844	1.835
845	1.887
846	1.931
847	1.968
848	2.012
849	2.076
850	1.868
851	1.549
852	1.332
853	1.220
854	1.189
855	1.195
856	1.236
857	1.350
858	1.546
859	1.858
860	1.818
861	1.786
862	1.801
863	1.919
864	2.005
865	2.123
866	2.174
867	2.238
868	2.268
869	2.210
870	2.094
871	1.937
872	1.812
873	1.743
874	1.745
875	1.695
876	1.653
877	1.593
878	1.609
879	1.663
880	1.772
881	1.897
882	1.921
883	1.887
884	1.761
885	1.615
886	1.496
887	1.314
888	1.114
889	0.934
890	0.787
891	0.700
892	0.647
893	0.633
894	0.670
895	0.725
896	0.799
897	0.919
898	1.104
899	1.355
900	1.683
901	1.939
902	2.028
903	1.944
904	1.816
905	1.649
906	1.391
907	1.224
908	1.142
909	1.132
910	1.192
911	1.340
912	1.583
913	1.693
914	1.429
915	1.090
916	0.906
917	0.828
918	0.840
919	0.952
920	1.173
921	1.444
922	1.273
923	0.946
924	0.720
925	0.553
926	0.440
927	0.372
928	0.264
929	0.251
930	0.277
931	0.317
932	0.368
933	0.437
934	0.500
935	0.585
936	0.738
937	1.008
938	1.668
939	1.528
940	1.362
941	1.362
942	1.448
943	1.575
944	1.642
945	1.663
946	1.689
947	1.650
948	1.531
949	1.398
950	1.285
951	1.159
952	1.048
953	0.993
954	0.989
955	0.923
956	0.809
957	0.699
958	0.595
959	0.511
960	0.445
961	0.395
962	0.374
963	0.351
964	0.362
965	0.338
966	0.330
967	0.347
968	0.384
969	0.429
970	0.490
971	0.576
972	0.710
973	0.686
974	0.574
975	0.512
976	0.487
977	0.469
978	0.453
979	0.451
980	0.453
981	0.449
982	0.422
983	0.391
984	0.333
985	0.283
986	0.268
987	0.335
988	0.393
989	0.414
990	0.438
991	0.506
992	0.655
993	0.812
994	1.013
995	1.227
996	0.248
997	0.397
998	0.479
999	0.531
1000	0.563
1001	0.594
1002	0.620
1003	0.611
1004	0.570
1005	0.434
1006	0.425
1007	0.581
1008	0.626
1009	0.584
1010	0.540
1011	0.567
1012	0.646
1013	0.627
1014	0.642
1015	0.601
1016	0.620
1017	0.631
1018	0.601
1019	0.516
1020	0.413
1021	0.304
1022	0.183
1023	0.189
1024	0.234
1025	0.211
1026	0.110
1027	0.081
1028	0.080

1029	0.095
1030	0.105
1031	0.125
1032	0.102
1033	0.059
1034	0.135
1035	0.213
1036	0.174
1037	0.117
1038	0.149
1039	0.289
1040	0.431
1041	0.521
1042	0.621
1043	0.665
1044	0.744
1045	0.866
1046	0.932
1047	0.785
1048	0.545
1049	0.412
1050	0.324
1051	0.352
1052	0.389
1053	0.449
1054	0.487
1055	0.528
1056	0.553
1057	0.594
1058	0.559
1059	0.497
1060	0.440
1061	0.502
1062	0.625
1063	0.776
1064	0.944
1065	1.115
1066	1.108
1067	0.943
1068	0.769
1069	0.679
1070	0.677
1071	0.720
1072	0.753
1073	0.790
1074	0.911
1075	1.067
1076	1.241
1077	1.384
1078	1.434
1079	1.329
1080	1.195
1081	1.048
1082	0.939
1083	0.966
1084	1.003
1085	0.980
1086	0.932
1087	0.852
1088	0.791
1089	0.740
1090	0.692
1091	0.629
1092	0.573
1093	0.517
1094	0.483
1095	0.478
1096	0.481
1097	0.473
1098	0.453
1099	0.437
1100	0.444
1101	0.453
1102	0.468
1103	0.498
1104	0.504
1105	0.491
1106	0.484
1107	0.463
1108	0.413
1109	0.349
1110	0.310
1111	0.290
1112	0.283
1113	0.301
1114	0.331
1115	0.378
1116	0.403
1117	0.394
1118	0.397
1119	0.411
1120	0.415
1121	0.423
1122	0.433
1123	0.430
1124	0.431
1125	0.489
1126	0.566
1127	0.679
1128	0.747
1129	0.729
1130	0.654
1131	0.666
1132	0.713
1133	0.723
1134	0.751
1135	0.822
1136	0.901
1137	0.991
1138	1.132
1139	1.250
1140	1.246
1141	1.126
1142	0.895
1143	0.803
1144	0.752
1145	0.698
1146	0.708
1147	0.730
1148	0.792
1149	0.848
1150	0.782
1151	0.659
1152	0.536
1153	0.437
1154	0.344
1155	0.266
1156	0.220
1157	0.180
1158	0.152
1159	0.159
1160	0.206
1161	0.264
1162	0.321
1163	0.392
1164	0.451
1165	0.453
1166	0.431
1167	0.455
1168	0.450
1169	0.415
1170	0.356
1171	0.389
1172	0.431
1173	0.510
1174	0.587
1175	0.684
1176	0.737
1177	0.746
1178	0.749
1179	0.744
1180	0.707
1181	0.683
1182	0.729
1183	0.759
1184	0.824
1185	0.842
1186	0.765
1187	0.659
1188	0.575
1189	0.514
1190	0.473
1191	0.457
1192	0.437
1193	0.451
1194	0.449
1195	0.440
1196	0.441
1197	0.446
1198	0.443
1199	0.432
1200	0.413
1201	0.370
1202	0.362
1203	0.355
1204	0.366
1205	0.429
1206	0.510
1207	0.528
1208	0.407
1209	0.268
1210	0.191
1211	0.205
1212	0.212
1213	0.193
1214	0.160
1215	0.160
1216	0.259
1217	0.444
1218	0.529
1219	0.503
1220	0.479
1221	0.468
1222	0.422
1223	0.293
1224	0.154
1225	0.052
1226	0.075
1227	0.061
1228	0.053
1229	0.173
1230	0.285
1231	0.359
1232	0.414
1233	0.460
1234	0.456
1235	0.461
1236	0.483
1237	0.502
1238	0.533
1239	0.582
1240	0.567
1241	0.561
1242	0.461
1243	0.417
1244	0.397
1245	0.403
1246	0.415
1247	0.462
1248	0.536
1249	0.610
1250	0.654
1251	0.642
1252	0.618
1253	0.533
1254	0.476
1255	0.389
1256	0.350
1257	0.329
1258	0.346

1259	0.305
1260	0.307
1261	0.308
1262	0.311
1263	0.310
1264	0.310
1265	0.301
1266	0.273
1267	0.541
1268	0.528
1269	0.329
1270	0.244
1271	0.229
1272	0.210
1273	0.186
1274	0.189
1275	0.143
1276	0.140
1277	0.260
1278	0.382
1279	0.525
1280	0.677
1281	0.830
1282	0.875
1283	0.670
1284	0.561
1285	0.505
1286	0.500
1287	0.528
1288	0.547
1289	0.533
1290	0.569
1291	0.614
1292	0.672
1293	0.729
1294	0.764
1295	0.754
1296	0.735
1297	0.771
1298	0.845
1299	0.923
1300	0.969
1301	0.996
1302	1.084
1303	1.162
1304	1.247
1305	1.204
1306	1.107
1307	1.039
1308	0.996
1309	1.006
1310	1.042
1311	1.074
1312	1.131
1313	1.221
1314	1.306
1315	1.371
1316	1.394
1317	1.374
1318	1.274
1319	1.143
1320	1.062
1321	1.018
1322	1.035
1323	1.031
1324	1.038
1325	1.026
1326	0.994
1327	0.940
1328	0.936
1329	0.931
1330	0.983
1331	0.954
1332	0.907
1333	0.876
1334	0.820
1335	0.791
1336	0.740
1337	0.654
1338	0.630
1339	0.650
1340	0.620
1341	0.653
1342	0.699
1343	0.775
1344	0.848
1345	0.909
1346	1.148
1347	1.141
1348	1.180
1349	1.215
1350	1.242
1410	1.265
1411	1.302
1412	1.334
1413	1.339
1414	1.115
1415	0.434
1416	0.468
1417	0.495
1418	0.481
1419	0.418
1420	0.281
1421	0.115
1422	0.344
1423	0.610
1424	0.757
1425	0.829
1426	0.773
1427	0.642
1428	0.438
1429	0.688
1430	0.926
1431	0.980
1432	0.961
1433	0.938
1434	0.905
1435	0.860
1436	0.821
1437	0.708
1438	0.213
1439	0.850
1440	0.897
1441	0.890
1442	0.878
1443	0.867
1444	0.848
1445	0.804
1446	0.699
1447	0.400
1448	0.152
1449	0.154
1450	0.024
1451	0.159
1452	0.308
1453	0.336
1454	0.309
1455	0.271
1456	0.178
1457	0.150
1458	0.265
1459	0.505
1460	0.650
1461	0.685
1462	0.613
1463	0.477
1464	0.337
1465	0.364
1466	0.509
1467	0.640
1468	0.762
1469	0.802
1470	0.814
1471	0.783
1472	0.703
1473	0.600
1474	0.490
1475	0.447
1476	0.398
1477	0.342
1478	0.412
1479	0.548
1480	0.736
1481	0.965
1482	1.006
1483	0.943
1484	0.928
1485	0.922
1486	0.943
1487	0.981
1488	1.023
1489	1.083
1490	1.124
1491	1.114
1492	1.153
1493	1.047
1494	0.911
1495	0.793
1496	0.754
1497	0.622
1498	0.655
1499	0.566
1500	0.435
1501	0.363
1502	0.352
1503	0.301
1504	0.413
1505	0.572
1506	0.575
1507	0.469
1508	0.439
1509	0.532
1510	0.770
1511	0.951
1512	1.007
1513	0.971
1514	0.881
1515	0.723
1516	0.612
1517	0.554
1518	0.502
1519	0.501
1520	0.509
1521	0.586
1522	0.690
1523	0.766
1524	0.705
1525	0.601
1526	0.448
1527	0.277
1528	0.162
1529	0.124
1530	0.165
1531	0.200
1532	0.259
1533	0.287
1534	0.295
1535	0.357
1536	0.375
1537	0.375
1538	0.378
1539	0.421
1540	0.428
1541	0.497
1542	0.491
1543	0.490
1544	0.465
1545	0.363
1546	0.299
1547	0.205

1548	0.200
1549	0.228
1550	0.241
1551	0.249
1552	0.254
1553	0.241
1554	0.247
1555	0.275
1556	0.320
1557	0.361
1558	0.452
1559	0.502
1560	0.553
1561	0.598
1562	0.669
1563	0.654
1564	0.665
1565	0.590
1566	0.550
1567	0.522
1568	0.526
1569	0.511
1570	0.353
1571	0.213
1572	0.144
1573	0.129
1574	0.197
1575	0.320
1576	0.450
1577	0.520
1578	0.541
1579	0.461
1580	0.383
1581	0.365
1582	0.316
1583	0.290
1584	0.252
1585	0.211
1586	0.213
1587	0.311
1588	0.372
1589	0.392
1590	0.386
1591	0.237
1592	0.190
1593	0.164
1594	0.175
1595	0.140
1596	0.101
1597	0.135
1598	0.160
1599	0.276
1600	0.418
1601	0.394
1602	0.381
1603	0.322
1604	0.347
1605	0.309
1606	0.141
1607	0.157
1608	0.287
1609	0.473
1610	0.502
1611	0.404
1612	0.314
1613	0.232
1614	0.210
1615	0.102
1616	0.221
1617	0.313
1618	0.404
1619	0.476
1620	0.450
1621	0.419
1622	0.459
1623	0.504
1624	0.509
1625	0.464
1626	0.405
1627	0.402
1628	0.404
1629	0.236
1630	0.083
1631	0.210
1632	0.361
1633	0.408
1634	0.405
1635	0.446
1636	0.517
1637	0.598
1638	0.643
1639	0.657
1640	0.640
1641	0.658
1642	0.621
1643	0.582
1644	0.596
1645	0.537
1646	0.476
1647	0.404
1648	0.451
1649	0.505
1650	0.479
1651	0.398
1652	0.337
1653	0.245
1654	0.144
1655	0.260
1656	0.441
1657	0.573
1658	0.696
1659	0.711
1660	0.670
1661	0.646
1662	0.627
1663	0.607
1664	0.545
1665	0.468
1666	0.458
1667	0.547
1668	0.655
1669	0.692
1670	0.616
1671	0.517
1672	0.460
1673	0.278
1674	0.153
1675	0.210
1676	0.177
1677	0.225
1678	0.209
1679	0.315
1680	0.444
1681	0.495
1682	0.417
1683	0.140
1684	0.072
1685	0.141
1686	0.273
1687	0.290
1688	0.321
1689	0.270
1690	0.199
1691	0.074
1692	0.078
1693	0.244
1694	0.432
1695	0.679
1696	0.803
1697	0.674
1698	0.600
1699	0.561
1700	0.551
1701	0.539
1702	0.538
1703	0.401
1704	0.279
1705	0.214
1706	0.190
1707	0.158
1708	0.146
1709	0.147
1710	0.172
1711	0.286
1712	0.346
1713	0.405
1714	0.254
1715	0.114
1716	0.088
1717	0.128
1718	0.090
1719	0.037
1720	0.090
1721	0.118
1722	0.169
1723	0.184
1724	0.164
1725	0.118
1726	0.135
1727	0.156
1728	0.251
1729	0.236
1730	0.235
1731	0.243
1732	0.191
1733	0.207
1734	0.267
1735	0.294
1736	0.298
1737	0.346
1738	0.429
1739	0.463
1740	0.456
1741	0.381
1742	0.339
1743	0.361
1744	0.416
1745	0.360
1746	0.374
1747	0.345
1748	0.330
1749	0.304
1750	0.299
1751	0.288
1752	0.288
1753	0.278
1754	0.259
1755	0.244
1756	0.277
1757	0.281
1758	0.351
1759	0.448
1760	0.556
1761	0.594
1762	0.516
1763	0.368
1764	0.273
1765	0.236
1766	0.224
1767	0.223
1768	0.337
1769	0.418
1770	0.405
1771	0.300
1772	0.240
1773	0.180
1774	0.145
1775	0.241
1776	0.281
1777	0.400

1778	0.551	1974	0.552	2020	0.575	2066	0.938	2112	0.470
1779	0.681	1975	0.585	2021	0.559	2067	0.924	2113	0.384
1780	0.773	1976	0.561	2022	0.583	2068	0.905	2114	0.319
1781	0.786	1977	0.506	2023	0.613	2069	0.894	2115	0.399
1782	0.671	1978	0.393	2024	0.672	2070	0.855	2116	0.503
1783	0.545	1979	0.282	2025	0.731	2071	0.773	2117	0.576
1784	0.412	1980	0.268	2026	0.746	2072	0.650	2118	0.623
1785	0.343	1981	0.351	2027	0.712	2073	0.545	2119	0.654
1786	0.318	1982	0.396	2028	0.708	2074	0.453	2120	0.649
1787	0.258	1983	0.349	2029	0.659	2075	0.412	2121	0.639
1788	0.339	1984	0.233	2030	0.564	2076	0.355	2122	0.620
1789	0.542	1985	0.230	2031	0.431	2077	0.310	2123	0.586
1790	0.692	1986	0.367	2032	0.228	2078	0.338	2124	0.507
1791	0.756	1987	0.618	2033	0.105	2079	0.294	2125	0.387
1792	0.711	1988	0.795	2034	0.149	2080	0.354	2126	0.113
1793	0.600	1989	0.821	2035	0.483	2081	0.473	2127	0.334
1794	0.451	1990	0.843	2036	0.750	2082	0.556	2128	0.545
1795	0.267	1991	0.853	2037	0.893	2083	0.536	2129	0.650
1796	0.592	1992	0.844	2038	0.932	2084	0.376	2130	0.669
1797	0.598	1993	0.860	2039	0.831	2085	0.379	2131	0.672
1798	0.586	1994	0.872	2040	0.677	2086	0.628	2132	0.710
1799	0.563	1995	0.892	2041	0.357	2087	0.819	2133	0.762
1800	0.554	1996	0.892	2042	0.117	2088	0.922	2134	0.817
1951	0.564	1997	0.854	2043	0.387	2089	0.958	2135	0.866
1952	0.582	1998	0.829	2044	0.507	2090	0.979	2136	0.868
1953	0.578	1999	0.804	2045	0.469	2091	0.952	2137	0.885
1954	0.568	2000	0.775	2046	0.385	2092	0.788	2138	0.842
1955	0.520	2001	0.754	2047	0.322	2093	0.472	2139	0.695
1956	0.328	2002	0.742	2048	0.236	2094	0.194	2140	0.452
1957	0.385	2003	0.682	2049	0.144	2095	0.277	2141	0.086
1958	0.468	2004	0.554	2050	0.133	2096	0.261	2142	0.293
1959	0.587	2005	0.467	2051	0.218	2097	0.309	2143	0.508
1960	0.695	2006	0.530	2052	0.320	2098	0.580	2144	0.652
1961	0.787	2007	0.568	2053	0.505	2099	0.829	2145	0.696
1962	0.818	2008	0.513	2054	0.668	2100	0.925	2146	0.611
1963	0.833	2009	0.443	2055	0.759	2101	0.974	2147	0.341
1964	0.819	2010	0.311	2056	0.779	2102	0.947	2148	0.101
1965	0.791	2011	0.299	2057	0.764	2103	0.793	2149	0.445
1966	0.740	2012	0.560	2058	0.706	2104	0.620	2150	0.647
1967	0.642	2013	0.666	2059	0.590	2105	0.439	2151	0.708
1968	0.477	2014	0.672	2060	0.390	2106	0.318	2152	0.628
1969	0.421	2015	0.694	2061	0.023	2107	0.255	2153	0.480
1970	0.432	2016	0.705	2062	0.526	2108	0.241	2154	0.239
1971	0.357	2017	0.700	2063	0.856	2109	0.336	2155	0.106
1972	0.335	2018	0.670	2064	0.950	2110	0.409	2156	0.282
1973	0.419	2019	0.619	2065	0.961	2111	0.468	2157	0.433

2158	0.450	2177	0.255	2196	0.350	2215	0.723	2234	0.570
2159	0.367	2178	0.432	2197	0.427	2216	0.644	2235	0.547
2160	0.327	2179	0.599	2198	0.492	2217	0.629	2236	0.441
2161	0.273	2180	0.658	2199	0.609	2218	0.574	2237	0.270
2162	0.264	2181	0.592	2200	0.653	2219	0.510	2238	0.280
2163	0.281	2182	0.426	2201	0.645	2220	0.378	2239	0.560
2164	0.318	2183	0.068	2202	0.635	2221	0.247	2240	0.622
2165	0.350	2184	0.417	2203	0.597	2222	0.071	2241	0.654
2166	0.375	2185	0.677	2204	0.454	2223	0.044	2242	0.648
2167	0.404	2186	0.726	2205	0.321	2224	0.066	2243	0.530
2168	0.390	2187	0.663	2206	0.159	2225	0.312	2244	0.439
2169	0.410	2188	0.537	2207	0.194	2226	0.434	2245	0.447
2170	0.522	2189	0.380	2208	0.276	2227	0.419	2246	1.542
2171	0.607	2190	0.235	2209	0.362	2228	0.331	2247	1.633
2172	0.679	2191	0.228	2210	0.261	2229	0.166	2248	1.635
2173	0.742	2192	0.269	2211	0.222	2230	0.119	2249	1.630
2174	0.719	2193	0.370	2212	0.383	2231	0.336	2250	1.634
2175	0.588	2194	0.375	2213	0.554	2232	0.475		
2176	0.292	2195	0.371	2214	0.683	2233	0.560		

Sunflower:

XAxis	vips
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351	0.881
352	0.886
353	0.902
354	0.960
355	0.855
356	0.924
357	0.828
358	0.781
359	0.841
360	0.808
361	0.843
362	0.914
363	0.887
364	0.795
365	0.781
366	0.784
367	0.792
368	0.783
369	0.766
370	0.776
371	0.784
372	0.811
373	0.838
374	0.839
375	0.823
376	0.831
377	0.840
378	0.831
379	0.833
380	0.842
381	0.865
382	0.896
383	0.902
384	0.887
385	0.862
386	0.846
387	0.846
388	0.848
389	0.848
390	0.847
391	0.845
392	0.842
393	0.839

394	0.830
395	0.820
396	0.811
397	0.798
398	0.793
399	0.793
400	0.782
401	0.775
402	0.759
403	0.736
404	0.718
405	0.711
406	0.707
407	0.697
408	0.683
409	0.676
410	0.672
411	0.668
412	0.666
413	0.668
414	0.677
415	0.690
416	0.707
417	0.727
418	0.750
419	0.778
420	0.809
421	0.844
422	0.882
423	0.923
424	0.966
425	1.009
426	1.049
427	1.086
428	1.121
429	1.152
430	1.177
431	1.199
432	1.223
433	1.248
434	1.274
435	1.301
436	1.329
437	1.354
438	1.376

439	1.396
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441	1.426
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447	1.365
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453	1.535
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461	1.568
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463	1.535
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470	1.412
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472	1.371
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479	1.401
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881	1.108
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885	1.083
886	1.058
887	1.023
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889	0.930
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891	0.864
892	0.845
893	0.834
894	0.830
895	0.833

896	0.844
897	0.864
898	0.901
899	0.946
900	0.991
901	1.024
902	1.041
903	1.043
904	1.029
905	0.995
906	0.953
907	0.925
908	0.915
909	0.924
910	0.950
911	0.997
912	1.054
913	1.082
914	1.058
915	1.018
916	0.991
917	0.983
918	0.992
919	1.020
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921	1.100
922	1.033
923	0.903
924	0.814
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927	0.740
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929	0.748
930	0.761
931	0.778
932	0.797
933	0.821
934	0.852
935	0.883
936	0.919
937	0.961
938	1.001
939	1.041
940	1.064
941	1.065

