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Research Article

Remote sensing and field analysis of *Erwinia amylovora* on quince

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Abstract

Fire blight is responsible for significant losses and affects production quality in all growing countries worldwide, including Romania. Despite the availability of various prevention and control strategies, their practical effectiveness has been notably limited, and no viable technologies have yet emerged. This research aims to investigate the impact of climatic conditions, genetic material and cultivation methods on the intensity of *Erwinia amylovora* attack on quince by using field determination techniques and satellite sensor systems. Over three years in a quince orchard naturally infected with *E. amylovora*, Normalized Difference Vegetation Index (NDVI) and Normalized Difference Red Edge (NDRE) indices were tested along with analyses of attack intensity (I), degree of attack (DA) and frequency (F). The results obtained showed that the genetic sensitivity and/or tolerance of the varieties is essential, together with the specific local climatic conditions. The two analyzed varieties ('Bereczky' and 'Aurii') cultivated under organic technology, showed different levels of tolerance to fire blight. While a significant correlation exists between the two vegetation indices, NDRE demonstrates higher accuracy due to its ability to conduct spectral analyses within the plant canopy. Furthermore, NDRE values closely align with those observed through assessments of attack intensity and frequency in the orchard.

Keywords: climatic conditions; fire blight; frequency and intensity of attack; NDRE; NDVI

Introduction

Precision agriculture aims to improve crop yields and minimize losses caused by different types of stress, using sensors, remote sensing and information technologies (Solano Alvarez *et al.*, 2022). At the same time, through precision agriculture, it is possible to monitor crops through satellite systems, with the provision of images and eEdge, information that characterizes the state of plant vegetation through indices such as: Normalized Difference Vegetation Index (NDVI), Normalized Difference Red Edge (NDRE), Green

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Normalized Difference Vegetation (GNDVI), or their relationship to the soil; Modified Vegetation Index Adjusted for Soil (MSAVI), normalized differential index of soil salinity (NDSI), to mention just a few of them.

In modern times, remote sensing technology has become essential in detecting changes in crop growth and development analysis over large areas and time frames (Weiss *et al.*, 2020; Liu *et al.*, 2024; Aziz *et al.*, 2025; Liu *et al.*, 2025). This method offers a set of benefits compared to traditional field analyses, including large-area monitoring, continuous spatial and temporal data, reduced costs (Fuentes-Peñailillo *et al.*, 2024; Kannan *et al.*, 2025) and successful identification of crop distribution.

Therefore, precision agriculture requires the collection of a significant amount of information about the environmental conditions and technology of crops to analyze them and provide innovative analysis tools (Karthikeyan 2020; Singh *et al.*, 2020; Kendall *et al.*, 2022; Vellingiri *et al.*, 2025). The monitoring of biotic stressors, especially plant diseases and pests by remote sensing provides the possibility of rapid identification of diseases on a large scale, which has the advantages of being timely, user-friendly, extensive, non-destructive and objective (Zhao *et al.*, 2020; Zevgolis *et al.*, 2023; Sen *et al.*, 2025). Remote sensing has been used to recognize, examine and evaluate a variety of diseases affecting a multitude of cultivated species. In this regard, detailed studies have been published on the use of sensor systems in the detection and evaluation of plant disease intensity (Oerke, 2020; Terentev *et al.*, 2022; Shahi *et al.*, 2023; Huang *et al.*, 2025)

Remote sensing determines vegetation bio parameters through spectral reflectance characteristics. A VI can be an indicator to describe the amount of chlorophyll pigments, the density and the health of the crop. One way to obtain the biophysical parameters of crops is to measure the basic data that takes samples from vegetation. Vegetation indices (VIs), calculated from satellite data and imagery, offer a practical approach to acquiring vegetation biophysical parameters at large spatial scales while ensuring comprehensive temporal coverage (Mazzia *et al.*, 2020; Amankulova *et al.*, 2023; Gong *et al.*, 2024).

Various advanced detection approaches are being used to monitor and diagnose plant diseases, aiming to provide precise assessments. Recent advances, particularly in hyperspectral spectroscopy (HS), have offered promising methods for accurate disease diagnosis and evaluation of attack intensity and frequency (Genangeli *et al.*, 2022; Martinelli *et al.*, 2024; Reis Perreira *et al.*, 2024).

The increased prevalence and rapid spread of phytobacterial diseases are facilitated by climate change, increased international trade and immigration, and the emergence of new pesticide resistance traits (Xu *et al.*, 2021).

Fire blight is a destructive necrotic disease that affects fruit species of the Rosaceae family, such as apples (*Malus domestica*), pears (Pyrus *communis*) and quince (*Cydonia oblonga*) with significant economic and ecological impact, representing a key concern for numerous research groups around the world (Pel *et al.*, 2021). *Erwinia amylovora*, known as fire blight of rosacea, is a well-studied plant pathogen. It survives as an endophyte or epiphyte in different plant organs, including those of asymptomatic hosts, making it's spread difficult to control (Viljevac *et al.*, 2009). In recent years, economic losses caused by fire blight outbreaks in fruit species have ranged from \$500 million to \$800 million, with crop losses ranging from 25 to 50% depending on the climatic conditions of each year (Sălceanu *et al.*, 2023).

Periodic epidemics exacerbate the ongoing spread of this disease. It has been documented in primary apple and pear-producing areas across North and Central America, Europe, New Zealand, Egypt, and Western Asia. In Europe, the disease was initially identified in 1957 in England; since then, it has disseminated to most European countries (van der Zwet and Keil, 1979).

The pathogen's activity is increasing due to hot, humid spring climates (Ault *et al.*, 2015; Wallis and Cox, 2020). Recent research carried out in the USA has shown that a 0.09 °C increase in temperature and precipitation of 10 mm per decade, associated with a 70% intensification of short periods of heavy rainfall, facilitates the formation of periods of 3-7 days with high potential for fire blight infection according to developed prediction models, often reaching very high values in just a few days, and allowing 3 to 9 fire blight infection events during flowering (Philion and Trapman, 2011*;* Rougerie-Durocher *et al.*, 2020).