942	1.064
943	1.059
944	1.053
945	1.050
946	1.045
947	1.033
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949	1.005
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953	0.979
954	0.973
955	0.965
956	0.955
957	0.944
958	0.928
959	0.912
960	0.896
961	0.884
962	0.874
963	0.866
964	0.860
965	0.857
966	0.858
967	0.862
968	0.871
969	0.883
970	0.894
971	0.896
972	0.883
973	0.868
974	0.856
975	0.841
976	0.815
977	0.792
978	0.774
979	0.758
980	0.746
981	0.737
982	0.728
983	0.718
984	0.704
985	0.688
986	0.664
987	0.637

988	0.609
989	0.574
990	0.531
991	0.499
992	0.475
993	0.451
994	0.435
995	0.440
996	0.457
997	0.492
998	0.512
999	0.527
1000	0.540
1001	0.555
1002	0.561
1003	0.565
1004	0.575
1005	0.593
1006	0.547
1007	0.538
1008	0.530
1009	0.522
1010	0.515
1011	0.511
1012	0.515
1013	0.516
1014	0.518
1015	0.519
1016	0.522
1017	0.535
1018	0.550
1019	0.565
1020	0.579
1021	0.579
1022	0.571
1023	0.572
1024	0.574
1025	0.578
1026	0.576
1027	0.569
1028	0.564
1029	0.556
1030	0.540
1031	0.529
1032	0.525
1033	0.525

1034	0.528
1035	0.532
1036	0.543
1037	0.563
1038	0.580
1039	0.602
1040	0.628
1041	0.621
1042	0.600
1043	0.577
1044	0.554
1045	0.547
1046	0.544
1047	0.555
1048	0.569
1049	0.570
1050	0.565
1051	0.562
1052	0.551
1053	0.540
1054	0.538
1055	0.544
1056	0.561
1057	0.574
1058	0.588
1059	0.605
1060	0.621
1061	0.645
1062	0.697
1063	0.756
1064	0.799
1065	0.832
1066	0.874
1067	0.907
1068	0.890
1069	0.864
1070	0.857
1071	0.853
1072	0.870
1073	0.926
1074	0.966
1075	0.976
1076	0.966
1077	0.955
1078	0.947
1079	0.944

1080	0.938
1081	0.930
1082	0.925
1083	0.927
1084	0.916
1085	0.905
1086	0.897
1087	0.872
1088	0.850
1089	0.825
1090	0.794
1091	0.773
1092	0.767
1093	0.768
1094	0.767
1095	0.764
1096	0.761
1097	0.755
1098	0.751
1099	0.747
1100	0.744
1101	0.740
1102	0.734
1103	0.728
1104	0.719
1105	0.709
1106	0.701
1107	0.694
1108	0.688
1109	0.687
1110	0.688
1111	0.687
1112	0.686
1113	0.683
1114	0.679
1115	0.675
1116	0.669
1117	0.663
1118	0.655
1119	0.649
1120	0.642
1121	0.632
1122	0.617
1123	0.599
1124	0.572
1125	0.551

1126	0.559
1127	0.625
1128	0.707
1129	0.760
1130	0.792
1131	0.814
1132	0.828
1133	0.838
1134	0.846
1135	0.854
1136	0.862
1137	0.871
1138	0.876
1139	0.881
1140	0.896
1141	0.917
1142	0.937
1143	0.949
1144	0.955
1145	0.959
1146	0.962
1147	0.965
1148	0.963
1149	0.950
1150	0.930
1151	0.910
1152	0.887
1153	0.867
1154	0.852
1155	0.840
1156	0.831
1157	0.826
1158	0.823
1159	0.822
1160	0.822
1161	0.821
1162	0.821
1163	0.821
1164	0.820
1165	0.820
1166	0.820
1167	0.821
1168	0.826
1169	0.830
1170	0.832
1171	0.829

1172	0.826
1173	0.813
1174	0.788
1175	0.742
1176	0.663
1177	0.570
1178	0.524
1179	0.513
1180	0.517
1181	0.532
1182	0.558
1183	0.615
1184	0.721
1185	0.889
1186	1.018
1187	1.034
1188	1.004
1189	0.964
1190	0.923
1191	0.885
1192	0.852
1193	0.821
1194	0.795
1195	0.769
1196	0.748
1197	0.735
1198	0.724
1199	0.715
1200	0.709
1201	0.701
1202	0.693
1203	0.684
1204	0.674
1205	0.665
1206	0.658
1207	0.655
1208	0.651
1209	0.643
1210	0.621
1211	0.605
1212	0.602
1213	0.609
1214	0.624
1215	0.640
1216	0.648
1217	0.645

1218	0.637
1219	0.629
1220	0.620
1221	0.613
1222	0.609
1223	0.607
1224	0.606
1225	0.606
1226	0.608
1227	0.610
1228	0.616
1229	0.627
1230	0.640
1231	0.651
1232	0.658
1233	0.663
1234	0.660
1235	0.660
1236	0.666
1237	0.679
1238	0.714
1239	0.751
1240	0.764
1241	0.769
1242	0.775
1243	0.778
1244	0.789
1245	0.804
1246	0.822
1247	0.842
1248	0.866
1249	0.899
1250	0.927
1251	0.938
1252	0.940
1253	0.932
1254	0.915
1255	0.895
1256	0.876
1257	0.862
1258	0.848
1259	0.836
1260	0.827
1261	0.819
1262	0.812
1263	0.805

1264	0.795
1265	0.775
1266	0.738
1267	0.717
1268	0.824
1269	0.875
1270	0.877
1271	0.874
1272	0.873
1273	0.877
1274	0.883
1275	0.891
1276	0.904
1277	0.919
1278	0.935
1279	0.948
1280	0.956
1281	0.959
1282	0.959
1283	0.953
1284	0.943
1285	0.929
1286	0.914
1287	0.900
1288	0.888
1289	0.883
1290	0.887
1291	0.894
1292	0.906
1293	0.916
1294	0.922
1295	0.924
1296	0.920
1297	0.914
1298	0.908
1299	0.902
1300	0.897
1301	0.890
1302	0.880
1303	0.872
1304	0.864
1305	0.856
1306	0.851
1307	0.850
1308	0.851
1309	0.858

1310	0.868
1311	0.881
1312	0.895
1313	0.908
1314	0.918
1315	0.928
1316	0.933
1317	0.938
1318	0.941
1319	0.940
1320	0.937
1321	0.931
1322	0.918
1323	0.901
1324	0.878
1325	0.853
1326	0.831
1327	0.814
1328	0.806
1329	0.807
1330	0.819
1331	0.839
1332	0.869
1333	0.898
1334	0.925
1335	0.948
1336	0.960
1337	0.957
1338	0.933
1339	0.879
1340	0.790
1341	0.686
1342	0.586
1343	0.523
1344	0.510
1345	0.525
1346	0.771
1347	0.816
1348	0.851
1349	0.885
1350	0.922
1410	0.951
1411	0.981
1412	1.001
1413	0.974
1414	0.821

1415	0.557
1416	0.538
1417	0.497
1418	0.449
1419	0.412
1420	0.416
1421	0.444
1422	0.476
1423	0.516
1424	0.556
1425	0.585
1426	0.571
1427	0.496
1428	0.433
1429	0.407
1430	0.413
1431	0.412
1432	0.387
1433	0.373
1434	0.415
1435	0.443
1436	0.458
1437	0.463
1438	0.442
1439	0.432
1440	0.467
1441	0.530
1442	0.542
1443	0.531
1444	0.530
1445	0.528
1446	0.524
1447	0.526
1448	0.522
1449	0.483
1450	0.419
1451	0.409
1452	0.442
1453	0.489
1454	0.527
1455	0.534
1456	0.507
1457	0.448
1458	0.356
1459	0.302
1460	0.354

1461	0.465
1462	0.601
1463	0.692
1464	0.761
1465	0.797
1466	0.836
1467	0.863
1468	0.854
1469	0.814
1470	0.746
1471	0.681
1472	0.628
1473	0.631
1474	0.648
1475	0.657
1476	0.659
1477	0.660
1478	0.668
1479	0.691
1480	0.705
1481	0.719
1482	0.729
1483	0.725
1484	0.726
1485	0.729
1486	0.723
1487	0.710
1488	0.703
1489	0.697
1490	0.695
1491	0.702
1492	0.717
1493	0.739
1494	0.765
1495	0.791
1496	0.815
1497	0.842
1498	0.868
1499	0.894
1500	0.916
1501	0.937
1502	0.955
1503	0.969
1504	0.982
1505	0.991
1506	0.996

1507	1.001
1508	1.007
1509	1.014
1510	1.021
1511	1.025
1512	1.030
1513	1.033
1514	1.035
1515	1.038
1516	1.037
1517	1.034
1518	1.032
1519	1.031
1520	1.036
1521	1.042
1522	1.048
1523	1.054
1524	1.059
1525	1.062
1526	1.065
1527	1.067
1528	1.068
1529	1.069
1530	1.073
1531	1.076
1532	1.079
1533	1.083
1534	1.087
1535	1.092
1536	1.097
1537	1.102
1538	1.106
1539	1.110
1540	1.113
1541	1.116
1542	1.117
1543	1.118
1544	1.118
1545	1.118
1546	1.118
1547	1.120
1548	1.121
1549	1.124
1550	1.127
1551	1.131
1552	1.134

1553	1.138
1554	1.140
1555	1.142
1556	1.144
1557	1.147
1558	1.150
1559	1.152
1560	1.155
1561	1.159
1562	1.163
1563	1.166
1564	1.169
1565	1.169
1566	1.169
1567	1.170
1568	1.171
1569	1.172
1570	1.172
1571	1.171
1572	1.171
1573	1.169
1574	1.168
1575	1.165
1576	1.162
1577	1.159
1578	1.158
1579	1.158
1580	1.159
1581	1.159
1582	1.160
1583	1.160
1584	1.161
1585	1.162
1586	1.161
1587	1.158
1588	1.154
1589	1.150
1590	1.144
1591	1.140
1592	1.136
1593	1.134
1594	1.135
1595	1.136
1596	1.136
1597	1.137
1598	1.136

1599	1.137
1600	1.140
1601	1.142
1602	1.141
1603	1.140
1604	1.136
1605	1.134
1606	1.133
1607	1.129
1608	1.126
1609	1.117
1610	1.106
1611	1.100
1612	1.096
1613	1.095
1614	1.097
1615	1.098
1616	1.096
1617	1.095
1618	1.093
1619	1.096
1620	1.105
1621	1.112
1622	1.114
1623	1.111
1624	1.105
1625	1.099
1626	1.094
1627	1.087
1628	1.080
1629	1.071
1630	1.064
1631	1.064
1632	1.063
1633	1.065
1634	1.067
1635	1.065
1636	1.057
1637	1.044
1638	1.029
1639	1.017
1640	1.005
1641	0.994
1642	0.983
1643	0.972
1644	0.961

1645	0.952
1646	0.946
1647	0.939
1648	0.931
1649	0.922
1650	0.914
1651	0.905
1652	0.895
1653	0.888
1654	0.876
1655	0.861
1656	0.845
1657	0.835
1658	0.834
1659	0.836
1660	0.839
1661	0.847
1662	0.853
1663	0.860
1664	0.879
1665	0.897
1666	0.895
1667	0.787
1668	0.554
1669	0.502
1670	0.553
1671	0.593
1672	0.625
1673	0.648
1674	0.654
1675	0.651
1676	0.632
1677	0.596
1678	0.540
1679	0.468
1680	0.456
1681	0.554
1682	0.654
1683	0.723
1684	0.761
1685	0.748
1686	0.701
1687	0.647
1688	0.614
1689	0.607
1690	0.613

1691	0.622
1692	0.631
1693	0.635
1694	0.635
1695	0.645
1696	0.663
1697	0.687
1698	0.710
1699	0.729
1700	0.744
1701	0.751
1702	0.757
1703	0.763
1704	0.761
1705	0.760
1706	0.755
1707	0.745
1708	0.735
1709	0.725
1710	0.709
1711	0.689
1712	0.667
1713	0.678
1714	0.718
1715	0.710
1716	0.667
1717	0.658
1718	0.658
1719	0.665
1720	0.664
1721	0.639
1722	0.633
1723	0.655
1724	0.698
1725	0.756
1726	0.833
1727	0.879
1728	0.913
1729	0.943
1730	0.954
1731	0.957
1732	0.959
1733	1.009
1734	1.081
1735	1.137
1736	1.168

1737	1.188
1738	1.192
1739	1.192
1740	1.191
1741	1.190
1742	1.191
1743	1.189
1744	1.188
1745	1.189
1746	1.194
1747	1.202
1748	1.211
1749	1.211
1750	1.206
1751	1.199
1752	1.188
1753	1.175
1754	1.151
1755	1.127
1756	1.106
1757	1.078
1758	1.038
1759	0.987
1760	0.935
1761	0.902
1762	0.886
1763	0.903
1764	0.941
1765	0.990
1766	1.030
1767	1.060
1768	1.073
1769	1.072
1770	1.052
1771	1.021
1772	0.997
1773	0.963
1774	0.934
1775	0.910
1776	0.898
1777	0.864
1778	0.827
1779	0.781
1780	0.742
1781	0.718
1782	0.671

1783	0.559
1784	0.411
1785	0.313
1786	0.303
1787	0.369
1788	0.429
1789	0.500
1790	0.583
1791	0.641
1792	0.664
1793	0.640
1794	0.602
1795	0.564
1796	0.740
1797	0.749
1798	0.755
1799	0.765
1800	0.771
1951	0.772
1952	0.773
1953	0.770
1954	0.756
1955	0.675
1956	0.642
1957	0.667
1958	0.697
1959	0.708
1960	0.707
1961	0.705
1962	0.705
1963	0.702
1964	0.703
1965	0.702
1966	0.712
1967	0.714
1968	0.705
1969	0.695
1970	0.684
1971	0.682
1972	0.682
1973	0.683
1974	0.681
1975	0.685
1976	0.692
1977	0.695
1978	0.691

1979	0.677
1980	0.661
1981	0.646
1982	0.639
1983	0.623
1984	0.604
1985	0.574
1986	0.536
1987	0.487
1988	0.413
1989	0.310
1990	0.210
1991	0.236
1992	0.428
1993	0.577
1994	0.621
1995	0.623
1996	0.626
1997	0.630
1998	0.635
1999	0.641
2000	0.643
2001	0.643
2002	0.639
2003	0.633
2004	0.611
2005	0.521
2006	0.344
2007	0.423
2008	0.512
2009	0.568
2010	0.596
2011	0.619
2012	0.642
2013	0.673
2014	0.675
2015	0.664
2016	0.662
2017	0.678
2018	0.698
2019	0.706
2020	0.702
2021	0.687
2022	0.673
2023	0.666
2024	0.655

2025	0.643
2026	0.641
2027	0.636
2028	0.629
2029	0.614
2030	0.602
2031	0.601
2032	0.607
2033	0.638
2034	0.696
2035	0.751
2036	0.778
2037	0.788
2038	0.792
2039	0.811
2040	0.853
2041	0.896
2042	0.890
2043	0.808
2045	0.772
2046	0.752
2047	0.739
2048	0.734
2049	0.742
2050	0.740
2051	0.733
2052	0.724
2053	0.700
2054	0.683
2055	0.668
2056	0.659
2057	0.640
2058	0.616
2059	0.576
2060	0.541
2061	0.498
2062	0.458
2063	0.444
2064	0.436
2065	0.441
2066	0.464
2067	0.470
2068	0.478
2069	0.512
2070	0.548

2071	0.600
2072	0.635
2073	0.647
2074	0.633
2075	0.617
2076	0.600
2077	0.582
2078	0.557
2079	0.542
2080	0.545
2081	0.544
2082	0.550
2083	0.548
2084	0.543
2085	0.542
2086	0.570
2087	0.614
2088	0.658
2089	0.708
2090	0.753
2091	0.768
2092	0.778
2093	0.771
2094	0.749
2095	0.732
2096	0.745
2097	0.781
2098	0.824
2099	0.822
2100	0.767
2101	0.718
2102	0.690
2103	0.712
2104	0.762
2105	0.796
2106	0.804
2107	0.824
2108	0.851
2109	0.898
2110	0.925
2111	0.934
2112	0.923
2113	0.921
2114	0.937
2115	0.953
2116	0.964

2117	0.955
2118	0.931
2119	0.896
2120	0.858
2121	0.831
2122	0.812
2123	0.784
2124	0.763
2125	0.746
2126	0.740
2127	0.743
2128	0.762
2129	0.799
2130	0.835
2131	0.831
2132	0.800
2133	0.755
2134	0.703
2135	0.671
2136	0.596
2137	0.449
2138	0.407
2139	0.479
2140	0.524
2141	0.537
2142	0.510
2143	0.457
2144	0.379
2145	0.297
2146	0.263
2147	0.306
2148	0.383
2149	0.456
2150	0.529
2151	0.587
2152	0.580
2153	0.513
2154	0.438
2155	0.381
2156	0.458
2157	0.588
2158	0.664
2159	0.701
2160	0.718
2161	0.703
2162	0.706

2163	0.720
2164	0.748
2165	0.770
2166	0.782
2167	0.797
2168	0.804
2169	0.789
2170	0.755
2171	0.733
2172	0.680
2173	0.591
2174	0.463
2175	0.355
2176	0.313
2177	0.344
2178	0.417
2179	0.483
2180	0.540
2181	0.578
2182	0.560
2183	0.531
2184	0.496
2185	0.442
2186	0.399
2187	0.430
2188	0.530
2189	0.635
2190	0.686
2191	0.696
2192	0.693
2193	0.671
2194	0.631
2195	0.581
2196	0.547
2197	0.513
2198	0.485
2199	0.441
2200	0.417
2201	0.426
2202	0.392
2203	0.352
2204	0.317
2205	0.304
2206	0.290
2207	0.259
2208	0.260

2209	0.282
2210	0.313
2211	0.321
2212	0.246
2213	0.230
2214	0.290
2215	0.377
2216	0.389
2217	0.380
2218	0.357
2219	0.343
2220	0.345
2221	0.359
2222	0.395
2223	0.432
2224	0.455
2225	0.477
2226	0.483
2227	0.507
2228	0.569
2229	0.671
2230	0.750
2231	0.791
2232	0.768
2233	0.662
2234	0.518
2235	0.377
2236	0.349
2237	0.404
2238	0.438
2239	0.439
2240	0.441
2241	0.494
2242	0.548
2243	0.584
2244	0.619
2245	0.648
2246	1.009
2247	1.011
2248	1.007
2249	1.004
2250	1.000

Regression

The most importance features are the wavelengths which got VIP above 2 (the rest in appendix):

Corn:

XAxis	vips								
561	2.525	868	2.215	683	2.162	681	2.049	564	2.010
562	2.469	792	2.214	579	2.140	576	2.047	730	2.003
569	2.331	684	2.211	865	2.135	729	2.047		
563	2.319	791	2.210	685	2.135	682	2.043		
800	2.305	798	2.197	571	2.135	481	2.040		
801	2.291	794	2.194	869	2.118	709	2.037		
560	2.286	795	2.190	708	2.107	706	2.035		
817	2.284	793	2.185	567	2.104	728	2.035		
570	2.271	802	2.182	803	2.087	864	2.026		
799	2.262	796	2.181	686	2.079	902	2.021		
578	2.249	577	2.179	804	2.056	474	2.020		
568	2.223	797	2.178	559	2.054	704	2.011		
867	2.220	866	2.173	707	2.049	883	2.010		

Sunflower: (above 1.9)

XAxis	vips
732	1.915
731	1.914
733	1.912
730	1.910
734	1.907

All wavelengths:

Corn:

XAxis	vips
350	1.737
351	1.744
352	1.742
353	1.759
354	1.798
355	1.070
356	1.127
357	1.125
358	1.129
359	1.171
360	1.034
361	0.976
362	0.997
363	1.033
364	1.016
365	0.999
366	1.003
367	0.993
368	1.010
369	1.023
370	1.341
371	1.446
372	1.450
373	1.548
374	1.600
375	1.541
376	1.420
377	1.228
378	1.172
379	1.020
380	0.964
381	1.004
382	1.037
383	1.023
384	1.022
385	1.013
386	1.071
387	1.227
388	1.343
389	1.401
390	1.367

391	1.516
392	1.486
393	1.537
394	1.534
395	1.509
396	1.458
397	1.369
398	1.250
399	1.127
400	0.864
401	0.496
402	0.409
403	0.543
404	0.696
405	0.779
406	0.866
407	0.890
408	1.040
409	1.227
410	1.342
411	1.363
412	1.406
413	1.438
414	1.460
415	1.481
416	1.505
417	1.497
418	1.486
419	1.466
420	1.456
421	1.585
422	1.736
423	1.796
424	1.877
425	1.874
426	1.793
427	1.614
428	1.489
429	1.406
430	1.374
431	1.351
432	1.198

433	1.126
434	0.995
435	0.883
436	0.719
437	0.630
438	0.590
439	0.589
440	0.737
441	1.025
442	1.245
443	1.580
444	1.129
445	0.855
446	0.800
447	0.806
448	0.824
449	0.847
450	0.922
451	0.964
452	1.042
453	1.181
454	1.234
455	1.423
456	1.429
457	1.126
458	1.127
459	1.189
460	1.362
461	1.548
462	1.675
463	1.675
464	1.574
465	1.318
466	1.177
467	1.095
468	1.116
469	1.085
470	1.165
471	1.322
472	1.525
473	1.834
474	2.020

475	1.737
476	1.511
477	1.369
478	1.538
479	1.750
480	1.936
481	2.040
482	1.995
483	1.837
484	1.456
485	1.093
486	0.820
487	0.851
488	1.125
489	1.442
490	1.608
491	1.569
492	1.320
493	1.072
494	0.970
495	1.007
496	1.135
497	1.287
498	1.228
499	1.053
500	0.899
501	0.901
502	0.955
503	1.014
504	1.148
505	1.212
506	1.191
507	1.090
508	1.009
509	1.005
510	1.058
511	1.224
512	1.288
513	1.335
514	1.468
515	1.490
516	1.514

517	1.594
518	1.688
519	1.675
520	1.636
521	1.572
522	1.514
523	1.518
524	1.502
525	1.538
526	1.388
527	1.337
528	1.335
529	1.332
530	1.191
531	0.975
532	0.641
533	0.554
534	0.493
535	0.445
536	0.419
537	0.504
538	0.628
539	0.636
540	0.622
541	0.544
542	0.476
543	0.464
544	0.482
545	0.560
546	0.623
547	0.681
548	0.676
549	0.683
550	0.730
551	0.826
552	0.816
553	0.810
554	0.839
555	0.996
556	1.253
557	1.525
558	1.808

559	2.054
560	2.286
561	2.525
562	2.469
563	2.319
564	2.010
565	1.929
566	1.990
567	2.104
568	2.223
569	2.331
570	2.271
571	2.135
572	1.973
573	1.866
574	1.838
575	1.932
576	2.047
577	2.179
578	2.249
579	2.140
580	1.997
581	1.983
582	1.952
583	1.876
584	1.744
585	1.756
586	1.588
587	1.355
588	1.068
589	0.901
590	0.729
591	0.623
592	0.531
593	0.462
594	0.529
595	0.672
596	0.673
597	0.713
598	0.816
599	0.955
600	0.895
601	0.875
602	0.834
603	0.849
604	0.807

605	0.836
606	0.826
607	0.726
608	0.596
609	0.501
610	0.432
611	0.529
612	0.740
613	1.012
614	1.213
615	1.376
616	1.374
617	1.342
618	1.288
619	1.221
620	1.133
621	0.983
622	0.901
623	0.750
624	0.677
625	0.614
626	0.577
627	0.597
628	0.615
629	0.612
630	0.674
631	0.863
632	1.074
633	1.255
634	1.402
635	1.404
636	1.347
637	1.247
638	1.241
639	1.269
640	1.336
641	1.432
642	1.504
643	1.525
644	1.449
645	1.372
646	1.361
647	1.322
648	1.309
649	1.291
650	1.249

651	1.311
652	1.345
653	1.349
654	1.283
655	1.311
656	1.265
657	1.199
658	1.147
659	1.159
660	1.302
661	1.437
662	1.568
663	1.666
664	1.683
665	1.595
666	1.517
667	1.362
668	1.461
669	1.574
670	1.579
671	1.466
672	1.345
673	1.172
674	1.100
675	1.213
676	1.372
677	1.545
678	1.384
679	1.317
680	1.671
681	2.049
682	2.043
683	2.162
684	2.211
685	2.135
686	2.079
687	1.981
688	1.803
689	1.678
690	1.540
691	1.456
692	1.351
693	1.304
694	1.288
695	1.277
696	1.331

697	1.417
698	1.482
699	1.589
700	1.641
701	1.736
702	1.822
703	1.982
704	2.011
705	1.972
706	2.035
707	2.049
708	2.107
709	2.037
710	1.981
711	1.833
712	1.773
713	1.772
714	1.800
715	1.768
716	1.769
717	1.868
718	1.869
719	1.889
720	1.904
721	1.955
722	1.942
723	1.896
724	1.902
725	1.873
726	1.852
727	1.939
728	2.035
729	2.047
730	2.003
731	1.919
732	1.923
733	1.927
734	1.972
735	1.986
736	1.861
737	1.662
738	1.605
739	1.539
740	1.487
741	1.505
742	1.413

743	1.219
744	1.098
745	1.015
746	0.971
747	0.927
748	0.958
749	0.972
750	1.119
751	1.093
752	0.888
753	0.795
754	0.712
755	0.562
756	0.459
757	0.578
758	0.694
759	0.794
760	0.900
761	1.035
762	1.278
763	1.533
764	0.942
765	0.652
766	0.638
767	0.629
768	0.585
769	0.559
770	0.581
771	0.665
772	0.788
773	0.836
774	0.816
775	0.796
776	0.798
777	0.878
778	1.037
779	1.315
780	1.767
781	1.954
782	1.676
783	1.488
784	1.384
785	1.331
786	1.325
787	1.381
788	1.463

789	1.626
790	1.935
791	2.210
792	2.214
793	2.185
794	2.194
795	2.190
796	2.181
797	2.178
798	2.197
799	2.262
800	2.305
801	2.291
802	2.182
803	2.087
804	2.056
805	1.702
806	1.243
807	0.992
808	0.881
809	0.845
810	0.855
811	0.891
812	0.960
813	1.080
814	1.293
815	1.624
816	1.980
817	2.284
818	1.829
819	1.292
820	1.015
821	0.910
822	0.881
823	0.906
824	0.964
825	1.040
826	1.189
827	1.424
828	1.572
829	1.508
830	1.435
831	1.317
832	1.191
833	1.036
834	0.900

835	0.829
836	0.801
837	0.807
838	0.838
839	0.890
840	0.988
841	1.125
842	1.264
843	1.424
844	1.526
845	1.565
846	1.642
847	1.724
848	1.807
849	1.914
850	1.863
851	1.630
852	1.448
853	1.362
854	1.348
855	1.361
856	1.403
857	1.517
858	1.703
859	1.975
860	1.841
861	1.814
862	1.832
863	1.943
864	2.026
865	2.135
866	2.173
867	2.220
868	2.215
869	2.118
870	1.950
871	1.776
872	1.659
873	1.594
874	1.590
875	1.560
876	1.567
877	1.547
878	1.595
879	1.665
880	1.799

881	1.948
882	1.995
883	2.010
884	1.933
885	1.835
886	1.765
887	1.642
888	1.485
889	1.335
890	1.213
891	1.136
892	1.086
893	1.067
894	1.081
895	1.109
896	1.161
897	1.252
898	1.381
899	1.557
900	1.791
901	1.984
902	2.021
903	1.973
904	1.966
905	1.904
906	1.717
907	1.581
908	1.511
909	1.490
910	1.525
911	1.616
912	1.728
913	1.605
914	1.125
915	0.747
916	0.595
917	0.542
918	0.534
919	0.670
920	0.951
921	1.395
922	1.459
923	1.284
924	1.125
925	1.026
926	0.966

927	0.953
928	0.899
929	0.885
930	0.872
931	0.882
932	0.890
933	0.905
934	0.904
935	0.914
936	0.977
937	1.122
938	1.620
939	1.347
940	1.123
941	1.115
942	1.151
943	1.269
944	1.348
945	1.387
946	1.398
947	1.320
948	1.133
949	0.950
950	0.808
951	0.679
952	0.575
953	0.516
954	0.492
955	0.439
956	0.378
957	0.351
958	0.369
959	0.385
960	0.433
961	0.481
962	0.539
963	0.533
964	0.545
965	0.502
966	0.466
967	0.434
968	0.406
969	0.353
970	0.321
971	0.361
972	0.457

973	0.491
974	0.455
975	0.427
976	0.409
977	0.387
978	0.367
979	0.351
980	0.332
981	0.325
982	0.352
983	0.376
984	0.433
985	0.450
986	0.485
987	0.505
988	0.509
989	0.540
990	0.583
991	0.630
992	0.691
993	0.758
994	0.884
995	1.045
996	0.447
997	0.623
998	0.685
999	0.719
1000	0.741
1001	0.766
1002	0.773
1003	0.750
1004	0.683
1005	0.482
1006	0.709
1007	0.795
1008	0.797
1009	0.757
1010	0.723
1011	0.706
1012	0.694
1013	0.665
1014	0.618
1015	0.604
1016	0.662
1017	0.709
1018	0.769

1019	0.816
1020	0.837
1021	0.816
1022	0.749
1023	0.701
1024	0.718
1025	0.683
1026	0.576
1027	0.512
1028	0.468
1029	0.463
1030	0.483
1031	0.517
1032	0.557
1033	0.601
1034	0.640
1035	0.519
1036	0.553
1037	0.554
1038	0.574
1039	0.622
1040	0.703
1041	0.715
1042	0.794
1043	0.848
1044	0.940
1045	1.012
1046	0.957
1047	0.840
1048	0.695
1049	0.637
1050	0.597
1051	0.634
1052	0.672
1053	0.731
1054	0.726
1055	0.730
1056	0.758
1057	0.810
1058	0.770
1059	0.746
1060	0.728
1061	0.719
1062	0.822
1063	0.919
1064	0.992

1065	1.057
1066	1.091
1067	1.009
1068	0.899
1069	0.823
1070	0.839
1071	0.916
1072	0.928
1073	0.954
1074	1.083
1075	1.200
1076	1.309
1077	1.443
1078	1.518
1079	1.458
1080	1.353
1081	1.242
1082	1.157
1083	1.226
1084	1.309
1085	1.319
1086	1.300
1087	1.237
1088	1.198
1089	1.161
1090	1.125
1091	1.073
1092	1.035
1093	0.990
1094	0.963
1095	0.968
1096	0.987
1097	0.980
1098	0.970
1099	0.958
1100	0.966
1101	0.984
1102	1.014
1103	1.061
1104	1.084
1105	1.072
1106	1.074
1107	1.068
1108	1.049
1109	1.010
1110	0.955

1111	0.920
1112	0.892
1113	0.880
1114	0.864
1115	0.865
1116	0.864
1117	0.876
1118	0.902
1119	0.923
1120	0.954
1121	0.987
1122	1.000
1123	0.999
1124	0.976
1125	0.990
1126	0.893
1127	0.740
1128	0.567
1129	0.468
1130	0.424
1131	0.456
1132	0.462
1133	0.461
1134	0.464
1135	0.484
1136	0.530
1137	0.598
1138	0.718
1139	0.842
1140	0.904
1141	0.870
1142	0.750
1143	0.711
1144	0.689
1145	0.662
1146	0.667
1147	0.651
1148	0.614
1149	0.526
1150	0.391
1151	0.293
1152	0.277
1153	0.318
1154	0.386
1155	0.442
1156	0.484

1157	0.503
1158	0.524
1159	0.499
1160	0.435
1161	0.378
1162	0.345
1163	0.350
1164	0.393
1165	0.441
1166	0.481
1167	0.517
1168	0.529
1169	0.484
1170	0.367
1171	0.324
1172	0.273
1173	0.239
1174	0.300
1175	0.466
1176	0.620
1177	0.759
1178	0.849
1179	0.891
1180	0.894
1181	0.920
1182	0.965
1183	0.979
1184	0.945
1185	0.770
1186	0.513
1187	0.281
1188	0.146
1189	0.193
1190	0.327
1191	0.458
1192	0.515
1193	0.586
1194	0.624
1195	0.638
1196	0.692
1197	0.748
1198	0.784
1199	0.806
1200	0.817
1201	0.786
1202	0.771

1203	0.735
1204	0.724
1205	0.773
1206	0.806
1207	0.844
1208	0.722
1209	0.571
1210	0.484
1211	0.439
1212	0.431
1213	0.454
1214	0.484
1215	0.531
1216	0.555
1217	0.629
1218	0.696
1219	0.690
1220	0.664
1221	0.676
1222	0.670
1223	0.629
1224	0.586
1225	0.521
1226	0.438
1227	0.342
1228	0.343
1229	0.511
1230	0.664
1231	0.709
1232	0.737
1233	0.760
1234	0.756
1235	0.767
1236	0.785
1237	0.789
1238	0.764
1239	0.768
1240	0.691
1241	0.616
1242	0.491
1243	0.439
1244	0.415
1245	0.419
1246	0.461
1247	0.541
1248	0.669

1249	0.806
1250	0.953
1251	0.951
1252	0.927
1253	0.840
1254	0.784
1255	0.688
1256	0.665
1257	0.681
1258	0.720
1259	0.726
1260	0.710
1261	0.679
1262	0.646
1263	0.616
1264	0.590
1265	0.550
1266	0.464
1267	0.604
1268	0.345
1269	0.282
1270	0.337
1271	0.396
1272	0.424
1273	0.426
1274	0.432
1275	0.396
1276	0.340
1277	0.269
1278	0.231
1279	0.329
1280	0.529
1281	0.750
1282	0.949
1283	0.862
1284	0.776
1285	0.728
1286	0.728
1287	0.740
1288	0.741
1289	0.727
1290	0.732
1291	0.751
1292	0.777
1293	0.824
1294	0.859

1295	0.870
1296	0.873
1297	0.923
1298	1.002
1299	1.075
1300	1.112
1301	1.169
1302	1.286
1303	1.396
1304	1.503
1305	1.496
1306	1.393
1307	1.324
1308	1.282
1309	1.271
1310	1.282
1311	1.308
1312	1.364
1313	1.441
1314	1.509
1315	1.547
1316	1.558
1317	1.513
1318	1.376
1319	1.235
1320	1.140
1321	1.083
1322	1.067
1323	1.058
1324	1.033
1325	1.050
1326	1.062
1327	1.051
1328	1.092
1329	1.114
1330	1.165
1331	1.124
1332	1.067
1333	1.016
1334	0.957
1335	0.910
1336	0.877
1337	0.784
1338	0.769
1339	0.813
1340	0.821

1341	0.787
1342	0.743
1343	0.716
1344	0.718
1345	0.745
1346	0.866
1347	0.850
1348	0.923
1349	0.978
1350	1.014
1410	1.040
1411	1.063
1412	1.082
1413	1.084
1414	0.935
1415	0.451
1416	0.261
1417	0.101
1418	0.055
1419	0.126
1420	0.230
1421	0.236
1422	0.188
1423	0.391
1424	0.547
1425	0.613
1426	0.531
1427	0.344
1428	0.237
1429	0.697
1430	0.898
1431	0.911
1432	0.863
1433	0.860
1434	0.848
1435	0.816
1436	0.791
1437	0.689
1438	0.266
1439	0.828
1440	0.886
1441	0.893
1442	0.899
1443	0.906
1444	0.903
1445	0.875

1446	0.791
1447	0.564
1448	0.368
1449	0.332
1450	0.311
1451	0.327
1452	0.410
1453	0.444
1454	0.441
1455	0.407
1456	0.317
1457	0.242
1458	0.251
1459	0.460
1460	0.607
1461	0.640
1462	0.583
1463	0.482
1464	0.396
1465	0.425
1466	0.577
1467	0.726
1468	0.842
1469	0.875
1470	0.885
1471	0.869
1472	0.813
1473	0.708
1474	0.580
1475	0.480
1476	0.405
1477	0.338
1478	0.223
1479	0.275
1480	0.478
1481	0.787
1482	0.953
1483	0.979
1484	1.013
1485	1.038
1486	1.062
1487	1.090
1488	1.123
1489	1.167
1490	1.189
1491	1.167

1492	1.154
1493	1.022
1494	0.875
1495	0.775
1496	0.737
1497	0.673
1498	0.653
1499	0.609
1500	0.541
1501	0.542
1502	0.507
1503	0.437
1504	0.475
1505	0.607
1506	0.698
1507	0.674
1508	0.594
1509	0.659
1510	0.762
1511	0.803
1512	0.819
1513	0.809
1514	0.904
1515	0.851
1516	0.754
1517	0.736
1518	0.681
1519	0.683
1520	0.717
1521	0.777
1522	0.826
1523	0.775
1524	0.627
1525	0.466
1526	0.320
1527	0.250
1528	0.253
1529	0.246
1530	0.228
1531	0.210
1532	0.196
1533	0.192
1534	0.208
1535	0.257
1536	0.315
1537	0.333

1538	0.352
1539	0.420
1540	0.404
1541	0.458
1542	0.479
1543	0.525
1544	0.541
1545	0.524
1546	0.461
1547	0.361
1548	0.266
1549	0.212
1550	0.207
1551	0.228
1552	0.243
1553	0.220
1554	0.213
1555	0.246
1556	0.340
1557	0.424
1558	0.384
1559	0.335
1560	0.324
1561	0.345
1562	0.418
1563	0.470
1564	0.535
1565	0.523
1566	0.512
1567	0.463
1568	0.472
1569	0.468
1570	0.290
1571	0.139
1572	0.143
1573	0.177
1574	0.257
1575	0.319
1576	0.401
1577	0.418
1578	0.434
1579	0.359
1580	0.342
1581	0.314
1582	0.279
1583	0.305

1584	0.358
1585	0.418
1586	0.504
1587	0.665
1588	0.735
1589	0.746
1590	0.631
1591	0.259
1592	0.123
1593	0.118
1594	0.109
1595	0.068
1596	0.057
1597	0.113
1598	0.123
1599	0.166
1600	0.210
1601	0.136
1602	0.138
1603	0.122
1604	0.139
1605	0.127
1606	0.240
1607	0.385
1608	0.502
1609	0.635
1610	0.606
1611	0.450
1612	0.385
1613	0.329
1614	0.287
1615	0.203
1616	0.212
1617	0.215
1618	0.208
1619	0.186
1620	0.156
1621	0.120
1622	0.210
1623	0.391
1624	0.479
1625	0.597
1626	0.659
1627	0.731
1628	0.767
1629	0.531

1630	0.256
1631	0.124
1632	0.208
1633	0.249
1634	0.231
1635	0.242
1636	0.252
1637	0.284
1638	0.294
1639	0.301
1640	0.290
1641	0.324
1642	0.331
1643	0.294
1644	0.291
1645	0.260
1646	0.221
1647	0.140
1648	0.149
1649	0.217
1650	0.231
1651	0.179
1652	0.132
1653	0.059
1654	0.349
1655	0.718
1656	1.008
1657	1.151
1658	1.357
1659	1.404
1660	1.390
1661	1.318
1662	1.165
1663	0.958
1664	0.707
1665	0.548
1666	0.459
1667	0.358
1668	0.193
1669	0.157
1670	0.309
1671	0.368
1672	0.348
1673	0.453
1674	0.554
1675	0.623

1676	0.438
1677	0.429
1678	0.406
1679	0.492
1680	0.519
1681	0.364
1682	0.176
1683	0.385
1684	0.483
1685	0.488
1686	0.441
1687	0.559
1688	0.486
1689	0.433
1690	0.430
1691	0.330
1692	0.261
1693	0.220
1694	0.227
1695	0.246
1696	0.291
1697	0.163
1698	0.143
1699	0.186
1700	0.229
1701	0.206
1702	0.179
1703	0.216
1704	0.239
1705	0.302
1706	0.269
1707	0.163
1708	0.113
1709	0.128
1710	0.174
1711	0.291
1712	0.353
1713	0.518
1714	0.453
1715	0.368
1716	0.247
1717	0.165
1718	0.230
1719	0.258
1720	0.359
1721	0.399

1722	0.465
1723	0.503
1724	0.480
1725	0.462
1726	0.411
1727	0.300
1728	0.122
1729	0.081
1730	0.061
1731	0.134
1732	0.148
1733	0.206
1734	0.260
1735	0.317
1736	0.332
1737	0.388
1738	0.449
1739	0.471
1740	0.487
1741	0.420
1742	0.314
1743	0.282
1744	0.285
1745	0.291
1746	0.282
1747	0.262
1748	0.236
1749	0.244
1750	0.247
1751	0.256
1752	0.224
1753	0.226
1754	0.224
1755	0.228
1756	0.269
1757	0.269
1758	0.303
1759	0.327
1760	0.368
1761	0.393
1762	0.370
1763	0.350
1764	0.386
1765	0.412
1766	0.370
1767	0.315

1768	0.360
1769	0.397
1770	0.458
1771	0.445
1772	0.424
1773	0.370
1774	0.330
1775	0.349
1776	0.307
1777	0.324
1778	0.383
1779	0.464
1780	0.558
1781	0.649
1782	0.694
1783	0.657
1784	0.540
1785	0.426
1786	0.374
1787	0.398
1788	0.445
1789	0.649
1790	0.798
1791	0.870
1792	0.864
1793	0.809
1794	0.711
1795	0.415
1796	0.437
1797	0.449
1798	0.458
1799	0.451
1800	0.448
1951	0.452
1952	0.452
1953	0.447
1954	0.466
1955	0.506
1956	0.107
1957	0.305
1958	0.357
1959	0.304
1960	0.288
1961	0.278
1962	0.328
1963	0.441

1964	0.559
1965	0.632
1966	0.637
1967	0.591
1968	0.481
1969	0.438
1970	0.494
1971	0.491
1972	0.538
1973	0.666
1974	0.768
1975	0.756
1976	0.679
1977	0.602
1978	0.485
1979	0.355
1980	0.268
1981	0.274
1982	0.255
1983	0.165
1984	0.090
1985	0.262
1986	0.461
1987	0.686
1988	0.817
1989	0.810
1990	0.781
1991	0.737
1992	0.698
1993	0.744
1994	0.804
1995	0.864
1996	0.910
1997	0.896
1998	0.886
1999	0.873
2000	0.850
2001	0.831
2002	0.839
2003	0.857
2004	0.874
2005	0.861
2006	0.812
2007	0.768
2008	0.718
2009	0.694

2010	0.623
2011	0.486
2012	0.497
2013	0.679
2014	0.801
2015	0.842
2016	0.861
2017	0.862
2018	0.844
2019	0.819
2020	0.795
2021	0.789
2022	0.789
2023	0.785
2024	0.798
2025	0.802
2026	0.755
2027	0.688
2028	0.674
2029	0.610
2030	0.484
2031	0.353
2032	0.419
2033	0.534
2034	0.608
2035	0.725
2036	0.835
2037	0.875
2038	0.873
2039	0.767
2040	0.626
2041	0.351
2042	0.105
2043	0.300
2044	0.416
2045	0.421
2046	0.483
2047	0.557
2048	0.555
2049	0.512
2050	0.451
2051	0.420
2052	0.408
2053	0.488
2054	0.618
2055	0.708

2056	0.749
2057	0.767
2058	0.762
2059	0.732
2060	0.664
2061	0.556
2062	0.626
2063	0.806
2064	0.884
2065	0.910
2066	0.906
2067	0.901
2068	0.885
2069	0.855
2070	0.794
2071	0.708
2072	0.608
2073	0.547
2074	0.505
2075	0.511
2076	0.472
2077	0.462
2078	0.547
2079	0.595
2080	0.665
2081	0.733
2082	0.765
2083	0.719
2084	0.603
2085	0.483
2086	0.601
2087	0.752
2088	0.838
2089	0.867
2090	0.871
2091	0.827
2092	0.697
2093	0.442
2094	0.227
2095	0.334
2096	0.403
2097	0.423
2098	0.585
2099	0.750
2100	0.839
2101	0.884

2102	0.888
2103	0.804
2104	0.679
2105	0.537
2106	0.402
2107	0.323
2108	0.322
2109	0.377
2110	0.427
2111	0.429
2112	0.407
2113	0.274
2114	0.140
2115	0.267
2116	0.411
2117	0.518
2118	0.593
2119	0.634
2120	0.628
2121	0.604
2122	0.570
2123	0.527
2124	0.457
2125	0.387
2126	0.443
2127	0.649
2128	0.761
2129	0.795
2130	0.786
2131	0.766
2132	0.755
2133	0.777
2134	0.822
2135	0.879
2136	0.900
2137	0.917
2138	0.870
2139	0.752
2140	0.598
2141	0.430
2142	0.471
2143	0.565
2144	0.609
2145	0.620
2146	0.543
2147	0.355

2148	0.312
2149	0.505
2150	0.552
2151	0.513
2152	0.407
2153	0.266
2154	0.125
2155	0.138
2156	0.230
2157	0.292
2158	0.218
2159	0.154
2160	0.225
2161	0.318
2162	0.358
2163	0.340
2164	0.367
2165	0.377
2166	0.409
2167	0.437
2168	0.423