While studies show that fire blight requires specific environmental conditions for cell movement and growth (Gusberti *et al.*, 2015; Dagher *et al.*, 2020; Sun *et al.*, 2023), weather is not the only factor involved. A growing body of evidence suggests that microbial communities residing in flowers may play a crucial role in the early stage of host colonisation, when *E. amylovora* proliferates on stigmatised surfaces (Cui *et al*. 2021).

Favorable weather is a key factor in rising disease incidence. Air humidity affects the population size of *E. amylovora* during flower colonization (Philion and Trapman, 2011) while temperature is also a key factor in the development of the disease (Pedroncelli and Puopollo, 2024).

E. amylovora grows best at 28 °C but remains pathogenic even at 14 °C and 4 °C; although cell growth slows at lower temperatures, infection still occurs (Santander *et al.* 2017; Pimentel, 2021). In addition, rainy weather and sluggish air currents play a key role in creating a suitable environment for *E. amylovora* cells to multiply; however, flower moisture can also be provided by dew that occurs at night and in the morning (Slack *et al.*, 2022; Pedroncelli and Puopolo, 2024).

The successful establishment of *E. amylovora* in plant flowers is influenced by humidity, temperature, and air currents. To survive adverse conditions such as drought, heat, or cold, the pathogen employs self-protection strategies like synthesizing protective chemicals and activating stress response mechanisms (MacLean *et al.*, 2025).

When pathogens attack plants, they quickly accumulate phenolic compounds at the infection site to contain the pathogen and disrupt its vital biochemical processes (Iakimova *et al.*, *2013*; Fallah *et al.*, 2025; Zhang *et al.*, 2025). For example, some phenolic derivatives can react with pathogenic proteins, causing the loss of their enzymatic functions, thus suppressing the viability of pathogens (Markakis *et al.*, *2010*; Mendes *et al.*, 2024). Flavonoids have been described as having antibacterial, antitoxin, antiviral, and/or antifungal activities, and as being involved in structural defense (Treutter*,* 2005; Abd El-Hameid *et al.*, 2025).

Disease severity ranges from minimal or no symptoms in tolerant species and genotypes to increased susceptibility and significant impact, depending on species and cultivar (Viljevac *et al.*, 2009).

Remote sensing (RS) efficiently monitors fire blight damage by detecting canopy changes. It estimates vegetation bio parameters using spectral reflectance characteristics (Quiñones *et al.*, 2025). Vegetation indices (VI´s) combine surface reflectance from multiple wavelengths to emphasize specific vegetation, aiding in damage assessment. Various VI's are used to detect and map plant diseases (Vidican *et al.*, 2023) and some of them have been used in applications on bacterial diseases in plants, such as kiwi (Reis-Pereira *et al.*, 2023), rice (Das *et al.*, 2015), grapes (Al-Saddik *et al.*, 2017) or apple tree (Skoneczny *et al.*, 2020).

This study evaluates two VI's, the NDVI and NDRE, generated by Sentinel 2, for their effectiveness in detecting and assessing fire intensity in quince during the plant vegetation period, considering climatic conditions and data on frequency, intensity, and degree of occurrence in the orchard. Early identification of fire blight may facilitate appropriate technological interventions to control or limit the disease and minimise losses. We hypothesize that symptom severity results from interactions between environmental factors and genotype tolerance, measurable through changes in VI's, and of these, NDRE has the highest accuracy in predicting and evaluating the intensity of the fire blight attack in quince.

Therefore, the present study is novel because there are no known studies that analyze the relationship between the values of some VIs (NDVI and NDRE) and the intensity of fire blight attack on quinces, which gives the experimental results obtained in addition to the certain scientific value and special practical implications. The high accuracy of NDRE values can accurately establish early intervention measures in the prevention and control of the pathogen.

Materials and Methods

Experimental field

The experimental field is located just outside Jucu, Cluj County, Romania (46.859N, 23.794E), at an altitude of 310 m on gently sloped terrain. It covers 3 ha of quince: 1.5 ha of 'Bereczky' and 1.5 ha of 'Aurii' varieties (both at 4 x 4 m spacing). Established in autumn 2017, the plantation (Figure 1) has been certified organic.

Figure 1. Jucu experimental field (2023)

Monitoring data show that the disease's first clear symptoms appeared in 2020, with their frequency and severity varying by yearly climate conditions.

Evaluation of the frequency and intensity of the attack

The evaluation of infection and intensity of E. *amylovora* attack was carried out in the field under natural infestation. The assessment was conducted over three years (2020-2022), following the standard methodology recommended in the literature. For this purpose, the frequency (F%) and intensity (I%) of the attack were determined, and then, based on these results, the degree of attack (GA%) was calculated (Sestras *et al.*, 2008; Pârvu, 2010).

Between May and October of each experimental year, twenty trees from each variety were systematically evaluated for the frequency and severity of fire blight infection. Frequency assessment involved recording both the total number of one-year-old shoots per tree and the number of shoots exhibiting symptoms characteristic of fire blight.

The frequency of the attack (F%) was calculated for each tree, according to the formula.

F (%) = NBA / NTB × 100, were,

Nba - Number of 1-year-old branches affected

Ntb - Total number of 1-year-old branches per plant

The intensity of the attack (I%) represents the percentage of a plant or its organ that is attacked and is calculated using the formula.

I (%) = $\sum(i\ x\ f)/100$

i-percentage of damage of the 1-year branches,

f- the number of branches attacked in the same percentage.

Attack intensity is typically measured using a scale with 4 to 7 classes; in Romania, a 7-class system is standard. The classes correspond to these percentage ranges: 0-0%, 1-1-3%, 2-4-10%, 3-11-25%, 4-26-50%, 5-51-75%, and 6-76-100% (Sestras *et al*., 2011).

The degree of attack (DA %) quantifies the severity of the infestation, reflecting its extent across the crop or the total number of plants assessed. The GA value (%) were determined using the following equation:

DA (%) = F (%) x I (%) / 100

Based on DA (%) values, genotype responses to biotic stress are categorized as follows: 0 = no attack; 0.1-1.0 = very low; 1.1-5.0 = low; 5.1-10.0 = medium; 10.1-25.0 = strong; 25.1-50.0 = very strong; >50.0 = extremely strong (potential plant death, e.g., with *Erwinia amylovora*) (Simionca Mărcășan *et al*., 2023).