2169	0.428
2170	0.488
2171	0.558
2172	0.632
2173	0.697
2174	0.694
2175	0.601
2176	0.357
2177	0.284
2178	0.385
2179	0.538
2180	0.613
2181	0.583
2182	0.503
2183	0.388
2184	0.517
2185	0.648
2186	0.665
2187	0.596
2188	0.462
2189	0.307

2190	0.188
2191	0.211
2192	0.281
2193	0.406
2194	0.407
2195	0.334
2196	0.164
2197	0.180
2198	0.324
2199	0.544
2200	0.658
2201	0.683
2202	0.673
2203	0.564
2204	0.429
2205	0.291
2206	0.168
2207	0.297
2208	0.373
2209	0.458
2210	0.322

2211	0.207
2212	0.355
2213	0.541
2214	0.580
2215	0.611
2216	0.520
2217	0.461
2218	0.420
2219	0.359
2220	0.263
2221	0.215
2222	0.144
2223	0.228
2224	0.354
2225	0.478
2226	0.561
2227	0.552
2228	0.487
2229	0.405
2230	0.315
2231	0.355

2232	0.489
2233	0.630
2234	0.669
2235	0.658
2236	0.528
2237	0.307
2238	0.229
2239	0.498
2240	0.595
2241	0.587
2242	0.572
2243	0.502
2244	0.433
2245	0.393
2246	1.718
2247	1.756
2248	1.746
2249	1.735
2250	1.734

Sunflower:

XAxis	vips
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351	0.754
352	0.767
353	0.790
354	0.860
355	0.403
356	0.421
357	0.425
358	0.431
359	0.428
360	0.441
361	0.424
362	0.408
363	0.399
364	0.386
365	0.377
366	0.402
367	0.476
368	0.493
369	0.485
370	0.481

371	0.474
372	0.438
373	0.435
374	0.468
375	0.514
376	0.512
377	0.501
378	0.528
379	0.515
380	0.487
381	0.461
382	0.441
383	0.443
384	0.464
385	0.509
386	0.561
387	0.588
388	0.601
389	0.609
390	0.612
391	0.611
392	0.589

393	0.544
394	0.535
395	0.515
396	0.470
397	0.434
398	0.380
399	0.326
400	0.291
401	0.288
402	0.331
403	0.396
404	0.459
405	0.507
406	0.538
407	0.550
408	0.550
409	0.552
410	0.557
411	0.563
412	0.573
413	0.587
414	0.606

415	0.629
416	0.655
417	0.682
418	0.711
419	0.742
420	0.777
421	0.815
422	0.857
423	0.901
424	0.947
425	0.991
426	1.030
427	1.063
428	1.091
429	1.113
430	1.130
431	1.144
432	1.159
433	1.175
434	1.192
435	1.211
436	1.232

437	1.251
438	1.269
439	1.283
440	1.293
441	1.296
442	1.290
443	1.277
444	1.258
445	1.239
446	1.224
447	1.216
448	1.221
449	1.239
450	1.271
451	1.317
452	1.374
453	1.434
454	1.493
455	1.545
456	1.582
457	1.607
458	1.621

459	1.628
460	1.628
461	1.620
462	1.608
463	1.592
464	1.573
465	1.552
466	1.532
467	1.510
468	1.486
469	1.463
470	1.439
471	1.416
472	1.394
473	1.373
474	1.357
475	1.347
476	1.344
477	1.352
478	1.373
479	1.406
480	1.452
481	1.505
482	1.555
483	1.596
484	1.625
485	1.642
486	1.652
487	1.654
488	1.652
489	1.649
490	1.644
491	1.639
492	1.634
493	1.626
494	1.616
495	1.603
496	1.588
497	1.570
498	1.549
499	1.526
500	1.503
501	1.479
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521	1.280
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523	1.308
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527	1.334
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532	1.281
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536	1.143
537	1.106
538	1.079
539	1.066
540	1.068
541	1.082
542	1.106
543	1.141
544	1.191
545	1.259
546	1.351
547	1.463
548	1.583
549	1.690
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553	1.793
554	1.767
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558	1.664
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561	1.617
562	1.607
563	1.598
564	1.592
565	1.587
566	1.584
567	1.581
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573	1.568
574	1.564
575	1.561
576	1.557
577	1.552
578	1.548
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582	1.523
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584	1.502
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586	1.480
587	1.471
588	1.463
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590	1.452
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593	1.442
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596	1.433

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605	1.562
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609	1.560
610	1.553
611	1.543
612	1.532
613	1.520
614	1.507
615	1.494
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617	1.473
618	1.468
619	1.466
620	1.468
621	1.471
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623	1.478
624	1.480
625	1.480
626	1.473
627	1.453
628	1.418
629	1.369
630	1.312
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632	1.229
633	1.225
634	1.242
635	1.265
636	1.286
637	1.302
638	1.313
639	1.320
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641	1.327
642	1.328

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644	1.310
645	1.288
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650	1.190
651	1.229
652	1.291
653	1.345
654	1.370
655	1.360
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657	1.270
658	1.216
659	1.173
660	1.144
661	1.130
662	1.129
663	1.134
664	1.141
665	1.147
666	1.148
667	1.142
668	1.127
669	1.101
670	1.064
671	1.017
672	0.966
673	0.929
674	0.953
675	1.117
676	1.419
677	1.683
678	1.799
679	1.820
680	1.802
681	1.769
682	1.730
683	1.697
684	1.668
685	1.639
686	1.602
687	1.555
688	1.495

689	1.426
690	1.354
691	1.285
692	1.225
693	1.188
694	1.180
695	1.198
696	1.235
697	1.282
698	1.335
699	1.387
700	1.437
701	1.482
702	1.525
703	1.564
704	1.601
705	1.635
706	1.665
707	1.691
708	1.714
709	1.734
710	1.750
711	1.761
712	1.765
713	1.763
714	1.761
715	1.763
716	1.773
717	1.788
718	1.802
719	1.815
720	1.827
721	1.840
722	1.851
723	1.857
724	1.855
725	1.850
726	1.850
727	1.861
728	1.881
729	1.899
730	1.910
731	1.914
732	1.915
733	1.912
734	1.907

735	1.898
736	1.887
737	1.875
738	1.863
739	1.851
740	1.835
741	1.812
742	1.777
743	1.727
744	1.658
745	1.568
746	1.456
747	1.325
748	1.185
749	1.057
750	0.966
751	0.928
752	0.929
753	0.924
754	0.831
755	0.663
756	0.657
757	0.682
758	0.670
759	0.642
760	0.617
761	0.665
762	0.954
763	1.316
764	1.335
765	1.234
766	1.155
767	1.127
768	1.150
769	1.211
770	1.305
771	1.408
772	1.482
773	1.517
774	1.529
775	1.532
776	1.532
777	1.533
778	1.532
779	1.530
780	1.526

781	1.517
782	1.499
783	1.472
784	1.440
785	1.415
786	1.406
787	1.419
788	1.446
789	1.477
790	1.500
791	1.513
792	1.520
793	1.522
794	1.520
795	1.511
796	1.493
797	1.476
798	1.473
799	1.486
800	1.505
801	1.518
802	1.522
803	1.523
804	1.524
805	1.517
806	1.478
807	1.376
808	1.214
809	1.053
810	0.939
811	0.878
812	0.864
813	0.893
814	0.976
815	1.120
816	1.302
817	1.441
818	1.472
819	1.441
820	1.410
821	1.399
822	1.411
823	1.437
824	1.458
825	1.468
826	1.471

827	1.464
828	1.449
829	1.427
830	1.403
831	1.375
832	1.342
833	1.309
834	1.288
835	1.280
836	1.283
837	1.290
838	1.298
839	1.307
840	1.317
841	1.329
842	1.341
843	1.355
844	1.368
845	1.379
846	1.386
847	1.384
848	1.372
849	1.354
850	1.333
851	1.317
852	1.306
853	1.298
854	1.290
855	1.284
856	1.280
857	1.273
858	1.260
859	1.248
860	1.236
861	1.222
862	1.210
863	1.205
864	1.206
865	1.210
866	1.220
867	1.231
868	1.241
869	1.246
870	1.246
871	1.241
872	1.233

873	1.222
874	1.213
875	1.205
876	1.198
877	1.192
878	1.187
879	1.180
880	1.172
881	1.164
882	1.154
883	1.140
884	1.117
885	1.080
886	1.023
887	0.948
888	0.864
889	0.788
890	0.733
891	0.700
892	0.682
893	0.672
894	0.668
895	0.668
896	0.673
897	0.686
898	0.716
899	0.770
900	0.848
901	0.933
902	0.996
903	1.021
904	0.997
905	0.927
906	0.853
907	0.807
908	0.790
909	0.800
910	0.843
911	0.925
912	1.044
913	1.146
914	1.170
915	1.143
916	1.115
917	1.106
918	1.116

919	1.152
920	1.210
921	1.219
922	1.068
923	0.853
924	0.719
925	0.657
926	0.634
927	0.625
928	0.622
929	0.622
930	0.626
931	0.633
932	0.646
933	0.669
934	0.709
935	0.777
936	0.880
937	0.994
938	1.071
939	1.113
940	1.148
941	1.185
942	1.214
943	1.227
944	1.238
945	1.245
946	1.238
947	1.211
948	1.182
949	1.164
950	1.150
951	1.135
952	1.120
953	1.111
954	1.100
955	1.084
956	1.066
957	1.047
958	1.017
959	0.983
960	0.958
961	0.941
962	0.926
963	0.910
964	0.902

965	0.898
966	0.898
967	0.902
968	0.919
969	0.935
970	0.949
971	0.961
972	0.959
973	0.947
974	0.930
975	0.900
976	0.856
977	0.818
978	0.786
979	0.759
980	0.733
981	0.714
982	0.700
983	0.686
984	0.669
985	0.646
986	0.617
987	0.583
988	0.546
989	0.503
990	0.458
991	0.421
992	0.386
993	0.360
994	0.346
995	0.343
996	0.411
997	0.430
998	0.437
999	0.448
1000	0.462
1001	0.480
1002	0.490
1003	0.503
1004	0.527
1005	0.575
1006	0.557
1007	0.541
1008	0.526
1009	0.510
1010	0.502

1011	0.500
1012	0.512
1013	0.522
1014	0.530
1015	0.532
1016	0.537
1017	0.554
1018	0.571
1019	0.591
1020	0.608
1021	0.600
1022	0.583
1023	0.572
1024	0.562
1025	0.558
1026	0.553
1027	0.545
1028	0.540
1029	0.536
1030	0.532
1031	0.528
1032	0.518
1033	0.512
1034	0.517
1035	0.526
1036	0.548
1037	0.574
1038	0.587
1039	0.594
1040	0.603
1041	0.589
1042	0.564
1043	0.535
1044	0.509
1045	0.501
1046	0.497
1047	0.508
1048	0.527
1049	0.545
1050	0.553
1051	0.556
1052	0.536
1053	0.506
1054	0.475
1055	0.460
1056	0.461

1057	0.458
1058	0.458
1059	0.458
1060	0.457
1061	0.460
1062	0.477
1063	0.503
1064	0.533
1065	0.566
1066	0.607
1067	0.643
1068	0.648
1069	0.653
1070	0.674
1071	0.714
1072	0.779
1073	0.828
1074	0.865
1075	0.898
1076	0.910
1077	0.924
1078	0.928
1079	0.918
1080	0.905
1081	0.887
1082	0.876
1083	0.874
1084	0.858
1085	0.851
1086	0.838
1087	0.796
1088	0.753
1089	0.709
1090	0.666
1091	0.635
1092	0.621
1093	0.617
1094	0.616
1095	0.616
1096	0.617
1097	0.618
1098	0.618
1099	0.617
1100	0.615
1101	0.612
1102	0.608

1103	0.606
1104	0.607
1105	0.611
1106	0.613
1107	0.613
1108	0.613
1109	0.611
1110	0.610
1111	0.611
1112	0.611
1113	0.609
1114	0.603
1115	0.596
1116	0.587
1117	0.576
1118	0.563
1119	0.545
1120	0.523
1121	0.498
1122	0.469
1123	0.443
1124	0.429
1125	0.461
1126	0.552
1127	0.660
1128	0.731
1129	0.776
1130	0.819
1131	0.856
1132	0.887
1133	0.917
1134	0.944
1135	0.969
1136	0.990
1137	1.007
1138	1.012
1139	1.015
1140	1.026
1141	1.042
1142	1.059
1143	1.071
1144	1.080
1145	1.089
1146	1.097
1147	1.103
1148	1.104

1149	1.093
1150	1.069
1151	1.038
1152	1.001
1153	0.966
1154	0.936
1155	0.911
1156	0.889
1157	0.872
1158	0.860
1159	0.853
1160	0.846
1161	0.838
1162	0.830
1163	0.822
1164	0.815
1165	0.806
1166	0.795
1167	0.786
1168	0.778
1169	0.771
1170	0.765
1171	0.758
1172	0.750
1173	0.737
1174	0.716
1175	0.675
1176	0.600
1177	0.489
1178	0.410
1179	0.385
1180	0.385
1181	0.385
1182	0.383
1183	0.415
1184	0.546
1185	0.808
1186	1.027
1187	1.089
1188	1.069
1189	1.025
1190	0.977
1191	0.929
1192	0.883
1193	0.839
1194	0.798

1195	0.760
1196	0.731
1197	0.712
1198	0.700
1199	0.690
1200	0.685
1201	0.681
1202	0.674
1203	0.666
1204	0.654
1205	0.639
1206	0.625
1207	0.609
1208	0.591
1209	0.575
1210	0.557
1211	0.545
1212	0.547
1213	0.551
1214	0.561
1215	0.571
1216	0.580
1217	0.582
1218	0.576
1219	0.561
1220	0.541
1221	0.521
1222	0.506
1223	0.495
1224	0.486
1225	0.479
1226	0.476
1227	0.480
1228	0.488
1229	0.500
1230	0.513
1231	0.522
1232	0.527
1233	0.531
1234	0.528
1235	0.521
1236	0.513
1237	0.507
1238	0.524
1239	0.551
1240	0.577

1241	0.610
1242	0.648
1243	0.687
1244	0.730
1245	0.773
1246	0.818
1247	0.859
1248	0.892
1249	0.927
1250	0.953
1251	0.960
1252	0.962
1253	0.953
1254	0.938
1255	0.915
1256	0.894
1257	0.883
1258	0.871
1259	0.860
1260	0.850
1261	0.836
1262	0.822
1263	0.808
1264	0.787
1265	0.749
1266	0.654
1267	0.502
1268	0.729
1269	0.890
1270	0.933
1271	0.953
1272	0.970
1273	0.988
1274	1.007
1275	1.028
1276	1.051
1277	1.076
1278	1.101
1279	1.124
1280	1.137
1281	1.145
1282	1.149
1283	1.142
1284	1.124
1285	1.099
1286	1.070

1287	1.042
1288	1.015
1289	0.994
1290	0.979
1291	0.971
1292	0.973
1293	0.980
1294	0.990
1295	0.997
1296	1.000
1297	1.001
1298	0.999
1299	0.993
1300	0.985
1301	0.971
1302	0.954
1303	0.937
1304	0.922
1305	0.908
1306	0.899
1307	0.894
1308	0.895
1309	0.902
1310	0.916
1311	0.937
1312	0.961
1313	0.985
1314	1.006
1315	1.023
1316	1.034
1317	1.041
1318	1.043
1319	1.039
1320	1.028
1321	1.012
1322	0.988
1323	0.958
1324	0.924
1325	0.886
1326	0.851
1327	0.827
1328	0.815
1329	0.818
1330	0.842
1331	0.876
1332	0.925

1333	0.972
1334	1.016
1335	1.052
1336	1.071
1337	1.069
1338	1.037
1339	0.967
1340	0.848
1341	0.706
1342	0.558
1343	0.441
1344	0.358
1345	0.327
1346	0.725
1347	0.794
1348	0.850
1349	0.907
1350	0.969
1410	1.019
1411	1.073
1412	1.109
1413	1.083
1414	0.860
1415	0.332
1416	0.336
1417	0.330
1418	0.319
1419	0.309
1420	0.292
1421	0.277
1422	0.328
1423	0.398
1424	0.447
1425	0.490
1426	0.523
1427	0.507
1428	0.444
1429	0.363
1430	0.306
1431	0.293
1432	0.309
1433	0.346
1434	0.317
1435	0.256
1436	0.211
1437	0.193

1438	0.241
1439	0.329
1440	0.452
1441	0.496
1442	0.476
1443	0.454
1444	0.458
1445	0.484
1446	0.520
1447	0.537
1448	0.535
1449	0.506
1450	0.423
1451	0.336
1452	0.278
1453	0.272
1454	0.285
1455	0.299
1456	0.299
1457	0.260
1458	0.222
1459	0.259
1460	0.356
1461	0.463
1462	0.612
1463	0.733
1464	0.833
1465	0.889
1466	0.938
1467	0.958
1468	0.927
1469	0.846
1470	0.720
1471	0.611
1472	0.565
1473	0.607
1474	0.640
1475	0.629
1476	0.616
1477	0.618
1478	0.643
1479	0.668
1480	0.671
1481	0.664
1482	0.638
1483	0.596

1484	0.559
1485	0.532
1486	0.518
1487	0.516
1488	0.525
1489	0.542
1490	0.565
1491	0.595
1492	0.629
1493	0.665
1494	0.701
1495	0.733
1496	0.761
1497	0.792
1498	0.829
1499	0.870
1500	0.906
1501	0.939
1502	0.967
1503	0.989
1504	1.011
1505	1.028
1506	1.039
1507	1.047
1508	1.054
1509	1.060
1510	1.069
1511	1.076
1512	1.083
1513	1.090
1514	1.096
1515	1.103
1516	1.106
1517	1.107
1518	1.108
1519	1.110
1520	1.116
1521	1.124
1522	1.133
1523	1.143
1524	1.152
1525	1.159
1526	1.164
1527	1.168
1528	1.172
1529	1.175

1530	1.180
1531	1.185
1532	1.190
1533	1.196
1534	1.204
1535	1.213
1536	1.222
1537	1.229
1538	1.236
1539	1.241
1540	1.245
1541	1.248
1542	1.249
1543	1.248
1544	1.247
1545	1.247
1546	1.249
1547	1.253
1548	1.257
1549	1.263
1550	1.268
1551	1.273
1552	1.278
1553	1.282
1554	1.285
1555	1.288
1556	1.291
1557	1.297
1558	1.302
1559	1.307
1560	1.314
1561	1.319
1562	1.325
1563	1.329
1564	1.333
1565	1.335
1566	1.337
1567	1.339
1568	1.341
1569	1.343
1570	1.343
1571	1.343
1572	1.340
1573	1.335
1574	1.329
1575	1.324

1576	1.317
1577	1.311
1578	1.306
1579	1.302
1580	1.299
1581	1.298
1582	1.298
1583	1.299
1584	1.301
1585	1.304
1586	1.304
1587	1.302
1588	1.298
1589	1.295
1590	1.292
1591	1.289
1592	1.287
1593	1.286
1594	1.286
1595	1.287
1596	1.289
1597	1.291
1598	1.293
1599	1.293
1600	1.294
1601	1.292
1602	1.288
1603	1.281
1604	1.273
1605	1.265
1606	1.257
1607	1.247
1608	1.238
1609	1.225
1610	1.208
1611	1.195
1612	1.184
1613	1.175
1614	1.171
1615	1.169
1616	1.167
1617	1.170
1618	1.174
1619	1.183
1620	1.196
1621	1.206

1622	1.210
1623	1.210
1624	1.203
1625	1.194
1626	1.185
1627	1.171
1628	1.158
1629	1.145
1630	1.133
1631	1.127
1632	1.120
1633	1.110
1634	1.101
1635	1.090
1636	1.075
1637	1.060
1638	1.045
1639	1.032
1640	1.018
1641	1.003
1642	0.988
1643	0.971
1644	0.952
1645	0.935
1646	0.919
1647	0.905
1648	0.891
1649	0.874
1650	0.853
1651	0.830
1652	0.808
1653	0.789
1654	0.770
1655	0.749
1656	0.728
1657	0.711
1658	0.702
1659	0.698
1660	0.696
1661	0.701
1662	0.710
1663	0.725
1664	0.763
1665	0.819
1666	0.884
1667	0.862

1668	0.605
1669	0.407
1670	0.386
1671	0.408
1672	0.432
1673	0.447
1674	0.443
1675	0.428
1676	0.406
1677	0.385
1678	0.355
1679	0.343
1680	0.412
1681	0.561
1682	0.726
1683	0.836
1684	0.920
1685	0.930
1686	0.857
1687	0.738
1688	0.607
1689	0.513
1690	0.438
1691	0.402
1692	0.389
1693	0.393
1694	0.410
1695	0.414
1696	0.420
1697	0.441
1698	0.465
1699	0.491
1700	0.515
1701	0.539
1702	0.567
1703	0.588
1704	0.603
1705	0.612
1706	0.617
1707	0.619
1708	0.626
1709	0.637
1710	0.645
1711	0.641
1712	0.610
1713	0.581

1714	0.585
1715	0.620
1716	0.659
1717	0.699
1718	0.688
1719	0.644
1720	0.614
1721	0.580
1722	0.586
1723	0.626
1724	0.688
1725	0.760
1726	0.833
1727	0.894
1728	0.937
1729	0.977
1730	1.014
1731	1.049
1732	1.080
1733	1.136
1734	1.190
1735	1.236
1736	1.273
1737	1.306
1738	1.315
1739	1.315
1740	1.307
1741	1.296
1742	1.284
1743	1.271
1744	1.268
1745	1.278
1746	1.296
1747	1.320
1748	1.342
1749	1.355
1750	1.359
1751	1.354
1752	1.339
1753	1.319
1754	1.290
1755	1.261
1756	1.230
1757	1.188
1758	1.127
1759	1.060

1760	0.997
1761	0.958
1762	0.944
1763	0.978
1764	1.037
1765	1.090
1766	1.125
1767	1.152
1768	1.159
1769	1.153
1770	1.121
1771	1.069
1772	1.024
1773	0.972
1774	0.936
1775	0.911
1776	0.881
1777	0.839
1778	0.794
1779	0.733
1780	0.683
1781	0.634
1782	0.571
1783	0.468
1784	0.336
1785	0.235
1786	0.233
1787	0.322
1788	0.426
1789	0.522
1790	0.591
1791	0.622
1792	0.606
1793	0.569
1794	0.524
1795	0.485
1796	0.487
1797	0.502
1798	0.510
1799	0.517
1800	0.523
1951	0.528
1952	0.536
1953	0.550
1954	0.574
1955	0.606