Satellite data acquisition

The MSI Sentinel-2A image from the European Space Agency's Sentinel Science Hub covers thirteen bands (433-2280 nm): four 10 m visible/NIR, six 20 m red-edge/NIR/SWIR, and three 60 m visible/NIR/SWIR bands. The narrow red edge bands at 703.9, 740.2, and 782.5 nm are useful for monitoring vegetation condition (Table 1).

Table 1. Sensors description (IDB - Show Bands for selected Sensors*)*

Name	Sentinel-2A
Bands	13
Spectrum [nm]	433-2280
Spat.Res. [m]	10-60
Inclination	98.6
Operator	ESA
Date of Launch	2015-06-23
Usable for Indices	yes

The sensor's high spectral resolution enables the assessment of disease effects at different stages (ESA 2025). The satellite mission produces two main products: Level-1C offers orthorectified peak atmospheric reflectance, including cloud and earth/water masks and sub-pixel multispectral data; Level-2A provides atmospherically corrected orthorectified reflectance with sub-pixel multispectral data (ESA User Handbook).

The vegetation indices

Normalized Difference Vegetation Index (NDVI)

NDVI is a widely utilized vegetation index in precision agriculture for assessing plant responses to stress conditions. Calculating NDVI involves applying linear algebra operations between NIR and RED radiation as described by the formula in Table 2.

Table 2. Index description (IDB - Information for Sensor and Index)

Name	Normalized Difference Vegetation Index
Abbreviation	NDVI
Formula	NIR−RED / NIR+RED
Variables	RED= [670;50;30], NIR= [800;10;10]
Expl. of Variables	RED = 620 at 700 nm (um 670 nm) NIR = ca. 800 nm
Wavelengths	670;50;30,800;10;10
Source	Original formula

NDVI ranges from -1 to 1, with healthy vegetation typically falling between 0.2 and 0.8. Negative values indicate water, while values near zero suggest bare soil, rock, or a lack of vegetation due to factors such as drought, fire, or pests (Nicoletti *et al*., 2024). NDVI measures the NIR reflectance of vegetation to quantify photosynthetic activity within each pixel. As a vegetation index, NDVI varies during plant growth and is affected by environmental and biological stressors as well as agricultural practices.

Normalized Difference Red Edge (NDRE)

The NDRE is a vegetation index used to assess chlorophyll activity, plant health, and nutrient needs, serving as an alternative to NDVI. NDRE utilises the near-infrared (NIR) spectral bands along with a band for the narrow range between the visible red transition zone and the red-NIR region (the red edge) (Table 3). For improved data accuracy, NDRE is often used in conjunction with NDVI. The red edge region can help identify vegetative stress and detect disease within the plant canopy, while NDVI typically assesses only the surface areas of vegetation.

The NDRE scale ranges from -1 to 1: values below 0.2 indicate no vegetation, 0.2-0.6 suggest diseased vegetation, and 0.6-1 signal healthy vegetation (EOS Data Analytics NDRE, 2023).

Table 3. Index description (IDB - Information for Sensor and Index)

Name	Normalized Difference Red-Edge
Abbreviation	NDRE
Formula	NIR−red edge / NIR+red edge
Wavelengths	690:730,780:1400
Source	Original formula

The collection and analysis of climate data was carried out using two sources, namely for the general climatic characterization of the studied area climateschart.net (https://climatecharts.net/) with monthly records, and for comparisons with the intensity of the attack and VI's the satellite data recorded daily.

Statistical analysis

The relationships between vegetation indices were analyzed through regression (linear and quadratic), the coefficient of determination (R^2), adjusted coefficient of determination (R^2_a) and the Pearson correlation coefficient (r). The significance of r value was expressed by symbols (***, **) according to associated p value.