1956	0.401
1957	0.409
1958	0.418
1959	0.414
1960	0.409
1961	0.404
1962	0.403
1963	0.401
1964	0.403
1965	0.401
1966	0.405
1967	0.409
1968	0.417
1969	0.430
1970	0.447
1971	0.461
1972	0.466
1973	0.459
1974	0.448
1975	0.450
1976	0.451
1977	0.452
1978	0.458
1979	0.447
1980	0.436
1981	0.428
1982	0.427
1983	0.436
1984	0.453
1985	0.455
1986	0.422
1987	0.367
1988	0.303
1989	0.233
1990	0.176
1991	0.171
1992	0.281
1993	0.366
1994	0.387
1995	0.385
1996	0.385
1997	0.391
1998	0.399
1999	0.414
2000	0.427
2001	0.439

2002	0.456
2003	0.477
2004	0.487
2005	0.452
2006	0.283
2007	0.284
2008	0.352
2009	0.404
2010	0.422
2011	0.437
2012	0.451
2013	0.451
2014	0.428
2015	0.417
2016	0.419
2017	0.431
2018	0.441
2019	0.444
2020	0.440
2021	0.430
2022	0.419
2023	0.414
2024	0.412
2025	0.416
2026	0.424
2027	0.428
2028	0.427
2029	0.421
2030	0.424
2031	0.456
2032	0.514
2033	0.592
2034	0.670
2035	0.740
2036	0.784
2037	0.818
2038	0.856
2039	0.904
2040	0.960
2041	0.996
2042	0.963
2043	0.905
2044	0.815
2045	0.752
2046	0.711
2047	0.662

2048	0.624
2049	0.621
2050	0.626
2051	0.637
2052	0.656
2053	0.657
2054	0.659
2055	0.666
2056	0.658
2057	0.621
2058	0.571
2059	0.493
2060	0.443
2061	0.410
2062	0.395
2063	0.397
2064	0.385
2065	0.348
2066	0.334
2067	0.319
2068	0.332
2069	0.371
2070	0.409
2071	0.457
2072	0.492
2073	0.496
2074	0.492
2075	0.485
2076	0.472
2077	0.469
2078	0.475
2079	0.504
2080	0.546
2081	0.578
2082	0.602
2083	0.611
2084	0.615
2085	0.621
2086	0.639
2087	0.673
2088	0.719
2089	0.778
2090	0.814
2091	0.811
2092	0.817
2093	0.808

2094	0.788
2095	0.767
2096	0.767
2097	0.788
2098	0.803
2099	0.818
2100	0.802
2101	0.793
2102	0.787
2103	0.798
2104	0.827
2105	0.846
2106	0.850
2107	0.873
2108	0.897
2109	0.922
2110	0.912
2111	0.894
2112	0.851
2113	0.834
2114	0.854
2115	0.884
2116	0.914
2117	0.905
2118	0.874
2119	0.810
2120	0.737
2121	0.684
2122	0.638
2123	0.586
2124	0.546
2125	0.517
2126	0.504
2127	0.509
2128	0.539
2129	0.587
2130	0.625
2131	0.609
2132	0.580
2133	0.553
2134	0.528
2135	0.541
2136	0.514
2137	0.415
2138	0.348
2139	0.359

2140	0.373
2141	0.399
2142	0.403
2143	0.397
2144	0.367
2145	0.303
2146	0.262
2147	0.281
2148	0.340
2149	0.401
2150	0.453
2151	0.512
2152	0.507
2153	0.469
2154	0.415
2155	0.364
2156	0.363
2157	0.412
2158	0.450
2159	0.439
2160	0.442
2161	0.454
2162	0.481
2163	0.507
2164	0.532
2165	0.549
2166	0.570
2167	0.580
2168	0.559
2169	0.521
2170	0.475
2171	0.439
2172	0.406
2173	0.380
2174	0.354
2175	0.332
2176	0.296
2177	0.281
2178	0.300
2179	0.349
2180	0.405
2181	0.435
2182	0.414
2183	0.344
2184	0.271
2185	0.211

2186	0.190
2187	0.242
2188	0.350
2189	0.437
2190	0.483
2191	0.500
2192	0.498
2193	0.484
2194	0.461
2195	0.430
2196	0.402
2197	0.374
2198	0.346
2199	0.315
2200	0.307
2201	0.333
2202	0.360
2203	0.391
2204	0.418
2205	0.426
2206	0.403
2207	0.341
2208	0.276
2209	0.238
2210	0.240
2211	0.255
2212	0.223
2213	0.143
2214	0.124
2215	0.180
2216	0.236
2217	0.271
2218	0.294
2219	0.304
2220	0.288
2221	0.279
2222	0.315
2223	0.349
2224	0.356
2225	0.346
2226	0.319
2227	0.330
2228	0.377
2229	0.451
2230	0.525
2231	0.587

2232	0.615
2233	0.578
2234	0.489
2235	0.341
2236	0.283
2237	0.345
2238	0.383
2239	0.344
2240	0.331
2241	0.405
2242	0.510
2243	0.566
2244	0.596
2245	0.603
2246	0.995
2247	0.985
2248	0.978
2249	0.973
2250	0.968

E.3. RANDOM FOREST FEATURE IMPORTANCE

Classification

Corn

W	importance	391	0.002	433	0.005	475	0.000	517	0.000
350	0.003	392	0.002	434	0.007	476	0.000	518	0.001
351	0.001	393	0.001	435	0.001	477	0.000	519	0.000
352	0.002	394	0.002	436	0.005	478	0.000	520	0.001
353	0.001	395	0.000	437	0.007	479	0.001	521	0.000
354	0.004	396	0.002	438	0.009	480	0.000	522	0.000
355	0.000	397	0.002	439	0.001	481	0.001	523	0.002
356	0.000	398	0.001	440	0.003	482	0.000	524	0.000
357	0.000	399	0.004	441	0.001	483	0.002	525	0.000
358	0.000	400	0.001	442	0.001	484	0.001	526	0.000
359	0.001	401	0.002	443	0.001	485	0.002	527	0.000
360	0.001	402	0.002	444	0.000	486	0.002	528	0.000
361	0.001	403	0.002	445	0.000	487	0.000	529	0.001
362	0.000	404	0.001	446	0.000	488	0.001	530	0.000
363	0.002	405	0.000	447	0.000	489	0.002	531	0.001
364	0.000	406	0.003	448	0.001	490	0.000	532	0.000
365	0.001	407	0.001	449	0.000	491	0.000	533	0.000
366	0.000	408	0.004	450	0.000	492	0.002	534	0.000
367	0.000	409	0.001	451	0.000	493	0.001	535	0.001
368	0.001	410	0.001	452	0.000	494	0.000	536	0.000
369	0.000	411	0.002	453	0.000	495	0.000	537	0.001
370	0.000	412	0.002	454	0.001	496	0.000	538	0.000
371	0.002	413	0.000	455	0.000	497	0.002	539	0.000
372	0.002	414	0.001	456	0.000	498	0.001	540	0.000
373	0.001	415	0.003	457	0.002	499	0.000	541	0.001
374	0.001	416	0.010	458	0.002	500	0.000	542	0.000
375	0.001	417	0.013	459	0.004	501	0.000	543	0.000
376	0.001	418	0.007	460	0.006	502	0.000	544	0.001
377	0.001	419	0.005	461	0.000	503	0.000	545	0.000
378	0.000	420	0.000	462	0.004	504	0.001	546	0.000
379	0.001	421	0.002	463	0.000	505	0.000	547	0.000
380	0.001	422	0.018	464	0.007	506	0.000	548	0.001
381	0.000	423	0.014	465	0.007	507	0.000	549	0.000
382	0.000	424	0.010	466	0.005	508	0.002	550	0.000
383	0.001	425	0.012	467	0.004	509	0.000	551	0.013
384	0.001	426	0.009	468	0.001	510	0.000	552	0.011
385	0.000	427	0.012	469	0.000	511	0.000	553	0.012
386	0.000	428	0.009	470	0.001	512	0.000	554	0.013
387	0.001	429	0.013	471	0.000	513	0.000	555	0.017
388	0.000	430	0.004	472	0.000	514	0.000	556	0.003
389	0.001	431	0.007	473	0.000	515	0.000	557	0.004
390	0.001	432	0.005	474	0.001	516	0.001	558	0.005

559	0.010
560	0.001
561	0.002
562	0.005
563	0.004
564	0.007
565	0.001
566	0.005
567	0.001
568	0.001
569	0.004
570	0.000
571	0.000
572	0.001
573	0.000
574	0.000
575	0.003
576	0.005
577	0.004
578	0.001
579	0.001
580	0.001
581	0.000
582	0.000
583	0.000
584	0.001
585	0.003
586	0.000
587	0.000
588	0.000
589	0.000
590	0.000
591	0.000
592	0.000
593	0.000
594	0.000
595	0.002
596	0.000
597	0.000
598	0.000
599	0.000
600	0.000
601	0.002
602	0.000
603	0.000
604	0.001
605	0.001
606	0.003
607	0.000
608	0.001
609	0.001
610	0.001
611	0.002
612	0.000
613	0.001
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622	0.000
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625	0.000
626	0.000
627	0.000
628	0.001
629	0.006
630	0.000
631	0.000
632	0.001
633	0.002
634	0.001
635	0.001
636	0.000
637	0.001
638	0.001
639	0.001
640	0.000
641	0.000
642	0.000
643	0.002
644	0.000
645	0.000
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670	0.001
671	0.000
672	0.001
673	0.002
674	0.001
675	0.004
676	0.003
677	0.001
678	0.001
679	0.001
680	0.001
681	0.002
682	0.000
683	0.002
684	0.000
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714	0.002
715	0.005
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717	0.002
718	0.005
719	0.000
720	0.002
721	0.000
722	0.003
723	0.000
724	0.000
725	0.001
726	0.000
727	0.000
728	0.001
729	0.002
730	0.002
731	0.003
732	0.004
733	0.000
734	0.005
735	0.004
736	0.000
737	0.000
738	0.001
739	0.003
740	0.003
741	0.000
742	0.001
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744	0.000
745	0.000
746	0.000
747	0.001
748	0.002
749	0.002
750	0.001
751	0.001
752	0.001
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755	0.000
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757	0.000
758	0.001
759	0.001
760	0.002
761	0.000
762	0.001
763	0.001
764	0.001
765	0.001
766	0.003
767	0.002
768	0.002
769	0.001
770	0.000
771	0.001
772	0.000
773	0.002
774	0.000
775	0.000
776	0.001
777	0.001
778	0.001
779	0.006
780	0.000
781	0.000
782	0.003
783	0.002
784	0.000
785	0.000
786	0.000
787	0.000
788	0.002

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790	0.001
791	0.001
792	0.001
793	0.000
794	0.008
795	0.004
796	0.000
797	0.001
798	0.000
799	0.000
800	0.002
801	0.009
802	0.003
803	0.002
804	0.002
805	0.005
806	0.000
807	0.000
808	0.001
809	0.000
810	0.000
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813	0.000
814	0.000
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843	0.000
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846	0.002
847	0.002
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850	0.001
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863	0.003
864	0.004
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866	0.003
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1000	0.000
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1002	0.000
1003	0.001
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1006	0.000
1007	0.000
1008	0.001
1009	0.000
1010	0.000
1011	0.000
1012	0.000
1013	0.001
1014	0.000
1015	0.000
1016	0.000
1017	0.000
1018	0.000

1019	0.000	1065	0.000	1111	0.000	1157	0.000	1203	0.000
1020	0.000	1066	0.000	1112	0.000	1158	0.000	1204	0.000
1021	0.000	1067	0.000	1113	0.001	1159	0.000	1205	0.000
1022	0.000	1068	0.000	1114	0.000	1160	0.001	1206	0.000
1023	0.000	1069	0.000	1115	0.000	1161	0.000	1207	0.000
1024	0.000	1070	0.000	1116	0.000	1162	0.000	1208	0.000
1025	0.000	1071	0.001	1117	0.001	1163	0.000	1209	0.000
1026	0.000	1072	0.001	1118	0.000	1164	0.000	1210	0.000
1027	0.001	1073	0.001	1119	0.000	1165	0.000	1211	0.000
1028	0.000	1074	0.000	1120	0.000	1166	0.000	1212	0.000
1029	0.000	1075	0.000	1121	0.000	1167	0.000	1213	0.000
1030	0.000	1076	0.000	1122	0.000	1168	0.000	1214	0.000
1031	0.000	1077	0.000	1123	0.000	1169	0.000	1215	0.000
1032	0.001	1078	0.001	1124	0.000	1170	0.000	1216	0.000
1033	0.001	1079	0.000	1125	0.000	1171	0.000	1217	0.000
1034	0.000	1080	0.000	1126	0.000	1172	0.000	1218	0.000
1035	0.000	1081	0.001	1127	0.000	1173	0.000	1219	0.000
1036	0.000	1082	0.001	1128	0.001	1174	0.000	1220	0.000
1037	0.001	1083	0.001	1129	0.001	1175	0.000	1221	0.000
1038	0.000	1084	0.000	1130	0.000	1176	0.000	1222	0.000
1039	0.000	1085	0.000	1131	0.001	1177	0.000	1223	0.001
1040	0.000	1086	0.000	1132	0.000	1178	0.000	1224	0.001
1041	0.000	1087	0.000	1133	0.000	1179	0.000	1225	0.000
1042	0.000	1088	0.000	1134	0.000	1180	0.001	1226	0.000
1043	0.000	1089	0.000	1135	0.000	1181	0.000	1227	0.000
1044	0.000	1090	0.000	1136	0.000	1182	0.000	1228	0.000
1045	0.000	1091	0.000	1137	0.000	1183	0.000	1229	0.000
1046	0.000	1092	0.000	1138	0.000	1184	0.000	1230	0.000
1047	0.000	1093	0.000	1139	0.000	1185	0.001	1231	0.000
1048	0.000	1094	0.000	1140	0.000	1186	0.000	1232	0.001
1049	0.000	1095	0.000	1141	0.000	1187	0.001	1233	0.000
1050	0.000	1096	0.001	1142	0.000	1188	0.000	1234	0.000
1051	0.000	1097	0.000	1143	0.000	1189	0.000	1235	0.000
1052	0.000	1098	0.000	1144	0.000	1190	0.000	1236	0.001
1053	0.000	1099	0.000	1145	0.000	1191	0.000	1237	0.000
1054	0.000	1100	0.000	1146	0.000	1192	0.000	1238	0.000
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1064	0.000	1110	0.000	1156	0.000	1202	0.000	1248	0.000

1249	0.000	1295	0.000	1341	0.001	1446	0.000	1492	0.000
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802	0.002	848	0.000	894	0.000	940	0.000	986	0.000
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807	0.000	853	0.000	899	0.000	945	0.000	991	0.000
808	0.000	854	0.000	900	0.000	946	0.000	992	0.000
809	0.000	855	0.000	901	0.000	947	0.000	993	0.000
810	0.000	856	0.000	902	0.000	948	0.000	994	0.000
811	0.000	857	0.000	903	0.000	949	0.000	995	0.000
812	0.000	858	0.000	904	0.000	950	0.000	996	0.000
813	0.000	859	0.000	905	0.000	951	0.000	997	0.000
814	0.000	860	0.000	906	0.000	952	0.000	998	0.000
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816	0.000	862	0.000	908	0.000	954	0.000	1000	0.000
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820	0.000	866	0.000	912	0.000	958	0.000	1004	0.000
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822	0.000	868	0.000	914	0.000	960	0.000	1006	0.000
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824	0.000	870	0.000	916	0.000	962	0.000	1008	0.000
825	0.000	871	0.000	917	0.000	963	0.000	1009	0.000
826	0.000	872	0.000	918	0.000	964	0.000	1010	0.000
827	0.000	873	0.000	919	0.000	965	0.000	1011	0.000
828	0.000	874	0.000	920	0.000	966	0.000	1012	0.000
829	0.000	875	0.000	921	0.000	967	0.000	1013	0.000
830	0.000	876	0.000	922	0.000	968	0.000	1014	0.000
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842	0.000	888	0.000	934	0.000	980	0.000	1026	0.000
843	0.000	889	0.000	935	0.000	981	0.000	1027	0.000
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2249	0.000
2250	0.000

Regression

Corn:

W	importance	393	0.000	437	0.005	481	0.000	525	0.000
350	0.001	394	0.001	438	0.000	482	0.000	526	0.000
351	0.005	395	0.003	439	0.001	483	0.000	527	0.000
352	0.001	396	0.001	440	0.000	484	0.004	528	0.000
353	0.002	397	0.003	441	0.000	485	0.000	529	0.000
354	0.002	398	0.001	442	0.000	486	0.000	530	0.000
355	0.000	399	0.000	443	0.000	487	0.001	531	0.000
356	0.000	400	0.001	444	0.000	488	0.000	532	0.000
357	0.000	401	0.001	445	0.000	489	0.000	533	0.000
358	0.000	402	0.002	446	0.000	490	0.000	534	0.000
359	0.001	403	0.000	447	0.000	491	0.002	535	0.000
360	0.000	404	0.001	448	0.000	492	0.000	536	0.000
361	0.000	405	0.001	449	0.000	493	0.000	537	0.000
362	0.000	406	0.000	450	0.000	494	0.000	538	0.001
363	0.000	407	0.000	451	0.000	495	0.000	539	0.000
364	0.000	408	0.001	452	0.000	496	0.000	540	0.000
365	0.000	409	0.001	453	0.000	497	0.000	541	0.000
366	0.000	410	0.001	454	0.000	498	0.000	542	0.000
367	0.001	411	0.000	455	0.000	499	0.000	543	0.001
368	0.001	412	0.000	456	0.001	500	0.000	544	0.000
369	0.000	413	0.001	457	0.000	501	0.000	545	0.000
370	0.000	414	0.000	458	0.001	502	0.001	546	0.001
371	0.001	415	0.001	459	0.010	503	0.000	547	0.000
372	0.000	416	0.000	460	0.000	504	0.000	548	0.001
373	0.001	417	0.004	461	0.002	505	0.000	549	0.000
374	0.003	418	0.000	462	0.013	506	0.000	550	0.006
375	0.003	419	0.000	463	0.001	507	0.000	551	0.016
376	0.001	420	0.000	464	0.007	508	0.000	552	0.020
377	0.000	421	0.000	465	0.006	509	0.000	553	0.003
378	0.000	422	0.000	466	0.018	510	0.000	554	0.020
379	0.000	423	0.001	467	0.007	511	0.000	555	0.017
380	0.001	424	0.000	468	0.004	512	0.000	556	0.002
381	0.001	425	0.006	469	0.000	513	0.000	557	0.007
382	0.000	426	0.000	470	0.002	514	0.001	558	0.016
383	0.000	427	0.006	471	0.000	515	0.000	559	0.012
384	0.001	428	0.000	472	0.000	516	0.000	560	0.010
385	0.000	429	0.001	473	0.000	517	0.000	561	0.005
386	0.000	430	0.001	474	0.000	518	0.000	562	0.008
387	0.001	431	0.000	475	0.000	519	0.000	563	0.008
388	0.000	432	0.000	476	0.000	520	0.000	564	0.007
389	0.000	433	0.001	477	0.000	521	0.000	565	0.000
390	0.001	434	0.015	478	0.000	522	0.000	566	0.007
391	0.001	435	0.005	479	0.000	523	0.000	567	0.006
392	0.001	436	0.011	480	0.000	524	0.013	568	0.013

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1783	0.000	1979	0.000	2025	0.000	2071	0.000	2117	0.000
1784	0.000	1980	0.000	2026	0.000	2072	0.000	2118	0.000
1785	0.000	1981	0.000	2027	0.000	2073	0.000	2119	0.000
1786	0.000	1982	0.000	2028	0.000	2074	0.000	2120	0.000
1787	0.000	1983	0.000	2029	0.000	2075	0.000	2121	0.000
1788	0.000	1984	0.000	2030	0.000	2076	0.000	2122	0.000
1789	0.000	1985	0.000	2031	0.000	2077	0.000	2123	0.000
1790	0.000	1986	0.000	2032	0.000	2078	0.000	2124	0.000
1791	0.000	1987	0.000	2033	0.000	2079	0.000	2125	0.000
1792	0.000	1988	0.000	2034	0.000	2080	0.000	2126	0.000
1793	0.000	1989	0.000	2035	0.000	2081	0.000	2127	0.000
1794	0.000	1990	0.000	2036	0.000	2082	0.000	2128	0.000
1795	0.000	1991	0.000	2037	0.000	2083	0.000	2129	0.000
1796	0.000	1992	0.000	2038	0.000	2084	0.000	2130	0.000
1797	0.000	1993	0.000	2039	0.000	2085	0.000	2131	0.000
1798	0.000	1994	0.000	2040	0.000	2086	0.000	2132	0.000
1799	0.000	1995	0.000	2041	0.000	2087	0.000	2133	0.000
1800	0.000	1996	0.000	2042	0.000	2088	0.000	2134	0.000
1951	0.000	1997	0.001	2043	0.000	2089	0.000	2135	0.000
1952	0.000	1998	0.000	2044	0.000	2090	0.000	2136	0.000
1953	0.000	1999	0.000	2045	0.000	2091	0.000	2137	0.000
1954	0.000	2000	0.000	2046	0.000	2092	0.000	2138	0.000
1955	0.000	2001	0.000	2047	0.000	2093	0.000	2139	0.000
1956	0.000	2002	0.000	2048	0.000	2094	0.000	2140	0.000
1957	0.000	2003	0.000	2049	0.000	2095	0.000	2141	0.000
1958	0.000	2004	0.000	2050	0.000	2096	0.000	2142	0.000
1959	0.000	2005	0.000	2051	0.000	2097	0.000	2143	0.000
1960	0.000	2006	0.000	2052	0.000	2098	0.000	2144	0.000
1961	0.000	2007	0.000	2053	0.000	2099	0.000	2145	0.000
1962	0.000	2008	0.000	2054	0.000	2100	0.000	2146	0.000
1963	0.000	2009	0.000	2055	0.000	2101	0.000	2147	0.000
1964	0.000	2010	0.000	2056	0.000	2102	0.000	2148	0.000
1965	0.000	2011	0.000	2057	0.000	2103	0.000	2149	0.000
1966	0.001	2012	0.000	2058	0.000	2104	0.000	2150	0.000
1967	0.000	2013	0.000	2059	0.000	2105	0.000	2151	0.000
1968	0.000	2014	0.000	2060	0.000	2106	0.000	2152	0.000
1969	0.000	2015	0.000	2061	0.000	2107	0.000	2153	0.000
1970	0.000	2016	0.000	2062	0.000	2108	0.001	2154	0.000
1971	0.000	2017	0.000	2063	0.000	2109	0.000	2155	0.000
1972	0.001	2018	0.000	2064	0.000	2110	0.000	2156	0.000
1973	0.000	2019	0.000	2065	0.000	2111	0.000	2157	0.000
1974	0.000	2020	0.000	2066	0.000	2112	0.000	2158	0.000
1975	0.000	2021	0.000	2067	0.000	2113	0.000	2159	0.000
1976	0.000	2022	0.000	2068	0.000	2114	0.000	2160	0.000
1977	0.000	2023	0.000	2069	0.000	2115	0.000	2161	0.000
1978	0.000	2024	0.000	2070	0.000	2116	0.000	2162	0.000