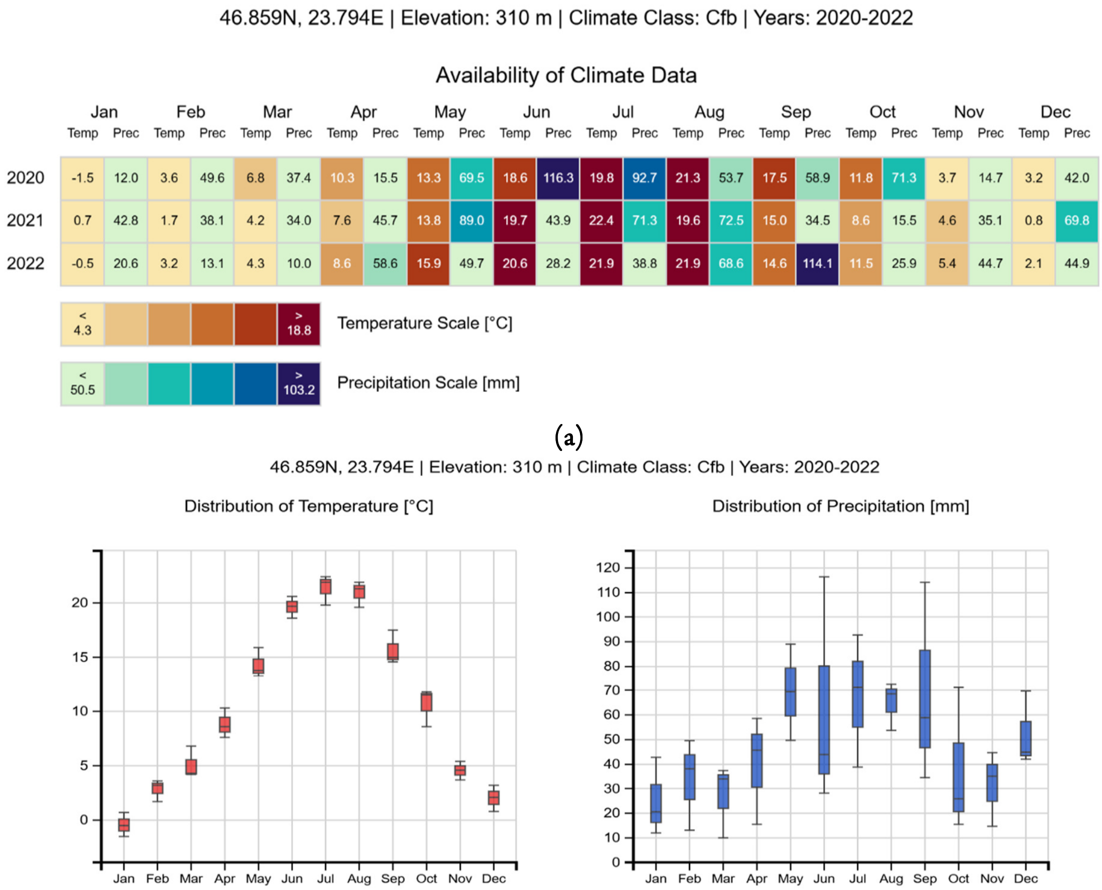
Results and Discussions

Climate overview for the study area and years

The characterization of the climatic conditions specific to the three years analysed (Table 1) highlights average daily temperature levels between -1.5 °C in January 2020 and 22.4 °C in July 2021. The analysis of climate data reveals an annual rainfall level of between 517.2 mm m^{-2} in 2022 and 633.6 mm m^{-2} in 2020. The temperature levels in the spring months were generally between 4 and 14 °C, with higher values in March 2020 and May 2022. For the summer months, the levels were between 18 and 21 °C, with lower values in June 2020 and higher values in August 2022.

The distribution of average daily temperatures (Figure 2) for the 2020-2022 experimental cycle indicates that temperatures were around 5 °C in March, increased to 10 °C in April, and reached 15 °C in May, reflecting an approximate rise of 5 °C between each month. During the summer months, the average daily temperature typically ranged from 19 °C to 22 °C, with notably higher values recorded in 2022 (Figure 2 a). In comparison, temperatures during the autumn and winter months remained relatively elevated across the three experimental years, varying from -1.5 °C in January to 17.5 °C in September 2020.

The climate varied over the three years, with monthly average temperatures and precipitation levels fluctuating significantly from month to month, season to season, and year to year (Figure 2 b).



46.859N, 23.794E | Elevation: 310 m | Climate Class: Cfb | Years: 2020-2022

Availability of Climate Data

	Jan		Feb		Mar		Apr		May		Jun		Jul		Aug		Sep		Oct		Nov		Dec	
	Temp	Prec	Temp	Prec	Temp	Prec	Temp	Prec	Temp	Prec	Temp	Prec	Temp	Prec	Temp	Prec	Temp	Prec	Temp	Prec	Temp	Prec	Temp	Prec
2020	-1.5	12.0	3.6	49.6	6.8	37.4	10.3	15.5	13.3	69.5	18.6	116.3	19.8	92.7	21.3	53.7	17.5	58.9	11.8	71.3	3.7	14.7	3.2	42.0
2021	0.7	42.8	1.7	38.1	4.2	34.0	7.6	45.7	13.8	89.0	19.7	43.9	22.4	71.3	19.6	72.5	15.0	34.5	8.6	15.5	4.6	35.1	0.8	69.8
2022	-0.5	20.6	3.2	13.1	4.3	10.0	8.6	58.6	15.9	49.7	20.6	28.2	21.9	38.8	21.9	68.6	14.6	114.1	11.5	25.9	5.4	44.7	2.1	44.9

(a)

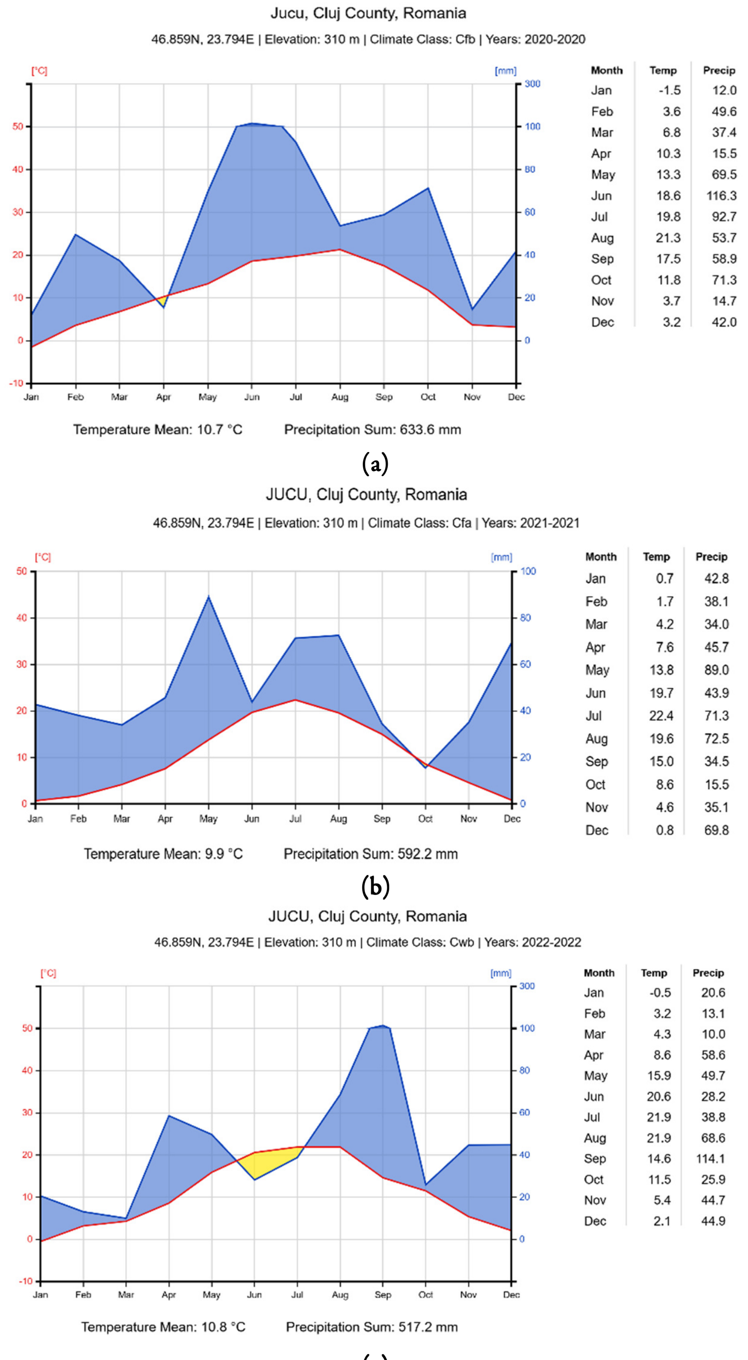
46.859N, 23.794E | Elevation: 310 m | Climate Class: Cfb | Years: 2020-2022