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2244	0.000
2245	0.000
2246	0.000
2247	0.000
2248	0.001
2249	0.000
2250	0.000

E.4. XGBOOST FEATURE IMPORTANCE

Classification

Corn:

W	importance	392	0.000	435	0.000	478	0.001	521	0.000
350	0.000	393	0.007	436	0.000	479	0.000	522	0.000
351	0.000	394	0.000	437	0.004	480	0.000	523	0.000
352	0.002	395	0.007	438	0.000	481	0.018	524	0.000
353	0.000	396	0.000	439	0.000	482	0.000	525	0.000
354	0.001	397	0.002	440	0.001	483	0.000	526	0.000
355	0.001	398	0.000	441	0.001	484	0.000	527	0.000
356	0.000	399	0.001	442	0.000	485	0.000	528	0.000
357	0.000	400	0.001	443	0.000	486	0.000	529	0.000
358	0.000	401	0.011	444	0.000	487	0.002	530	0.000
359	0.002	402	0.001	445	0.000	488	0.000	531	0.000
360	0.000	403	0.001	446	0.000	489	0.000	532	0.000
361	0.000	404	0.014	447	0.000	490	0.000	533	0.000
362	0.000	405	0.000	448	0.000	491	0.000	534	0.000
363	0.000	406	0.000	449	0.000	492	0.000	535	0.000
364	0.001	407	0.000	450	0.000	493	0.000	536	0.000
365	0.000	408	0.015	451	0.000	494	0.000	537	0.000
366	0.000	409	0.000	452	0.000	495	0.000	538	0.000
367	0.000	410	0.000	453	0.000	496	0.000	539	0.000
368	0.000	411	0.000	454	0.000	497	0.000	540	0.000
369	0.002	412	0.000	455	0.000	498	0.000	541	0.000
370	0.000	413	0.000	456	0.000	499	0.000	542	0.000
371	0.000	414	0.000	457	0.000	500	0.000	543	0.000
372	0.001	415	0.000	458	0.000	501	0.000	544	0.000
373	0.004	416	0.000	459	0.000	502	0.000	545	0.000
374	0.000	417	0.000	460	0.000	503	0.000	546	0.000
375	0.000	418	0.000	461	0.000	504	0.000	547	0.000
376	0.000	419	0.000	462	0.000	505	0.000	548	0.000
377	0.001	420	0.007	463	0.014	506	0.000	549	0.000
378	0.000	421	0.000	464	0.008	507	0.000	550	0.000
379	0.000	422	0.000	465	0.000	508	0.000	551	0.001
380	0.015	423	0.000	466	0.030	509	0.000	552	0.000
381	0.000	424	0.000	467	0.000	510	0.000	553	0.109
382	0.001	425	0.000	468	0.000	511	0.000	554	0.004
383	0.000	426	0.031	469	0.000	512	0.000	555	0.004
384	0.000	427	0.004	470	0.000	513	0.000	556	0.004
385	0.000	428	0.000	471	0.000	514	0.000	557	0.000
386	0.000	429	0.032	472	0.001	515	0.000	558	0.000
387	0.000	430	0.000	473	0.000	516	0.000	559	0.000
388	0.000	431	0.001	474	0.014	517	0.000	560	0.000
389	0.000	432	0.000	475	0.000	518	0.000	561	0.000
390	0.000	433	0.000	476	0.000	519	0.000	562	0.002
391	0.000	434	0.005	477	0.001	520	0.000	563	0.000

564	0.000	610	0.000	656	0.000	702	0.000	748	0.000
565	0.001	611	0.001	657	0.000	703	0.002	749	0.000
566	0.000	612	0.000	658	0.000	704	0.001	750	0.000
567	0.000	613	0.000	659	0.000	705	0.000	751	0.000
568	0.000	614	0.001	660	0.000	706	0.000	752	0.000
569	0.000	615	0.000	661	0.000	707	0.000	753	0.000
570	0.000	616	0.000	662	0.000	708	0.002	754	0.002
571	0.000	617	0.000	663	0.000	709	0.000	755	0.000
572	0.001	618	0.000	664	0.000	710	0.000	756	0.000
573	0.000	619	0.003	665	0.000	711	0.000	757	0.000
574	0.020	620	0.000	666	0.000	712	0.000	758	0.004
575	0.000	621	0.000	667	0.000	713	0.000	759	0.000
576	0.000	622	0.000	668	0.000	714	0.004	760	0.000
577	0.000	623	0.000	669	0.000	715	0.000	761	0.000
578	0.001	624	0.000	670	0.000	716	0.000	762	0.000
579	0.000	625	0.000	671	0.000	717	0.000	763	0.003
580	0.000	626	0.000	672	0.000	718	0.000	764	0.000
581	0.000	627	0.000	673	0.000	719	0.000	765	0.002
582	0.000	628	0.000	674	0.000	720	0.000	766	0.029
583	0.000	629	0.002	675	0.000	721	0.000	767	0.000
584	0.000	630	0.002	676	0.012	722	0.000	768	0.000
585	0.000	631	0.003	677	0.000	723	0.000	769	0.000
586	0.000	632	0.000	678	0.007	724	0.000	770	0.000
587	0.000	633	0.000	679	0.000	725	0.000	771	0.000
588	0.000	634	0.000	680	0.002	726	0.000	772	0.000
589	0.000	635	0.000	681	0.000	727	0.000	773	0.000
590	0.000	636	0.000	682	0.000	728	0.000	774	0.000
591	0.000	637	0.000	683	0.000	729	0.000	775	0.000
592	0.000	638	0.000	684	0.000	730	0.011	776	0.000
593	0.000	639	0.001	685	0.000	731	0.000	777	0.000
594	0.000	640	0.000	686	0.000	732	0.000	778	0.000
595	0.000	641	0.000	687	0.000	733	0.000	779	0.000
596	0.000	642	0.000	688	0.000	734	0.002	780	0.000
597	0.000	643	0.000	689	0.000	735	0.000	781	0.000
598	0.000	644	0.000	690	0.000	736	0.000	782	0.000
599	0.000	645	0.000	691	0.000	737	0.000	783	0.000
600	0.000	646	0.000	692	0.000	738	0.000	784	0.000
601	0.000	647	0.000	693	0.000	739	0.000	785	0.000
602	0.000	648	0.000	694	0.011	740	0.000	786	0.000
603	0.000	649	0.000	695	0.000	741	0.000	787	0.000
604	0.008	650	0.000	696	0.000	742	0.000	788	0.000
605	0.001	651	0.000	697	0.000	743	0.000	789	0.000
606	0.001	652	0.000	698	0.000	744	0.000	790	0.000
607	0.000	653	0.000	699	0.000	745	0.000	791	0.000
608	0.004	654	0.000	700	0.000	746	0.000	792	0.000
609	0.000	655	0.000	701	0.000	747	0.000	793	0.007

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1024	0.000	1070	0.000	1116	0.000	1162	0.000	1208	0.000
1025	0.000	1071	0.002	1117	0.000	1163	0.000	1209	0.000
1026	0.000	1072	0.000	1118	0.000	1164	0.000	1210	0.000
1027	0.000	1073	0.000	1119	0.000	1165	0.000	1211	0.000
1028	0.000	1074	0.000	1120	0.000	1166	0.000	1212	0.000
1029	0.000	1075	0.000	1121	0.000	1167	0.000	1213	0.000
1030	0.000	1076	0.000	1122	0.000	1168	0.000	1214	0.000
1031	0.000	1077	0.000	1123	0.008	1169	0.000	1215	0.000
1032	0.000	1078	0.000	1124	0.000	1170	0.012	1216	0.000
1033	0.000	1079	0.002	1125	0.000	1171	0.000	1217	0.000
1034	0.000	1080	0.000	1126	0.003	1172	0.000	1218	0.000
1035	0.000	1081	0.000	1127	0.000	1173	0.000	1219	0.000
1036	0.000	1082	0.000	1128	0.000	1174	0.000	1220	0.000
1037	0.000	1083	0.000	1129	0.000	1175	0.000	1221	0.000
1038	0.000	1084	0.000	1130	0.000	1176	0.000	1222	0.001
1039	0.000	1085	0.000	1131	0.000	1177	0.001	1223	0.000
1040	0.000	1086	0.000	1132	0.000	1178	0.002	1224	0.000
1041	0.000	1087	0.000	1133	0.000	1179	0.000	1225	0.000
1042	0.000	1088	0.000	1134	0.000	1180	0.000	1226	0.000
1043	0.000	1089	0.000	1135	0.000	1181	0.000	1227	0.000
1044	0.000	1090	0.000	1136	0.000	1182	0.000	1228	0.000
1045	0.000	1091	0.000	1137	0.000	1183	0.000	1229	0.000
1046	0.000	1092	0.000	1138	0.000	1184	0.000	1230	0.000
1047	0.000	1093	0.000	1139	0.000	1185	0.000	1231	0.000
1048	0.000	1094	0.000	1140	0.000	1186	0.000	1232	0.000
1049	0.001	1095	0.000	1141	0.000	1187	0.000	1233	0.000
1050	0.000	1096	0.000	1142	0.000	1188	0.000	1234	0.000
1051	0.000	1097	0.000	1143	0.000	1189	0.000	1235	0.000
1052	0.003	1098	0.000	1144	0.009	1190	0.000	1236	0.000
1053	0.000	1099	0.000	1145	0.000	1191	0.000	1237	0.000
1054	0.001	1100	0.000	1146	0.000	1192	0.000	1238	0.000
1055	0.000	1101	0.000	1147	0.000	1193	0.000	1239	0.000
1056	0.000	1102	0.000	1148	0.000	1194	0.000	1240	0.000
1057	0.000	1103	0.000	1149	0.000	1195	0.000	1241	0.000
1058	0.000	1104	0.000	1150	0.000	1196	0.000	1242	0.001
1059	0.000	1105	0.000	1151	0.000	1197	0.000	1243	0.001
1060	0.000	1106	0.000	1152	0.000	1198	0.000	1244	0.000
1061	0.000	1107	0.000	1153	0.000	1199	0.000	1245	0.000
1062	0.000	1108	0.000	1154	0.000	1200	0.000	1246	0.001
1063	0.000	1109	0.000	1155	0.000	1201	0.000	1247	0.000
1064	0.000	1110	0.000	1156	0.001	1202	0.000	1248	0.000
1065	0.000	1111	0.000	1157	0.000	1203	0.000	1249	0.001
1066	0.000	1112	0.000	1158	0.000	1204	0.000	1250	0.000
1067	0.000	1113	0.000	1159	0.000	1205	0.000	1251	0.000
1068	0.000	1114	0.000	1160	0.000	1206	0.000	1252	0.000
1069	0.000	1115	0.000	1161	0.000	1207	0.000	1253	0.005

1254	0.000	1300	0.000	1346	0.000	1451	0.000	1497	0.000
1255	0.000	1301	0.000	1347	0.000	1452	0.000	1498	0.000
1256	0.000	1302	0.000	1348	0.000	1453	0.000	1499	0.000
1257	0.000	1303	0.000	1349	0.000	1454	0.000	1500	0.000
1258	0.000	1304	0.000	1350	0.000	1455	0.000	1501	0.000
1259	0.000	1305	0.000	1410	0.000	1456	0.001	1502	0.000
1260	0.000	1306	0.000	1411	0.001	1457	0.000	1503	0.000
1261	0.000	1307	0.000	1412	0.000	1458	0.000	1504	0.001
1262	0.000	1308	0.000	1413	0.000	1459	0.000	1505	0.000
1263	0.000	1309	0.000	1414	0.000	1460	0.000	1506	0.000
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1265	0.000	1311	0.000	1416	0.000	1462	0.000	1508	0.000
1266	0.000	1312	0.000	1417	0.000	1463	0.000	1509	0.000
1267	0.000	1313	0.000	1418	0.000	1464	0.000	1510	0.000
1268	0.005	1314	0.000	1419	0.004	1465	0.000	1511	0.000
1269	0.000	1315	0.000	1420	0.000	1466	0.000	1512	0.000
1270	0.000	1316	0.000	1421	0.002	1467	0.000	1513	0.000
1271	0.000	1317	0.000	1422	0.004	1468	0.000	1514	0.000
1272	0.000	1318	0.000	1423	0.000	1469	0.000	1515	0.000
1273	0.000	1319	0.000	1424	0.000	1470	0.000	1516	0.000
1274	0.000	1320	0.000	1425	0.000	1471	0.000	1517	0.000
1275	0.000	1321	0.000	1426	0.000	1472	0.002	1518	0.000
1276	0.000	1322	0.000	1427	0.002	1473	0.000	1519	0.000
1277	0.000	1323	0.000	1428	0.000	1474	0.000	1520	0.000
1278	0.000	1324	0.000	1429	0.001	1475	0.002	1521	0.000
1279	0.000	1325	0.000	1430	0.000	1476	0.000	1522	0.000
1280	0.000	1326	0.000	1431	0.000	1477	0.000	1523	0.000
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1282	0.005	1328	0.000	1433	0.006	1479	0.000	1525	0.000
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1284	0.000	1330	0.000	1435	0.000	1481	0.000	1527	0.000
1285	0.000	1331	0.000	1436	0.000	1482	0.000	1528	0.000
1286	0.000	1332	0.000	1437	0.000	1483	0.000	1529	0.000
1287	0.000	1333	0.000	1438	0.000	1484	0.000	1530	0.000
1288	0.000	1334	0.000	1439	0.000	1485	0.000	1531	0.000
1289	0.000	1335	0.000	1440	0.000	1486	0.000	1532	0.000
1290	0.000	1336	0.000	1441	0.000	1487	0.000	1533	0.000
1291	0.000	1337	0.000	1442	0.000	1488	0.000	1534	0.000
1292	0.000	1338	0.000	1443	0.000	1489	0.000	1535	0.000
1293	0.002	1339	0.002	1444	0.000	1490	0.000	1536	0.000
1294	0.000	1340	0.000	1445	0.000	1491	0.000	1537	0.000
1295	0.002	1341	0.002	1446	0.000	1492	0.000	1538	0.004
1296	0.000	1342	0.000	1447	0.004	1493	0.000	1539	0.000
1297	0.000	1343	0.000	1448	0.000	1494	0.000	1540	0.000
1298	0.000	1344	0.000	1449	0.003	1495	0.008	1541	0.000
1299	0.000	1345	0.000	1450	0.000	1496	0.000	1542	0.000

1543	0.000	1589	0.000	1635	0.000	1681	0.000	1727	0.000
1544	0.000	1590	0.000	1636	0.000	1682	0.000	1728	0.000
1545	0.000	1591	0.000	1637	0.000	1683	0.000	1729	0.000
1546	0.000	1592	0.000	1638	0.000	1684	0.000	1730	0.000
1547	0.000	1593	0.000	1639	0.000	1685	0.000	1731	0.000
1548	0.000	1594	0.000	1640	0.000	1686	0.003	1732	0.003
1549	0.000	1595	0.000	1641	0.000	1687	0.000	1733	0.000
1550	0.000	1596	0.000	1642	0.000	1688	0.000	1734	0.002
1551	0.000	1597	0.000	1643	0.000	1689	0.000	1735	0.022
1552	0.000	1598	0.000	1644	0.000	1690	0.000	1736	0.000
1553	0.000	1599	0.000	1645	0.000	1691	0.000	1737	0.000
1554	0.000	1600	0.000	1646	0.000	1692	0.000	1738	0.000
1555	0.000	1601	0.000	1647	0.000	1693	0.000	1739	0.000
1556	0.002	1602	0.000	1648	0.000	1694	0.001	1740	0.000
1557	0.000	1603	0.000	1649	0.000	1695	0.000	1741	0.000
1558	0.000	1604	0.000	1650	0.000	1696	0.000	1742	0.000
1559	0.000	1605	0.000	1651	0.000	1697	0.000	1743	0.000
1560	0.000	1606	0.000	1652	0.000	1698	0.000	1744	0.000
1561	0.000	1607	0.000	1653	0.000	1699	0.007	1745	0.000
1562	0.000	1608	0.000	1654	0.000	1700	0.000	1746	0.000
1563	0.000	1609	0.000	1655	0.007	1701	0.000	1747	0.000
1564	0.000	1610	0.000	1656	0.000	1702	0.000	1748	0.000
1565	0.000	1611	0.000	1657	0.000	1703	0.000	1749	0.000
1566	0.001	1612	0.000	1658	0.000	1704	0.000	1750	0.000
1567	0.000	1613	0.000	1659	0.000	1705	0.000	1751	0.000
1568	0.000	1614	0.000	1660	0.000	1706	0.000	1752	0.000
1569	0.000	1615	0.000	1661	0.000	1707	0.000	1753	0.000
1570	0.000	1616	0.004	1662	0.000	1708	0.000	1754	0.000
1571	0.000	1617	0.000	1663	0.000	1709	0.000	1755	0.000
1572	0.000	1618	0.000	1664	0.000	1710	0.000	1756	0.000
1573	0.000	1619	0.000	1665	0.000	1711	0.000	1757	0.002
1574	0.000	1620	0.000	1666	0.000	1712	0.000	1758	0.000
1575	0.001	1621	0.000	1667	0.000	1713	0.000	1759	0.000
1576	0.005	1622	0.000	1668	0.001	1714	0.000	1760	0.000
1577	0.000	1623	0.000	1669	0.000	1715	0.000	1761	0.000
1578	0.000	1624	0.000	1670	0.000	1716	0.007	1762	0.000
1579	0.000	1625	0.000	1671	0.000	1717	0.000	1763	0.000
1580	0.004	1626	0.000	1672	0.000	1718	0.000	1764	0.013
1581	0.006	1627	0.001	1673	0.000	1719	0.000	1765	0.000
1582	0.000	1628	0.000	1674	0.000	1720	0.000	1766	0.000
1583	0.000	1629	0.000	1675	0.000	1721	0.002	1767	0.006
1584	0.000	1630	0.000	1676	0.002	1722	0.002	1768	0.000
1585	0.000	1631	0.000	1677	0.000	1723	0.000	1769	0.000
1586	0.000	1632	0.000	1678	0.000	1724	0.000	1770	0.002
1587	0.000	1633	0.001	1679	0.000	1725	0.000	1771	0.000
1588	0.000	1634	0.000	1680	0.000	1726	0.000	1772	0.000

1773	0.000	1969	0.000	2015	0.000	2061	0.000	2107	0.000
1774	0.000	1970	0.000	2016	0.005	2062	0.000	2108	0.000
1775	0.000	1971	0.000	2017	0.002	2063	0.000	2109	0.000
1776	0.000	1972	0.000	2018	0.002	2064	0.000	2110	0.000
1777	0.000	1973	0.001	2019	0.000	2065	0.000	2111	0.000
1778	0.000	1974	0.000	2020	0.000	2066	0.000	2112	0.000
1779	0.000	1975	0.004	2021	0.000	2067	0.000	2113	0.000
1780	0.000	1976	0.000	2022	0.000	2068	0.000	2114	0.000
1781	0.000	1977	0.001	2023	0.000	2069	0.000	2115	0.000
1782	0.000	1978	0.000	2024	0.000	2070	0.000	2116	0.000
1783	0.000	1979	0.000	2025	0.001	2071	0.000	2117	0.000
1784	0.000	1980	0.000	2026	0.000	2072	0.000	2118	0.000
1785	0.000	1981	0.000	2027	0.000	2073	0.000	2119	0.000
1786	0.000	1982	0.001	2028	0.000	2074	0.000	2120	0.000
1787	0.000	1983	0.000	2029	0.000	2075	0.000	2121	0.000
1788	0.011	1984	0.000	2030	0.003	2076	0.000	2122	0.000
1789	0.000	1985	0.000	2031	0.000	2077	0.000	2123	0.000
1790	0.000	1986	0.000	2032	0.000	2078	0.000	2124	0.000
1791	0.000	1987	0.000	2033	0.001	2079	0.000	2125	0.000
1792	0.000	1988	0.000	2034	0.000	2080	0.000	2126	0.000
1793	0.001	1989	0.000	2035	0.000	2081	0.000	2127	0.001
1794	0.000	1990	0.000	2036	0.001	2082	0.000	2128	0.000
1795	0.002	1991	0.004	2037	0.000	2083	0.000	2129	0.000
1796	0.000	1992	0.000	2038	0.009	2084	0.000	2130	0.001
1797	0.000	1993	0.000	2039	0.000	2085	0.000	2131	0.002
1798	0.000	1994	0.000	2040	0.000	2086	0.000	2132	0.000
1799	0.000	1995	0.000	2041	0.000	2087	0.000	2133	0.000
1800	0.000	1996	0.000	2042	0.000	2088	0.000	2134	0.000
1951	0.000	1997	0.000	2043	0.000	2089	0.000	2135	0.000
1952	0.000	1998	0.002	2044	0.015	2090	0.000	2136	0.000
1953	0.000	1999	0.000	2045	0.000	2091	0.000	2137	0.000
1954	0.000	2000	0.000	2046	0.000	2092	0.000	2138	0.000
1955	0.000	2001	0.000	2047	0.000	2093	0.001	2139	0.000
1956	0.000	2002	0.000	2048	0.000	2094	0.000	2140	0.000
1957	0.000	2003	0.000	2049	0.000	2095	0.000	2141	0.000
1958	0.004	2004	0.000	2050	0.000	2096	0.000	2142	0.003
1959	0.000	2005	0.000	2051	0.002	2097	0.000	2143	0.000
1960	0.000	2006	0.000	2052	0.000	2098	0.000	2144	0.000
1961	0.000	2007	0.000	2053	0.000	2099	0.000	2145	0.000
1962	0.002	2008	0.000	2054	0.000	2100	0.000	2146	0.000
1963	0.000	2009	0.000	2055	0.000	2101	0.000	2147	0.000
1964	0.000	2010	0.000	2056	0.000	2102	0.000	2148	0.000
1965	0.000	2011	0.000	2057	0.000	2103	0.000	2149	0.002
1966	0.000	2012	0.000	2058	0.000	2104	0.000	2150	0.000
1967	0.000	2013	0.001	2059	0.000	2105	0.000	2151	0.000
1968	0.001	2014	0.004	2060	0.000	2106	0.000	2152	0.001