(b)

Figure 2. (a) Mean monthly temperature and precipitation data for the period 2020–2022 in Jucu; (b) Average daily temperatures (°C) and monthly precipitation (mm) in Jucu, Cluj County, 2020-2022 (Zepner *et al*., 2020; *ClimateCharts*)

In 2020 (Figure 3a), total recorded rainfall was 633.6 mm, with higher precipitation during June (116.3 mm m^{-2}), July (92.7 mm m^{-2}), April (69.5 mm m^{-2}), and November (71.3 mm m^{-2}). Average monthly temperatures ranged from -1.5 °C in January to 21.3 °C in August, with elevated temperatures observed in spring, summer, and autumn. Climate diagram analysis indicates a moisture deficit linked to higher temperatures in April, and increased rainfall in June and July.

In 2021, rainfall was abundant in April and May but low in June, September, and October (Figure 3b). Autumn was marked by moderate soil drought and higher-than-average monthly temperatures.



Month	Temp	Precip
Jan	-1.5	12.0
Feb	3.6	49.6
Mar	6.8	37.4
Apr	10.3	15.5
May	13.3	69.5
Jun	18.6	116.3
Jul	19.8	92.7
Aug	21.3	53.7
Sep	17.5	58.9
Oct	11.8	71.3
Nov	3.7	14.7
Dec	3.2	42.0

(a)

Month	Temp	Precip
Jan	0.7	42.8
Feb	1.7	38.1
Mar	4.2	34.0
Apr	7.6	45.7
May	13.8	89.0
Jun	19.7	43.9
Jul	22.4	71.3
Aug	19.6	72.5
Sep	15.0	34.5
Oct	8.6	15.5
Nov	4.6	35.1
Dec	0.8	69.8

(b)

Month	Temp	Precip
Jan	-0.5	20.6
Feb	3.2	13.1
Mar	4.3	10.0
Apr	8.6	58.6
May	15.9	49.7
Jun	20.6	28.2
Jul	21.9	38.8
Aug	21.9	68.6
Sep	14.6	114.1
Oct	11.5	25.9
Nov	5.4	44.7
Dec	2.1	44.9

(c)

Figure 3. Climate diagram of the experimental years 2020 (a), 2021 (b) and 2022 (c)

In 2022, rainfall was low, particularly during the early plant growth stages (Figure 3c). From winter's end to summer, persistent dry conditions and moderate soil drought persisted. Although September brought increased rainfall, it was insufficient to offset the earlier deficit.

Over the three years, climatic conditions varied significantly in temperature and precipitation, which often triggered fire blight outbreaks in the Jucu experimental field.

Evaluation of fire blight effects on quince plants using vegetation indices correlated with field measurements

The value of vegetable agricultural production is significantly diminished by disease attacks, with a greater intensity in recent decades. Effective management methods involve regular monitoring of plant health with early detection of pathogens to reduce the spread of disease. Traditionally, various techniques are used to diagnose plant diseases, most of them based on the destruction of plant tissue. By comparison, non-invasive techniques for identifying and assessing the intensity of disease attack are more feasible and practical ways to monitor plants, through real-time applications, without affecting tissue integrity (Meena *et al.*, 2020). To identify the disease, a series of biophysical parameters that characterize vegetation indices was determined.

NDVI and NDRE are VI's capable of providing information on the vegetative vigor of crops (D'Auria *et al.*, 2016; Daglio *et al.*, 2022; Kaur *et al.*, 2025). They are characterized by a high spatial and temporal variability, reflecting the impact of physicochemical and physiological parameters on plants (Padua *et al.*, 2019; Jang *et al.*, 2024; Hari Haran *et al.*, 2025).

The analysis of experimental data highlights that for 2020 (Figure 4), variable values of the analyzed vegetation indices correlated with precipitation and atmospheric humidity conditions. Thus, NDVI registered increases from 01.03 (0.11), reaching its peak in 29.06 (0.80), followed by a period of decline at the end of the second decade of July (0.42-0.45). The NDVI values then followed an upward curve starting with the end of June and throughout August, generally between 0.50 and 0.70, then a new decline occurred at the end of September and the first decade of October (0.37-0.41). NDRE generally recorded NDVI-like trends during 2020, but with around 30% lower values.

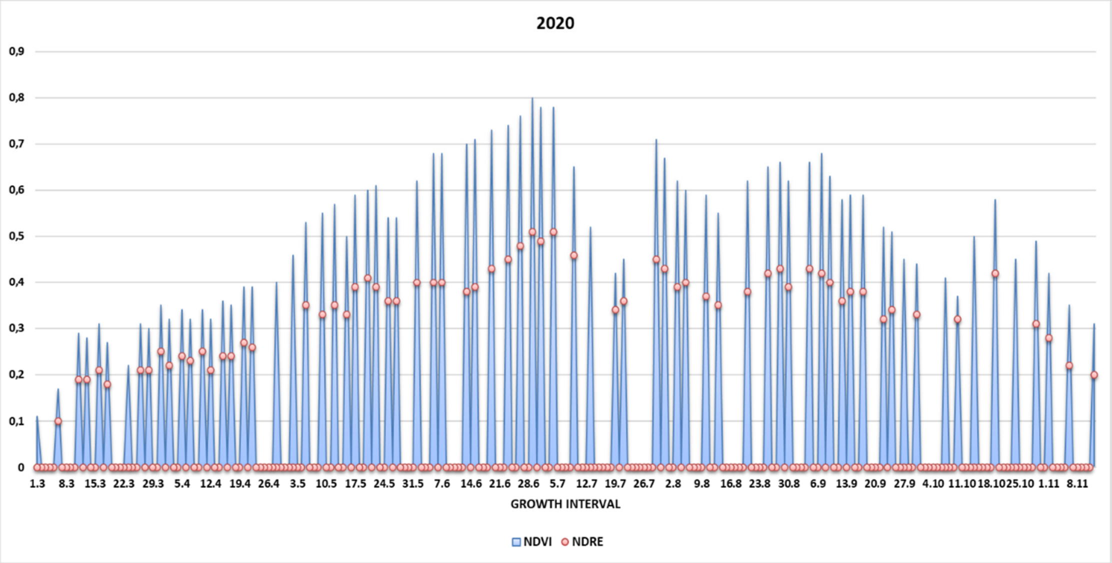


Figure 4. Comparative representation of VI's values in the experimental year 2020 at the quince plantation affected by fire blight