2153	0.000	2173	0.000	2193	0.000	2213	0.000	2233	0.000
2154	0.000	2174	0.000	2194	0.000	2214	0.006	2234	0.000
2155	0.000	2175	0.000	2195	0.000	2215	0.001	2235	0.000
2156	0.000	2176	0.000	2196	0.000	2216	0.000	2236	0.000
2157	0.000	2177	0.000	2197	0.000	2217	0.000	2237	0.000
2158	0.000	2178	0.000	2198	0.000	2218	0.000	2238	0.002
2159	0.000	2179	0.000	2199	0.000	2219	0.000	2239	0.000
2160	0.000	2180	0.000	2200	0.000	2220	0.000	2240	0.000
2161	0.004	2181	0.000	2201	0.005	2221	0.000	2241	0.000
2162	0.000	2182	0.001	2202	0.000	2222	0.000	2242	0.001
2163	0.000	2183	0.000	2203	0.000	2223	0.000	2243	0.000
2164	0.000	2184	0.000	2204	0.006	2224	0.000	2244	0.000
2165	0.000	2185	0.000	2205	0.000	2225	0.000	2245	0.000
2166	0.000	2186	0.000	2206	0.000	2226	0.000	2246	0.003
2167	0.000	2187	0.000	2207	0.000	2227	0.000	2247	0.000
2168	0.000	2188	0.000	2208	0.000	2228	0.000	2248	0.000
2169	0.000	2189	0.001	2209	0.000	2229	0.011	2249	0.000
2170	0.000	2190	0.000	2210	0.000	2230	0.000		
2171	0.004	2191	0.000	2211	0.000	2231	0.000		
2172	0.000	2192	0.000	2212	0.000	2232	0.000		

Sunflower:

W	importance
350	0.000
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574	0.000	620	0.000	666	0.000	712	0.000	758	0.000
575	0.000	621	0.000	667	0.000	713	0.000	759	0.000
576	0.000	622	0.000	668	0.000	714	0.000	760	0.000
577	0.000	623	0.000	669	0.000	715	0.000	761	0.000
578	0.000	624	0.000	670	0.000	716	0.000	762	0.000
579	0.000	625	0.000	671	0.005	717	0.000	763	0.000
580	0.000	626	0.000	672	0.000	718	0.000	764	0.000
581	0.000	627	0.000	673	0.000	719	0.000	765	0.000
582	0.000	628	0.000	674	0.000	720	0.000	766	0.000
583	0.000	629	0.000	675	0.004	721	0.000	767	0.000
584	0.000	630	0.003	676	0.001	722	0.000	768	0.000
585	0.000	631	0.001	677	0.008	723	0.001	769	0.000
586	0.000	632	0.000	678	0.000	724	0.000	770	0.000
587	0.000	633	0.000	679	0.016	725	0.000	771	0.000
588	0.000	634	0.000	680	0.000	726	0.000	772	0.000
589	0.000	635	0.000	681	0.000	727	0.000	773	0.000
590	0.000	636	0.000	682	0.000	728	0.000	774	0.001
591	0.000	637	0.000	683	0.000	729	0.018	775	0.033
592	0.000	638	0.000	684	0.000	730	0.033	776	0.000
593	0.000	639	0.000	685	0.000	731	0.000	777	0.000
594	0.000	640	0.000	686	0.000	732	0.666	778	0.000
595	0.000	641	0.000	687	0.000	733	0.006	779	0.000
596	0.000	642	0.000	688	0.000	734	0.006	780	0.000
597	0.000	643	0.000	689	0.000	735	0.000	781	0.000
598	0.000	644	0.000	690	0.000	736	0.000	782	0.002
599	0.000	645	0.000	691	0.000	737	0.000	783	0.000
600	0.000	646	0.000	692	0.000	738	0.000	784	0.000
601	0.000	647	0.000	693	0.000	739	0.000	785	0.000
602	0.000	648	0.000	694	0.000	740	0.000	786	0.000
603	0.000	649	0.000	695	0.000	741	0.000	787	0.000
604	0.000	650	0.000	696	0.000	742	0.000	788	0.000
605	0.000	651	0.000	697	0.000	743	0.000	789	0.000
606	0.000	652	0.000	698	0.000	744	0.000	790	0.000
607	0.000	653	0.000	699	0.000	745	0.000	791	0.000
608	0.000	654	0.000	700	0.000	746	0.000	792	0.000
609	0.002	655	0.000	701	0.000	747	0.000	793	0.000
610	0.000	656	0.000	702	0.000	748	0.000	794	0.000
611	0.000	657	0.000	703	0.000	749	0.000	795	0.000
612	0.000	658	0.000	704	0.000	750	0.000	796	0.000
613	0.000	659	0.001	705	0.000	751	0.000	797	0.000
614	0.000	660	0.000	706	0.000	752	0.001	798	0.000
615	0.000	661	0.000	707	0.000	753	0.000	799	0.000
616	0.000	662	0.000	708	0.000	754	0.003	800	0.000
617	0.000	663	0.000	709	0.000	755	0.000	801	0.000
618	0.000	664	0.000	710	0.000	756	0.000	802	0.000
619	0.000	665	0.000	711	0.000	757	0.000	803	0.000

804	0.000	850	0.000	896	0.000	942	0.003	988	0.000
805	0.000	851	0.000	897	0.000	943	0.000	989	0.000
806	0.000	852	0.000	898	0.000	944	0.000	990	0.000
807	0.000	853	0.000	899	0.000	945	0.000	991	0.000
808	0.000	854	0.000	900	0.000	946	0.000	992	0.000
809	0.000	855	0.000	901	0.000	947	0.000	993	0.000
810	0.000	856	0.000	902	0.003	948	0.000	994	0.000
811	0.000	857	0.000	903	0.000	949	0.000	995	0.000
812	0.000	858	0.000	904	0.000	950	0.000	996	0.001
813	0.000	859	0.000	905	0.000	951	0.000	997	0.000
814	0.004	860	0.000	906	0.000	952	0.000	998	0.000
815	0.000	861	0.000	907	0.000	953	0.000	999	0.000
816	0.000	862	0.000	908	0.000	954	0.000	1000	0.000
817	0.000	863	0.000	909	0.000	955	0.000	1001	0.000
818	0.000	864	0.000	910	0.000	956	0.000	1002	0.000
819	0.000	865	0.000	911	0.000	957	0.000	1003	0.000
820	0.000	866	0.000	912	0.000	958	0.000	1004	0.000
821	0.000	867	0.000	913	0.000	959	0.000	1005	0.000
822	0.000	868	0.000	914	0.000	960	0.000	1006	0.000
823	0.000	869	0.000	915	0.000	961	0.000	1007	0.000
824	0.000	870	0.000	916	0.000	962	0.000	1008	0.000
825	0.000	871	0.000	917	0.000	963	0.000	1009	0.001
826	0.000	872	0.000	918	0.000	964	0.000	1010	0.000
827	0.000	873	0.007	919	0.000	965	0.000	1011	0.000
828	0.000	874	0.000	920	0.000	966	0.000	1012	0.000
829	0.000	875	0.000	921	0.000	967	0.000	1013	0.000
830	0.000	876	0.000	922	0.000	968	0.000	1014	0.000
831	0.000	877	0.000	923	0.000	969	0.000	1015	0.000
832	0.000	878	0.000	924	0.000	970	0.000	1016	0.000
833	0.000	879	0.000	925	0.000	971	0.000	1017	0.000
834	0.000	880	0.000	926	0.000	972	0.000	1018	0.000
835	0.000	881	0.000	927	0.000	973	0.001	1019	0.000
836	0.000	882	0.000	928	0.000	974	0.000	1020	0.000
837	0.000	883	0.000	929	0.000	975	0.000	1021	0.000
838	0.000	884	0.000	930	0.000	976	0.000	1022	0.000
839	0.000	885	0.000	931	0.000	977	0.000	1023	0.000
840	0.000	886	0.000	932	0.000	978	0.000	1024	0.000
841	0.000	887	0.000	933	0.000	979	0.000	1025	0.000
842	0.000	888	0.000	934	0.000	980	0.000	1026	0.000
843	0.000	889	0.000	935	0.000	981	0.000	1027	0.000
844	0.000	890	0.000	936	0.000	982	0.000	1028	0.000
845	0.000	891	0.000	937	0.000	983	0.000	1029	0.000
846	0.000	892	0.000	938	0.000	984	0.000	1030	0.000
847	0.000	893	0.000	939	0.000	985	0.000	1031	0.000
848	0.000	894	0.000	940	0.000	986	0.000	1032	0.000
849	0.000	895	0.000	941	0.001	987	0.000	1033	0.000

1034	0.000	1080	0.000	1126	0.000	1172	0.000	1218	0.000
1035	0.000	1081	0.000	1127	0.000	1173	0.000	1219	0.000
1036	0.000	1082	0.000	1128	0.000	1174	0.000	1220	0.000
1037	0.000	1083	0.000	1129	0.000	1175	0.000	1221	0.000
1038	0.000	1084	0.000	1130	0.000	1176	0.000	1222	0.000
1039	0.000	1085	0.000	1131	0.000	1177	0.000	1223	0.000
1040	0.000	1086	0.000	1132	0.000	1178	0.000	1224	0.000
1041	0.000	1087	0.000	1133	0.000	1179	0.000	1225	0.000
1042	0.000	1088	0.000	1134	0.000	1180	0.000	1226	0.000
1043	0.000	1089	0.000	1135	0.000	1181	0.000	1227	0.000
1044	0.000	1090	0.000	1136	0.000	1182	0.000	1228	0.000
1045	0.000	1091	0.000	1137	0.000	1183	0.000	1229	0.000
1046	0.000	1092	0.000	1138	0.000	1184	0.000	1230	0.000
1047	0.000	1093	0.000	1139	0.000	1185	0.000	1231	0.000
1048	0.000	1094	0.000	1140	0.000	1186	0.000	1232	0.000
1049	0.000	1095	0.000	1141	0.000	1187	0.000	1233	0.000
1050	0.000	1096	0.000	1142	0.000	1188	0.000	1234	0.000
1051	0.001	1097	0.000	1143	0.000	1189	0.000	1235	0.000
1052	0.000	1098	0.000	1144	0.000	1190	0.000	1236	0.000
1053	0.000	1099	0.000	1145	0.000	1191	0.000	1237	0.000
1054	0.000	1100	0.000	1146	0.000	1192	0.000	1238	0.000
1055	0.000	1101	0.000	1147	0.000	1193	0.000	1239	0.000
1056	0.000	1102	0.000	1148	0.000	1194	0.000	1240	0.000
1057	0.000	1103	0.000	1149	0.000	1195	0.000	1241	0.000
1058	0.000	1104	0.000	1150	0.000	1196	0.000	1242	0.000
1059	0.000	1105	0.000	1151	0.000	1197	0.000	1243	0.000
1060	0.000	1106	0.000	1152	0.000	1198	0.000	1244	0.000
1061	0.000	1107	0.000	1153	0.000	1199	0.000	1245	0.000
1062	0.000	1108	0.000	1154	0.000	1200	0.000	1246	0.000
1063	0.000	1109	0.000	1155	0.000	1201	0.000	1247	0.000
1064	0.000	1110	0.000	1156	0.000	1202	0.000	1248	0.000
1065	0.000	1111	0.000	1157	0.000	1203	0.000	1249	0.000
1066	0.000	1112	0.000	1158	0.000	1204	0.000	1250	0.000
1067	0.003	1113	0.000	1159	0.000	1205	0.000	1251	0.000
1068	0.000	1114	0.000	1160	0.000	1206	0.000	1252	0.000
1069	0.000	1115	0.000	1161	0.000	1207	0.000	1253	0.000
1070	0.000	1116	0.000	1162	0.000	1208	0.000	1254	0.000
1071	0.000	1117	0.000	1163	0.000	1209	0.000	1255	0.000
1072	0.000	1118	0.000	1164	0.000	1210	0.000	1256	0.000
1073	0.000	1119	0.000	1165	0.000	1211	0.000	1257	0.000
1074	0.000	1120	0.000	1166	0.000	1212	0.000	1258	0.000
1075	0.000	1121	0.000	1167	0.000	1213	0.000	1259	0.000
1076	0.000	1122	0.000	1168	0.000	1214	0.000	1260	0.000
1077	0.000	1123	0.000	1169	0.000	1215	0.000	1261	0.000
1078	0.000	1124	0.000	1170	0.000	1216	0.000	1262	0.000
1079	0.001	1125	0.000	1171	0.000	1217	0.000	1263	0.000

1264	0.000	1310	0.000	1415	0.000	1461	0.000	1507	0.000
1265	0.000	1311	0.000	1416	0.000	1462	0.000	1508	0.000
1266	0.001	1312	0.000	1417	0.000	1463	0.000	1509	0.000
1267	0.001	1313	0.000	1418	0.000	1464	0.000	1510	0.000
1268	0.000	1314	0.000	1419	0.000	1465	0.000	1511	0.000
1269	0.000	1315	0.000	1420	0.000	1466	0.000	1512	0.000
1270	0.000	1316	0.000	1421	0.000	1467	0.000	1513	0.000
1271	0.000	1317	0.000	1422	0.000	1468	0.000	1514	0.000
1272	0.000	1318	0.000	1423	0.000	1469	0.000	1515	0.000
1273	0.000	1319	0.000	1424	0.000	1470	0.000	1516	0.000
1274	0.000	1320	0.000	1425	0.000	1471	0.000	1517	0.000
1275	0.000	1321	0.000	1426	0.000	1472	0.000	1518	0.000
1276	0.000	1322	0.000	1427	0.000	1473	0.000	1519	0.000
1277	0.000	1323	0.000	1428	0.000	1474	0.000	1520	0.000
1278	0.000	1324	0.000	1429	0.000	1475	0.000	1521	0.000
1279	0.000	1325	0.000	1430	0.000	1476	0.000	1522	0.000
1280	0.000	1326	0.000	1431	0.000	1477	0.000	1523	0.000
1281	0.000	1327	0.005	1432	0.000	1478	0.000	1524	0.000
1282	0.000	1328	0.000	1433	0.000	1479	0.000	1525	0.000
1283	0.000	1329	0.000	1434	0.000	1480	0.000	1526	0.000
1284	0.000	1330	0.000	1435	0.000	1481	0.000	1527	0.000
1285	0.000	1331	0.000	1436	0.000	1482	0.000	1528	0.000
1286	0.000	1332	0.000	1437	0.000	1483	0.000	1529	0.000
1287	0.000	1333	0.000	1438	0.000	1484	0.000	1530	0.000
1288	0.000	1334	0.000	1439	0.000	1485	0.000	1531	0.000
1289	0.000	1335	0.000	1440	0.000	1486	0.000	1532	0.000
1290	0.000	1336	0.000	1441	0.000	1487	0.000	1533	0.000
1291	0.000	1337	0.000	1442	0.002	1488	0.000	1534	0.000
1292	0.000	1338	0.000	1443	0.000	1489	0.000	1535	0.000
1293	0.000	1339	0.000	1444	0.000	1490	0.000	1536	0.000
1294	0.000	1340	0.000	1445	0.000	1491	0.000	1537	0.000
1295	0.000	1341	0.000	1446	0.000	1492	0.000	1538	0.000
1296	0.000	1342	0.000	1447	0.000	1493	0.000	1539	0.000
1297	0.000	1343	0.000	1448	0.000	1494	0.000	1540	0.000
1298	0.000	1344	0.000	1449	0.000	1495	0.000	1541	0.000
1299	0.000	1345	0.000	1450	0.000	1496	0.000	1542	0.000
1300	0.000	1346	0.000	1451	0.000	1497	0.000	1543	0.000
1301	0.000	1347	0.000	1452	0.000	1498	0.000	1544	0.000
1302	0.000	1348	0.000	1453	0.000	1499	0.000	1545	0.000
1303	0.000	1349	0.000	1454	0.000	1500	0.000	1546	0.000
1304	0.000	1350	0.000	1455	0.000	1501	0.000	1547	0.000
1305	0.000	1410	0.000	1456	0.000	1502	0.000	1548	0.000
1306	0.000	1411	0.000	1457	0.000	1503	0.000	1549	0.000
1307	0.000	1412	0.000	1458	0.000	1504	0.000	1550	0.000
1308	0.000	1413	0.000	1459	0.000	1505	0.000	1551	0.000
1309	0.000	1414	0.000	1460	0.000	1506	0.000	1552	0.000

1553	0.000	1599	0.000	1645	0.000	1691	0.000	1737	0.000
1554	0.000	1600	0.000	1646	0.000	1692	0.000	1738	0.000
1555	0.000	1601	0.000	1647	0.000	1693	0.000	1739	0.000
1556	0.000	1602	0.000	1648	0.000	1694	0.000	1740	0.000
1557	0.000	1603	0.000	1649	0.000	1695	0.000	1741	0.000
1558	0.000	1604	0.000	1650	0.000	1696	0.000	1742	0.000
1559	0.000	1605	0.000	1651	0.000	1697	0.000	1743	0.000
1560	0.000	1606	0.000	1652	0.000	1698	0.000	1744	0.000
1561	0.000	1607	0.000	1653	0.000	1699	0.000	1745	0.000
1562	0.000	1608	0.000	1654	0.000	1700	0.000	1746	0.000
1563	0.000	1609	0.000	1655	0.000	1701	0.000	1747	0.000
1564	0.000	1610	0.000	1656	0.000	1702	0.000	1748	0.000
1565	0.000	1611	0.000	1657	0.000	1703	0.000	1749	0.000
1566	0.000	1612	0.000	1658	0.000	1704	0.000	1750	0.000
1567	0.000	1613	0.000	1659	0.000	1705	0.000	1751	0.000
1568	0.000	1614	0.000	1660	0.000	1706	0.000	1752	0.000
1569	0.000	1615	0.000	1661	0.000	1707	0.000	1753	0.000
1570	0.000	1616	0.000	1662	0.000	1708	0.000	1754	0.000
1571	0.000	1617	0.000	1663	0.000	1709	0.000	1755	0.000
1572	0.000	1618	0.000	1664	0.000	1710	0.000	1756	0.001
1573	0.000	1619	0.000	1665	0.000	1711	0.000	1757	0.000
1574	0.000	1620	0.000	1666	0.000	1712	0.000	1758	0.000
1575	0.000	1621	0.000	1667	0.001	1713	0.000	1759	0.000
1576	0.000	1622	0.000	1668	0.000	1714	0.000	1760	0.000
1577	0.000	1623	0.000	1669	0.000	1715	0.000	1761	0.000
1578	0.000	1624	0.000	1670	0.000	1716	0.000	1762	0.000
1579	0.000	1625	0.000	1671	0.000	1717	0.000	1763	0.000
1580	0.000	1626	0.000	1672	0.000	1718	0.000	1764	0.000
1581	0.000	1627	0.000	1673	0.000	1719	0.000	1765	0.000
1582	0.000	1628	0.000	1674	0.000	1720	0.000	1766	0.000
1583	0.000	1629	0.000	1675	0.000	1721	0.000	1767	0.000
1584	0.000	1630	0.000	1676	0.000	1722	0.000	1768	0.000
1585	0.000	1631	0.000	1677	0.000	1723	0.000	1769	0.000
1586	0.000	1632	0.000	1678	0.000	1724	0.000	1770	0.000
1587	0.000	1633	0.000	1679	0.000	1725	0.000	1771	0.000
1588	0.000	1634	0.000	1680	0.000	1726	0.000	1772	0.000
1589	0.000	1635	0.001	1681	0.000	1727	0.000	1773	0.000
1590	0.000	1636	0.003	1682	0.000	1728	0.000	1774	0.000
1591	0.000	1637	0.000	1683	0.000	1729	0.000	1775	0.000
1592	0.000	1638	0.000	1684	0.000	1730	0.000	1776	0.000
1593	0.000	1639	0.000	1685	0.000	1731	0.000	1777	0.000
1594	0.000	1640	0.000	1686	0.000	1732	0.000	1778	0.000
1595	0.000	1641	0.000	1687	0.000	1733	0.000	1779	0.000
1596	0.000	1642	0.000	1688	0.000	1734	0.000	1780	0.000
1597	0.000	1643	0.000	1689	0.004	1735	0.000	1781	0.000
1598	0.000	1644	0.000	1690	0.000	1736	0.000	1782	0.000

1783	0.000	1979	0.000	2025	0.000	2071	0.000	2117	0.000
1784	0.000	1980	0.000	2026	0.000	2072	0.000	2118	0.000
1785	0.000	1981	0.000	2027	0.000	2073	0.000	2119	0.000
1786	0.000	1982	0.000	2028	0.000	2074	0.000	2120	0.000
1787	0.000	1983	0.000	2029	0.000	2075	0.000	2121	0.000
1788	0.000	1984	0.000	2030	0.000	2076	0.000	2122	0.000
1789	0.000	1985	0.000	2031	0.000	2077	0.000	2123	0.000
1790	0.000	1986	0.000	2032	0.000	2078	0.003	2124	0.002
1791	0.001	1987	0.000	2033	0.000	2079	0.000	2125	0.000
1792	0.000	1988	0.000	2034	0.000	2080	0.000	2126	0.002
1793	0.000	1989	0.001	2035	0.000	2081	0.000	2127	0.000
1794	0.000	1990	0.000	2036	0.005	2082	0.000	2128	0.000
1795	0.000	1991	0.000	2037	0.000	2083	0.000	2129	0.000
1796	0.000	1992	0.000	2038	0.000	2084	0.000	2130	0.000
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1799	0.000	1995	0.000	2041	0.004	2087	0.000	2133	0.000
1800	0.000	1996	0.000	2042	0.000	2088	0.000	2134	0.000
1951	0.000	1997	0.000	2043	0.000	2089	0.000	2135	0.000
1952	0.000	1998	0.000	2044	0.014	2090	0.000	2136	0.001
1953	0.000	1999	0.000	2045	0.000	2091	0.000	2137	0.000
1954	0.000	2000	0.000	2046	0.002	2092	0.000	2138	0.000
1955	0.000	2001	0.000	2047	0.000	2093	0.000	2139	0.000
1956	0.000	2002	0.000	2048	0.000	2094	0.000	2140	0.000
1957	0.000	2003	0.000	2049	0.000	2095	0.006	2141	0.000
1958	0.000	2004	0.000	2050	0.000	2096	0.000	2142	0.000
1959	0.000	2005	0.000	2051	0.000	2097	0.000	2143	0.000
1960	0.000	2006	0.000	2052	0.000	2098	0.000	2144	0.000
1961	0.000	2007	0.000	2053	0.000	2099	0.000	2145	0.000
1962	0.000	2008	0.000	2054	0.000	2100	0.000	2146	0.000
1963	0.000	2009	0.000	2055	0.000	2101	0.000	2147	0.000
1964	0.000	2010	0.000	2056	0.000	2102	0.000	2148	0.000
1965	0.000	2011	0.000	2057	0.000	2103	0.000	2149	0.000
1966	0.000	2012	0.000	2058	0.001	2104	0.000	2150	0.000
1967	0.000	2013	0.000	2059	0.000	2105	0.000	2151	0.000
1968	0.000	2014	0.000	2060	0.000	2106	0.000	2152	0.000
1969	0.000	2015	0.000	2061	0.000	2107	0.000	2153	0.000
1970	0.000	2016	0.000	2062	0.000	2108	0.000	2154	0.000
1971	0.000	2017	0.000	2063	0.000	2109	0.000	2155	0.000
1972	0.000	2018	0.000	2064	0.000	2110	0.000	2156	0.000
1973	0.000	2019	0.000	2065	0.000	2111	0.000	2157	0.000
1974	0.000	2020	0.001	2066	0.000	2112	0.000	2158	0.000
1975	0.000	2021	0.009	2067	0.000	2113	0.000	2159	0.000
1976	0.000	2022	0.000	2068	0.000	2114	0.000	2160	0.000
1977	0.000	2023	0.000	2069	0.000	2115	0.000	2161	0.004
1978	0.000	2024	0.008	2070	0.000	2116	0.000	2162	0.000