It is interesting to note that during periods of stress (July and October), the NDRE values are more closely aligned with the NDVI. Because the NDRE is a vegetation index with increased capacity to assess the vegetation state within the canopy, the values close to the NDVI suggest an intense attack of *E. amylovora* at the tree's depths. The comparison with the atmospheric humidity values shows that, in general, the low values of NDVI and NDRE are associated with high levels of vapor in the air, previously determined by a rich rainfall regime.

The correlation analysis between the NDVI and NDRE variation for the year 2020 shows that they are very significantly positive. The quadratic regressions express the differences between the parameters with an accuracy of 90.82% (Figure 5). Thus, it is observed that the minimum values of the two VI's are 0.1-0.2 superimposed on the period of plant onset (March), The maximum values (0.5 for NDRE and 0.8 for NDVI) are superimposed on the maximum vegetation, end of June and beginning of July. The stress induced by the fire blight attack in the first and second decades of July determined the decrease and approach of the values of both VI's (0.3-0.4 NDRE and 0.4-0.5 NDVI). Based on these results, lower VI values recorded by the optical sensor characterized periods of intense biotic stress compared to less stressful periods.

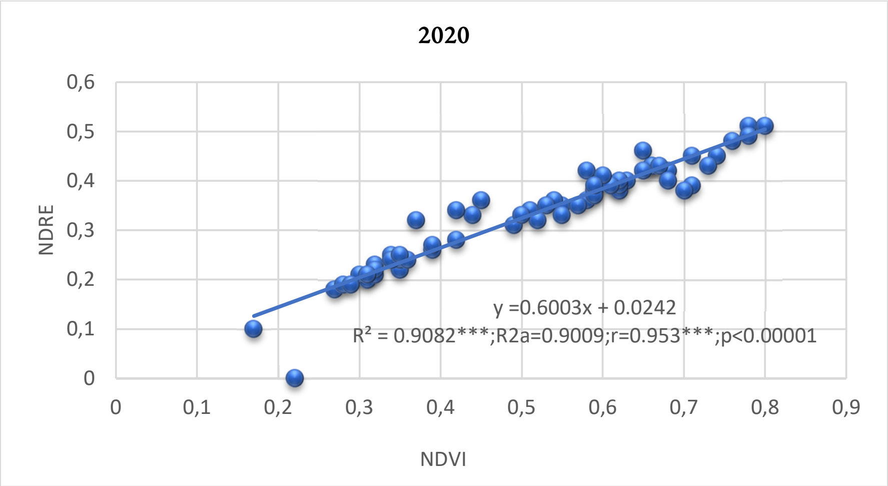
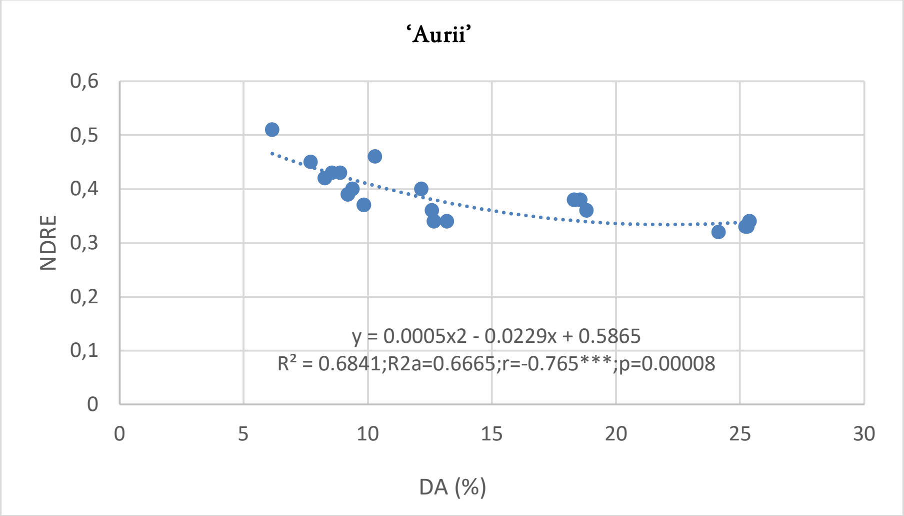
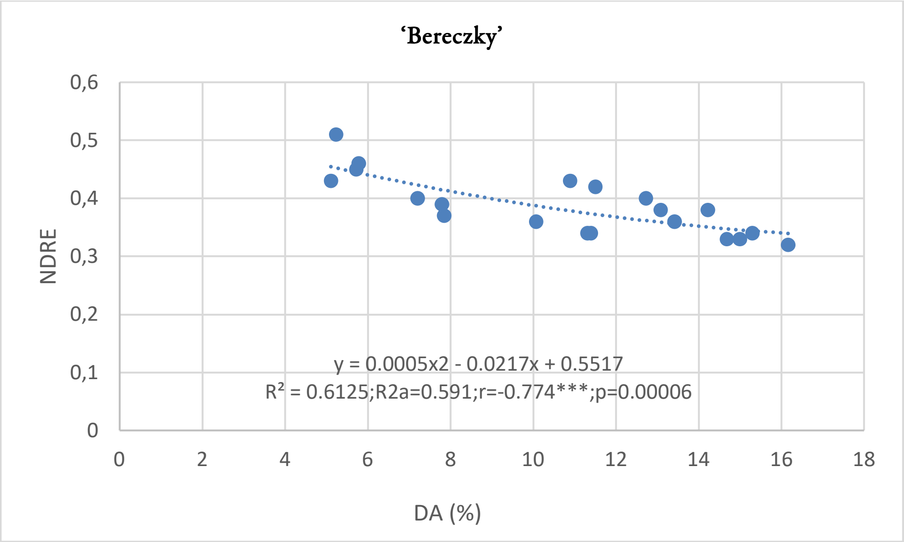


Figure 5. Regression between NDVI and NDRE in the experimental year 2020 at the quince plantation affected by fire blight

The analysis of the data on the regression between NDRE and DA (5) in quince varieties affected by fire blight (Figure 6) reveals a negative correlation. The values of the DA (%) show that in 2020, the 'Bereczky' variety was less affected compared to the 'Aurii'. Therefore, it appears that the DA of fire blight is the primary and most significant factor that determines the reduction of NDRE values. In 2020, DA caused by fire blight in the two quince varieties has influenced to an extent of 61.25-68.41% the variation of NDVI, according to data from Figure 6.



(a)



(b)

Figure 6. Regression between NDRE and DA in the two quince varieties (a-'Aurii'; b-'Bereczki') affected by fire blight (2020)

The values of DA show that in 2020, the 'Bereczky' variety was less affected compared to 'Aurii'. Thus, the maximum attack rates were approximately 16% in 'Bereczky' and 25% in 'Aurii', as determined in October. Therefore, it appears that the degree of fire blight attack is the primary and most crucial factor determining the reduction of NDRE values.

The experimental data specific to 2021 (Figure 7) show that the VI's values recorded during the quince plant's vegetation period are quite fluctuating, depending on the stage of plant development, climatic conditions, and the intensity of biotic stress produced by *E. amylovora*. NDRE values represent approximately two-thirds of NDVI, except during stress intervals, when these differences are reduced. During the vegetation cycle specific to 2021, several periods of reduction in the values of the analyzed VI's as follows were determined at the end of May (0.4 -NDVI; 0.29 NDRE), mid-June (0.46-NDVI; 0.3 NDRE), the beginning of August (0.46-NDVI; 0.31-NDRE) and the second decade of September (0.46-NDVI; 0.27- NDRE).

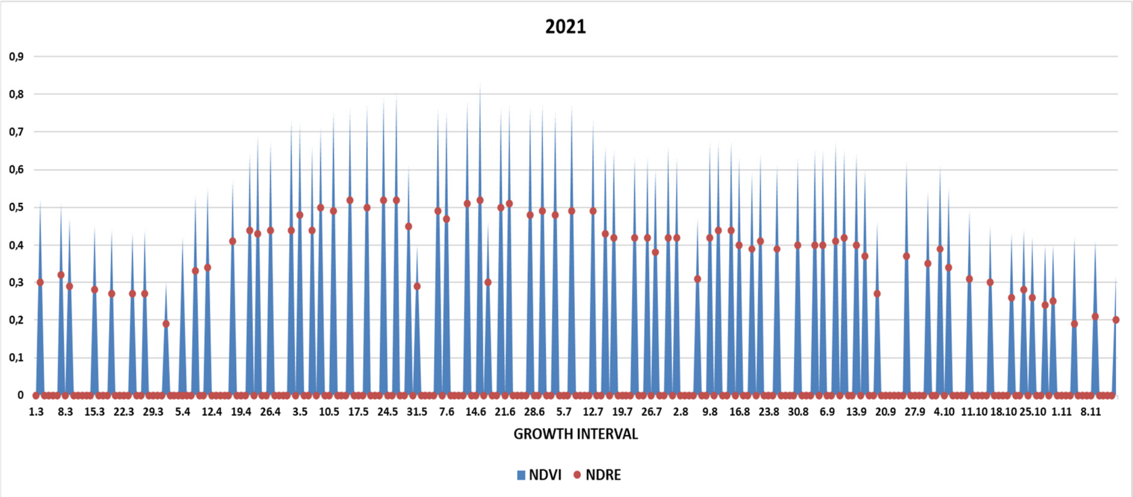


Figure 7. Comparative representation of VI's values in the experimental year 2021 at the quince plantation affected by fire blight

The correlations between the NDVI variation and the NDRE specific to 2021 show that they are highly significant and positive, and the quadratic regressions express the differences between the parameters with an accuracy of 95.65% (Figure 8). The minimum values of NDVI were around 0.3, and the NDRE values, which were around 0.2, were recorded at the end of March and November. Meanwhile, the maximum values reached 0.8 at NDVI and 0.51 at NDRE in May and June. The amplitude of the variations was significantly smaller in the case of NDRE, which indicates the stability of this vegetation index. Numerous studies have shown that NDRE is positively and strongly correlated with NDVI, and NDRE exhibits higher sensitivity to changes in plant canopy and is more efficient in assessing green biomass compared to NDVI (Boiarskii and Hasegawa, 2019; Carneiro *et al.*, 2017; Melnyk and Brunn, 2025).

The NDVI limits in the assessment of the plant's health canopy could be explained by the saturation of the band of red electromagnetic waves. This is due to the intense absorption of red radiation by chlorophyll pigments, which causes saturation in this band of the crown of plants.

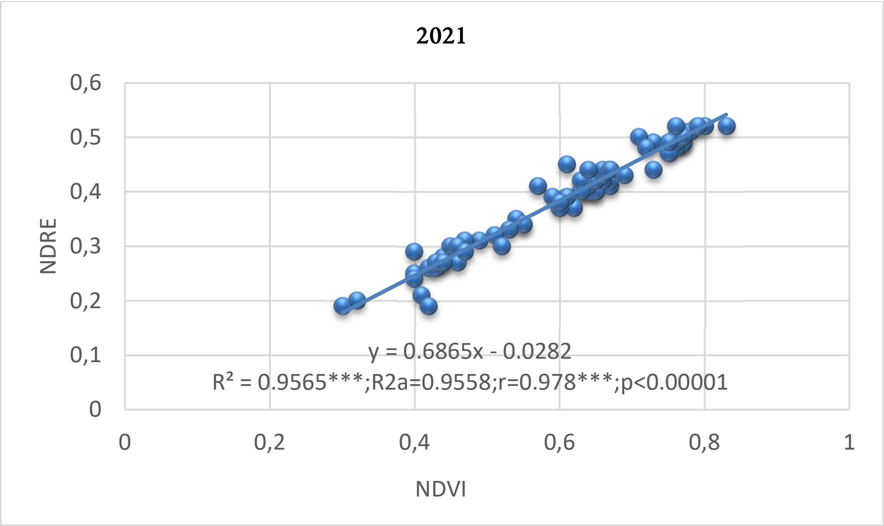


Figure 8. Regression between NDVI and NDRE in the experimental year 2021 at the quince plantation affected by fire blight

The data on the regression between NDRE and DA in the two quince cultivars (Figure 9) shows a negative correlation. The variation of DA has a contribution of 90.07% to the values of NDRE in the case of 'Aurii' variety, and a 64.11% contribution to the NDVI of 'Bereczky' variety, respectively. The degree of attack (%) shows that in 2021, the 'Aurii' variety was less affected compared to 'Bereczky'.