2163	0.000	2181	0.002	2199	0.000	2217	0.000	2235	0.000
2164	0.000	2182	0.000	2200	0.000	2218	0.000	2236	0.000
2165	0.000	2183	0.000	2201	0.000	2219	0.000	2237	0.000
2166	0.000	2184	0.000	2202	0.000	2220	0.000	2238	0.000
2167	0.000	2185	0.004	2203	0.000	2221	0.000	2239	0.000
2168	0.000	2186	0.000	2204	0.000	2222	0.000	2240	0.000
2169	0.000	2187	0.000	2205	0.000	2223	0.000	2241	0.000
2170	0.004	2188	0.000	2206	0.000	2224	0.000	2242	0.000
2171	0.004	2189	0.000	2207	0.000	2225	0.000	2243	0.000
2172	0.000	2190	0.000	2208	0.000	2226	0.000	2244	0.000
2173	0.000	2191	0.000	2209	0.000	2227	0.000	2245	0.000
2174	0.001	2192	0.002	2210	0.000	2228	0.000	2246	0.000
2175	0.000	2193	0.000	2211	0.000	2229	0.000	2247	0.000
2176	0.000	2194	0.000	2212	0.000	2230	0.000	2248	0.000
2177	0.000	2195	0.000	2213	0.000	2231	0.000	2249	0.000
2178	0.000	2196	0.000	2214	0.000	2232	0.000	2250	0.000
2179	0.000	2197	0.000	2215	0.000	2233	0.000		
2180	0.000	2198	0.000	2216	0.000	2234	0.000		

Regression

Corn:

W	importance	393	0.000	437	0.001	481	0.000	525	0.000
350	0.000	394	0.001	438	0.007	482	0.000	526	0.000
351	0.008	395	0.005	439	0.001	483	0.001	527	0.000
352	0.000	396	0.002	440	0.001	484	0.000	528	0.002
353	0.000	397	0.000	441	0.005	485	0.000	529	0.000
354	0.001	398	0.003	442	0.000	486	0.000	530	0.000
355	0.001	399	0.000	443	0.000	487	0.001	531	0.000
356	0.000	400	0.002	444	0.000	488	0.000	532	0.000
357	0.000	401	0.000	445	0.000	489	0.000	533	0.000
358	0.000	402	0.000	446	0.001	490	0.000	534	0.000
359	0.000	403	0.000	447	0.000	491	0.000	535	0.000
360	0.000	404	0.002	448	0.000	492	0.000	536	0.000
361	0.000	405	0.009	449	0.000	493	0.000	537	0.000
362	0.000	406	0.000	450	0.000	494	0.000	538	0.000
363	0.002	407	0.000	451	0.000	495	0.000	539	0.003
364	0.001	408	0.000	452	0.000	496	0.000	540	0.000
365	0.000	409	0.000	453	0.000	497	0.002	541	0.002
366	0.000	410	0.000	454	0.001	498	0.000	542	0.000
367	0.002	411	0.003	455	0.000	499	0.000	543	0.000
368	0.005	412	0.000	456	0.000	500	0.000	544	0.000
369	0.000	413	0.004	457	0.000	501	0.000	545	0.000
370	0.006	414	0.000	458	0.000	502	0.000	546	0.000
371	0.000	415	0.000	459	0.000	503	0.000	547	0.002
372	0.000	416	0.000	460	0.000	504	0.000	548	0.000
373	0.000	417	0.001	461	0.000	505	0.001	549	0.005
374	0.000	418	0.001	462	0.000	506	0.000	550	0.001
375	0.000	419	0.000	463	0.000	507	0.000	551	0.000
376	0.000	420	0.000	464	0.014	508	0.000	552	0.000
377	0.000	421	0.000	465	0.001	509	0.000	553	0.047
378	0.000	422	0.000	466	0.000	510	0.000	554	0.001
379	0.000	423	0.000	467	0.002	511	0.000	555	0.000
380	0.001	424	0.000	468	0.000	512	0.000	556	0.001
381	0.000	425	0.001	469	0.000	513	0.000	557	0.230
382	0.000	426	0.022	470	0.000	514	0.000	558	0.001
383	0.000	427	0.000	471	0.000	515	0.000	559	0.000
384	0.000	428	0.001	472	0.000	516	0.000	560	0.001
385	0.004	429	0.003	473	0.000	517	0.001	561	0.002
386	0.000	430	0.014	474	0.004	518	0.000	562	0.000
387	0.000	431	0.000	475	0.000	519	0.000	563	0.000
388	0.001	432	0.000	476	0.006	520	0.000	564	0.000
389	0.002	433	0.000	477	0.002	521	0.000	565	0.000
390	0.000	434	0.000	478	0.000	522	0.000	566	0.000
391	0.000	435	0.000	479	0.000	523	0.000	567	0.000
392	0.000	436	0.000	480	0.000	524	0.000	568	0.000

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1632	0.000
1633	0.000
1634	0.000
1635	0.000
1636	0.000
1637	0.000
1638	0.000
1639	0.001
1640	0.000
1641	0.000
1642	0.000
1643	0.000
1644	0.000
1645	0.000
1646	0.000
1647	0.000
1648	0.000
1649	0.000
1650	0.000
1651	0.000
1652	0.000
1653	0.000
1654	0.000
1655	0.000
1656	0.000
1657	0.000
1658	0.000
1659	0.000
1660	0.000
1661	0.000
1662	0.000
1663	0.000
1664	0.000
1665	0.000
1666	0.000
1667	0.000
1668	0.000
1669	0.000
1670	0.001
1671	0.011
1672	0.000
1673	0.001
1674	0.000
1675	0.000
1676	0.000
1677	0.000
1678	0.000
1679	0.000
1680	0.000
1681	0.000
1682	0.000
1683	0.000
1684	0.000
1685	0.000
1686	0.000
1687	0.001
1688	0.000
1689	0.000
1690	0.000
1691	0.000
1692	0.000
1693	0.000
1694	0.000
1695	0.000
1696	0.000
1697	0.000
1698	0.000
1699	0.000
1700	0.000
1701	0.000
1702	0.000
1703	0.000
1704	0.000
1705	0.000
1706	0.000
1707	0.000
1708	0.000
1709	0.000
1710	0.000
1711	0.000
1712	0.000
1713	0.001
1714	0.000
1715	0.000
1716	0.000
1717	0.000
1718	0.000
1719	0.001
1720	0.000
1721	0.000
1722	0.001
1723	0.000
1724	0.000
1725	0.000
1726	0.003
1727	0.000
1728	0.000
1729	0.001
1730	0.000
1731	0.000
1732	0.000
1733	0.000
1734	0.000
1735	0.000
1736	0.002
1737	0.001
1738	0.000
1739	0.000
1740	0.000
1741	0.000
1742	0.000
1743	0.000
1744	0.000
1745	0.000
1746	0.000
1747	0.000
1748	0.003
1749	0.002
1750	0.000
1751	0.000
1752	0.000
1753	0.000
1754	0.000
1755	0.000
1756	0.000
1757	0.000
1758	0.000
1759	0.000
1760	0.000
1761	0.000
1762	0.000
1763	0.000
1764	0.001
1765	0.000
1766	0.000
1767	0.005
1768	0.000
1769	0.000
1770	0.000
1771	0.000
1772	0.000
1773	0.000
1774	0.000
1775	0.000
1776	0.000
1777	0.000
1778	0.000
1779	0.000
1780	0.000
1781	0.000
1782	0.000

1783	0.000	1979	0.001	2025	0.000	2071	0.000	2117	0.000
1784	0.000	1980	0.000	2026	0.000	2072	0.000	2118	0.000
1785	0.000	1981	0.000	2027	0.001	2073	0.000	2119	0.000
1786	0.001	1982	0.001	2028	0.001	2074	0.001	2120	0.000
1787	0.000	1983	0.000	2029	0.000	2075	0.000	2121	0.000
1788	0.001	1984	0.000	2030	0.000	2076	0.000	2122	0.001
1789	0.000	1985	0.000	2031	0.000	2077	0.000	2123	0.000
1790	0.000	1986	0.000	2032	0.000	2078	0.000	2124	0.001
1791	0.000	1987	0.006	2033	0.000	2079	0.000	2125	0.000
1792	0.000	1988	0.000	2034	0.004	2080	0.000	2126	0.008
1793	0.000	1989	0.000	2035	0.000	2081	0.000	2127	0.003
1794	0.000	1990	0.001	2036	0.000	2082	0.005	2128	0.000
1795	0.002	1991	0.000	2037	0.001	2083	0.001	2129	0.000
1796	0.001	1992	0.000	2038	0.000	2084	0.000	2130	0.001
1797	0.001	1993	0.000	2039	0.000	2085	0.000	2131	0.000
1798	0.000	1994	0.000	2040	0.000	2086	0.000	2132	0.000
1799	0.000	1995	0.002	2041	0.000	2087	0.002	2133	0.000
1800	0.000	1996	0.008	2042	0.000	2088	0.001	2134	0.000
1951	0.000	1997	0.000	2043	0.000	2089	0.000	2135	0.000
1952	0.000	1998	0.001	2044	0.000	2090	0.000	2136	0.000
1953	0.000	1999	0.001	2045	0.000	2091	0.000	2137	0.001
1954	0.000	2000	0.002	2046	0.000	2092	0.000	2138	0.000
1955	0.000	2001	0.000	2047	0.000	2093	0.000	2139	0.000
1956	0.001	2002	0.001	2048	0.000	2094	0.000	2140	0.002
1957	0.000	2003	0.000	2049	0.000	2095	0.004	2141	0.000
1958	0.000	2004	0.001	2050	0.000	2096	0.000	2142	0.000
1959	0.000	2005	0.000	2051	0.000	2097	0.000	2143	0.000
1960	0.001	2006	0.000	2052	0.001	2098	0.007	2144	0.000
1961	0.001	2007	0.002	2053	0.000	2099	0.003	2145	0.000
1962	0.000	2008	0.000	2054	0.000	2100	0.001	2146	0.001
1963	0.000	2009	0.001	2055	0.000	2101	0.001	2147	0.000
1964	0.002	2010	0.003	2056	0.000	2102	0.000	2148	0.001
1965	0.000	2011	0.000	2057	0.001	2103	0.000	2149	0.001
1966	0.000	2012	0.000	2058	0.000	2104	0.000	2150	0.000
1967	0.000	2013	0.000	2059	0.000	2105	0.000	2151	0.000
1968	0.000	2014	0.001	2060	0.001	2106	0.000	2152	0.000
1969	0.007	2015	0.001	2061	0.000	2107	0.000	2153	0.001
1970	0.000	2016	0.002	2062	0.000	2108	0.000	2154	0.000
1971	0.000	2017	0.000	2063	0.000	2109	0.000	2155	0.000
1972	0.000	2018	0.001	2064	0.000	2110	0.000	2156	0.000
1973	0.000	2019	0.000	2065	0.000	2111	0.000	2157	0.000
1974	0.007	2020	0.000	2066	0.000	2112	0.000	2158	0.000
1975	0.000	2021	0.000	2067	0.000	2113	0.000	2159	0.000
1976	0.000	2022	0.011	2068	0.000	2114	0.000	2160	0.000
1977	0.001	2023	0.001	2069	0.000	2115	0.000	2161	0.001
1978	0.000	2024	0.001	2070	0.000	2116	0.000	2162	0.000

2163	0.002
2164	0.001
2165	0.000
2166	0.000
2167	0.001
2168	0.000
2169	0.000
2170	0.000
2171	0.000
2172	0.000
2173	0.001
2174	0.000
2175	0.000
2176	0.000
2177	0.003
2178	0.000
2179	0.000
2180	0.000
2181	0.000
2182	0.001
2183	0.000
2184	0.000
2185	0.000
2186	0.000
2187	0.000
2188	0.000
2189	0.000
2190	0.000
2191	0.000
2192	0.000
2193	0.000
2194	0.000
2195	0.000
2196	0.000
2197	0.000
2198	0.000
2199	0.000
2200	0.000
2201	0.000
2202	0.000
2203	0.000
2204	0.001
2205	0.000
2206	0.000
2207	0.000
2208	0.000

2209	0.001
2210	0.000
2211	0.000
2212	0.000
2213	0.001
2214	0.000
2215	0.000
2216	0.000
2217	0.000
2218	0.000
2219	0.000
2220	0.001
2221	0.000
2222	0.000
2223	0.002
2224	0.000
2225	0.000
2226	0.000
2227	0.000
2228	0.000
2229	0.000
2230	0.001
2231	0.000
2232	0.000
2233	0.000
2234	0.000
2235	0.002
2236	0.000
2237	0.000
2238	0.000
2239	0.000
2240	0.000
2241	0.000
2242	0.001
2243	0.000
2244	0.000
2245	0.000
2246	0.001
2247	0.000
2248	0.000
2249	0.000
2250	0.001

APPENDIX F. CHEMICALS DETAILS

Experiment 1		
Chemical	solvent	MOA
Control 1- not treated	-	
Control 2- Water (DDW)	DDW	
Control 3 - Solvent	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	
Amitrole	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Pigment metabolism
Isoxaflutole	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Pigment metabolism
sulcotrione	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Pigment metabolism
Glufosinate-ammonium	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Nitrogen metabolism
Benfuresate	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Lipid metabolism
Clethodim	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Lipid metabolism
Cycloxydim	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Lipid metabolism
Haloxyfop	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Lipid metabolism
Pinoxaden	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Lipid metabolism
Tepraloxoxydim	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Lipid metabolism
Paraquat	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Inhibition of photosynthesis PSII
Diuron	49.5% Acetone; 39% water; 10% Isopropyl alcohol ; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Inhibition of photosynthesis
Saflufenacil	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Inhibition of photosynthesis
Oxyfluorfen	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Inhibition of photosynthesis
Asulam	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Folic acid metabolism
indaziflam	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Cell wall metabolism

Chlorsulfuron	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Amino acid metabolism
Flucarbazone-sodium	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Amino acid metabolism
Imazapyr	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Amino acid metabolism
Pyriftalid	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Amino acid metabolism
glyphosate	DDW	Amino acid metabolism
florasulam	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba	Amino acid metabolism

Experiment 2	
Chemical	solvent
Cycloxydim	49.5% Acetone; 39% water; 10% Isopropyl alcohol; 1.5% DMSO; 0.02% Tergitol 15-S-7; 1% Romba

APPENDIX G. SEGMENTATION ALGORITHM

```
import numpy as np
from spectral import *
import glob
import cv2

def NDVI(img):
    red = img.read_band(100) # 680nm
    nir = img.read_band(124) # 750nm
    img1 = (nir - red) / (nir + red)
    return img1

def Mask(NDVIIImage):
    Mask = NDVIIImage
    height = Mask.shape[0]
    width = Mask.shape[1]
    # threshold = 0.4
    threshold = 0.05
    for i in np.arange(height):
        for j in np.arange(width):
            a = Mask.item(i, j)
            if a > threshold:
                b = a
            else:
                b = 0
            Mask.itemset((i, j), b)
    median = cv2.medianBlur(Mask, 9)
    return median

def ApplyAllImage(img, MaskImage):
    for h in range(img.shape[0]):
        for w in range(img.shape[1]):
            if MaskImage[h,w] == 0:
                for i in range(210):
                    img.itemset((h, w, i), 0)
    return img

def segmentation(img, name):
    NDVIIImage = NDVI(img)
    # img2 = imshow(NDVIIImage)
    MaskImage = Mask(NDVIIImage)
    # img2 = imshow(MaskImage)
    # temp = scipy.ndimage.measurements.label(MaskImage)
    # temp = np.fft.fft2(MaskImage)
    NewImage = ApplyAllImage(img, MaskImage)
```

```

envi.save_image(name, NewImage, dtype=np.float32)
return NewImage

def getOutputName(input, plant, date, plot):
    input1 = input[0:8]
    if plant == "corn":
        output = input1 + "SegmentImages/" + date + "/corn/" + plot + ".hdr"
    else:
        output = input1 + "SegmentImages/" + date + "/sf/" + plot + ".hdr"
    return output

def GetPlot(input, plant):
    if plant == "corn":
        plot = input[43:len(input)-4]
    else:
        plot = input[45:len(input)-4]#maby 41
    return plot

#main
if __name__ == "__main__":
    Path = "E:/Hyperspectral/Exp2/croppedReflectance"
    dates = ["181106", "181113", "181115"]
    dates = ["181106"]
    plants = ["corn", "sf"]
    plants = ["corn"]
    for d in dates:
        for p in plants:
            AllPathes = glob.glob(Path+"/"+d+"/"+p+"/*.hdr")
            for filename in AllPathes:
                plot = GetPlot(filename, p)
                img = envi.open(filename).load()
                output = getOutputName(filename, p, d, plot)
                img_seg = segmentation(img, output)
                print(1)
            print(0)

```

תקציר

הערכת פונטיפים עבור מספר רב של צמחים משלבת אמצעי חישה מתקדמים עם אלגורתמייה. אחתמן המשימות החשובות בתחום זה היא איתור עקה אビוטית בצמח. עבודה זו מתמקדת בזיהוי עקה אבוטית בצמח תירס וחמניה באמצעות החרזר הספקטורי של העלים בתחום האור הנראה, האינפרא האדום הקרוב וכן האינפרא האדום הקצר. שני סוגי מודלים פותחו: מודלים לסייע ביןארי להבחנה בין צמחים בריאים וצמחים תחת עקה אבוטית וכן מודלי וגרסיה לחיזוי חומרת העקה בצמח.

70 צמחי תירס ו 70 צמחי חמניה אשר גודלו בחממה רוסטו בקוטלי העשבים במטרה ליצור עקה אבוטית. קוטלי העשבים השתיכו לקבוצות שונות של חומרים המפריעות למנגנוןים שונים בצמח. ההחרזר הספקטורי של עלי הצמחים נמדד באמצעות ספקטרומטר בעל רזולוציה ספקטוריית של 3 ננומטר עד תחום האינפרא הקרוב וכן 8 ננומטר בתחום האינפרא הקצר, כולל של 350-2500 ננומטר. המדידות נערכו בשש נקודות זמן לאורך 30 ימים. אגרונים מומחה העירך ביום אחד-עשר פונטיפים ויוזאלים אשר סוכמו לשני ערכים: מצב פונטיפי (צמח תחת עקה או לא) וממצע פונטיפי (חומרת העקה).

הניסוי נערך בשתי שנים עוקבות (2018 ו 2019). מודלים לסייע וגרסיה נבנו ונבחנו על המדידות משנת 2018 וכן נבחנו בשנית על מדידות משנת 2019.

המודלים לסייע ביןארי כללו וגרסיה לוגיסטיבית באמצעות אורכי גל, PCA, PLS, XGBoost, DA, יער אקראי וכן אלגוריתם XGBoost. כל המודלים הללו פותחו על נתונים הנגזרת הראשונה של הספקטרום האלקטרומגנטי. מודלים לחיזוי חומרת העקה כללו וגרסיה ליניארית באמצעות אורכי גל אחד וכן באמצעות שבעה אורכי גל, PCA, PLS, יער אקראי וכן אלגוריתם XGBoost.

התוצאות הטובות ביותר הושגו באמצעות אלגוריתם היער האקראי (random forest) עם F1 של 88% לסייע צמחי התירס וכן 92% לסייע צמחי החמניה, RMSE של 0.221-0.190 להערכת חומרת העקה בצמח התירס וחמניה בהתאם. מודלים אילו הניבו F1 של 79.9% וכן RMSE של 0.243 על דגימות התירס בשנה שלאחר מכן. המודלים שפותחו בערת וגרסיה לוגיסטיבית וכן וגרסיה ליניארית הניבו תוצאות דומות על הנגזרת הראשונה של הספקטרום באמצעות שבעה אורכי גל. F1 של 79.9% ו 94.7% למשימת הסיוג וכן RMSE של 0.249 ו 0.222 למשימת הרגסיה לצמחי תירס וחמניה בהתאם. תוצאות האימוט שניה לאחר מכן RMSE 0.269 ו F1 76.4%.

מילות מפתח: עקה אבוטית, פונטיפים, וגרסיה ליניארית, וגרסיה לוגיסטיבית, PCA, PLS, DA-PLS, לימוד מכונה, random forest, machine learning, XGBOOST, תירס, חמניה, קלאלות מדיקט, ספקטרוסקופיה.

אוניברסיטת בן-גוריון בנגב
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על ידי מידע ספקטRALI**

חיבור זה מהווה חלק מהדרישות לקבלת תואר מגיסטר בהנדסה

מאת: שחר גד שרייקי

מנחים: פרופסור יעל אידן
פרופסור ויקטור אלחנתי

תאריך...24.2.2020

חתימת המחבר.....
nel

תאריך...24.2.2020

אישור המנחה/ים.....
Yael Eden

תאריך...24.2.2020

.....
עקבות נקי

תאריך...24.2.2020

אישור י"ר ועדת תואר שני מחלקטית.....
וועדת תואר שני מחלקטית

פברואר, 2020

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