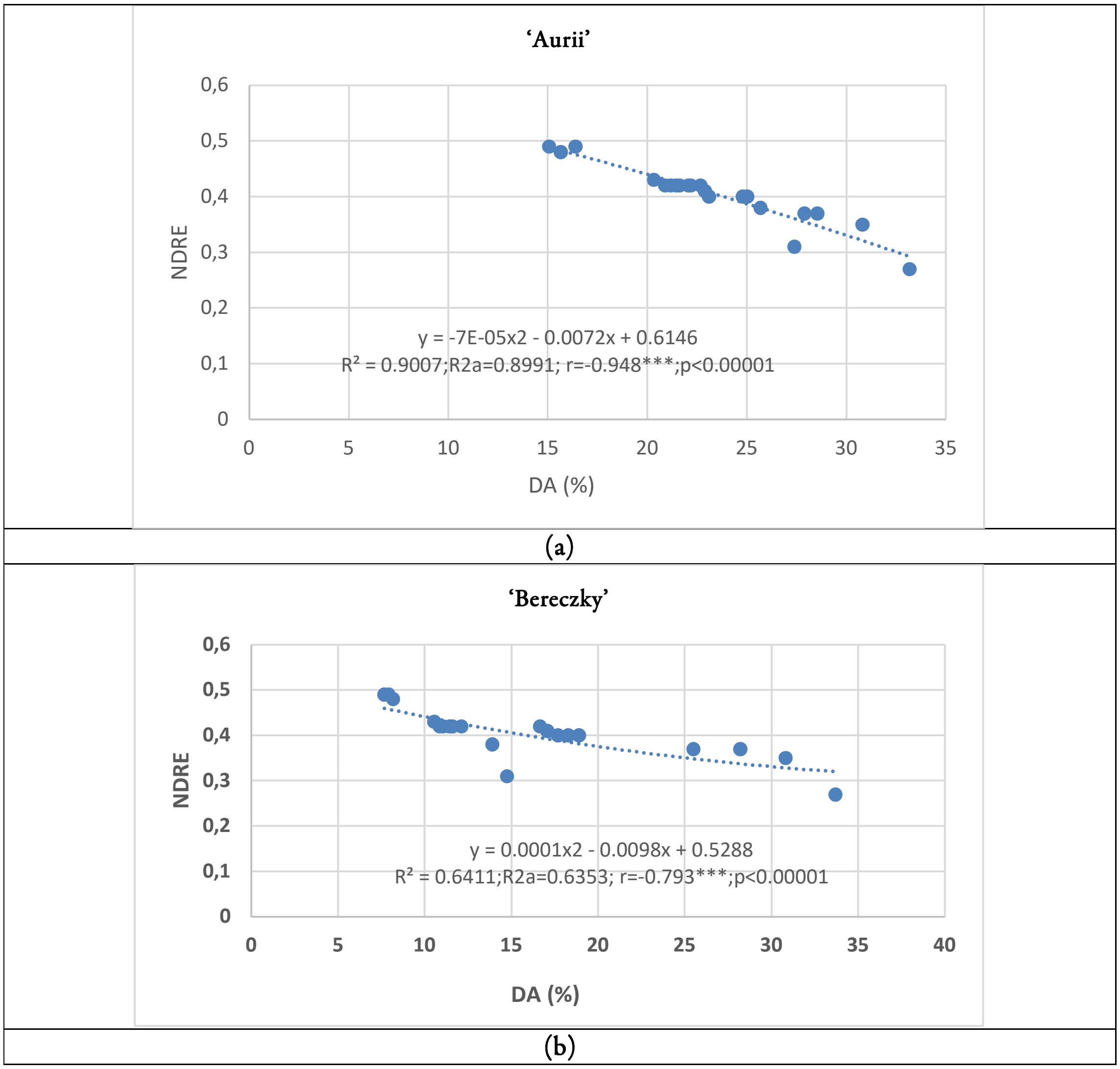


Figure 9. Regression between NDRE and GA in the two quince varieties (a-'Aurii'; b- 'Bereczki') affected by fire blight (2021)

The determinations regarding the degree of attack (DA), calculated based on the intensity (I) and frequency of the fire blight attack (F) on the two quince cultivars showed a different sensitivity of the genotypes, in direct correlation with the specific climatic conditions, with the age and stage of development of the plants, but also with the technological measures applied in the prevention and/or control of the disease. Our results show a lower DA in July and a higher DA in autumn, with an amplitude of variation between 4% and 40%, depending on the cultivar, stage of development, specific climatic conditions, and plant age.

These results are also in line with other recent studies attesting to the importance of the cultivar (Dougherty *et al.*, 2021; Kapytina *et al.*, 2023; Simionca Mascasan *et al.*, 2023; Schlathölter *et al.*, 2023), plant age (Slack *et al.*, 2025; Zeng *et al.*, 2021), the developmental stage (Gheorghiu and Cosmulescu, 2022; Roșu-Mareș *et al.*, 2022;) and climatic conditions (Santander and Bioska, 2017; Slack *et al.*, 2022) in the manifestation of fire blight attack on different fruit species.

The comparative analysis of the NDVI and NDRE values specific to 2022 (Figure 10) shows the same behavioral trends as in previous years, with some variations driven by specific climatic conditions. Low values of the two VI's were recorded at the start of vegetation (March and the first decade of April), at the end of the annual cycle before the leaves fall in November, as well as in the periods of strong manifestation of fire blight in mid-July, late August and early September.

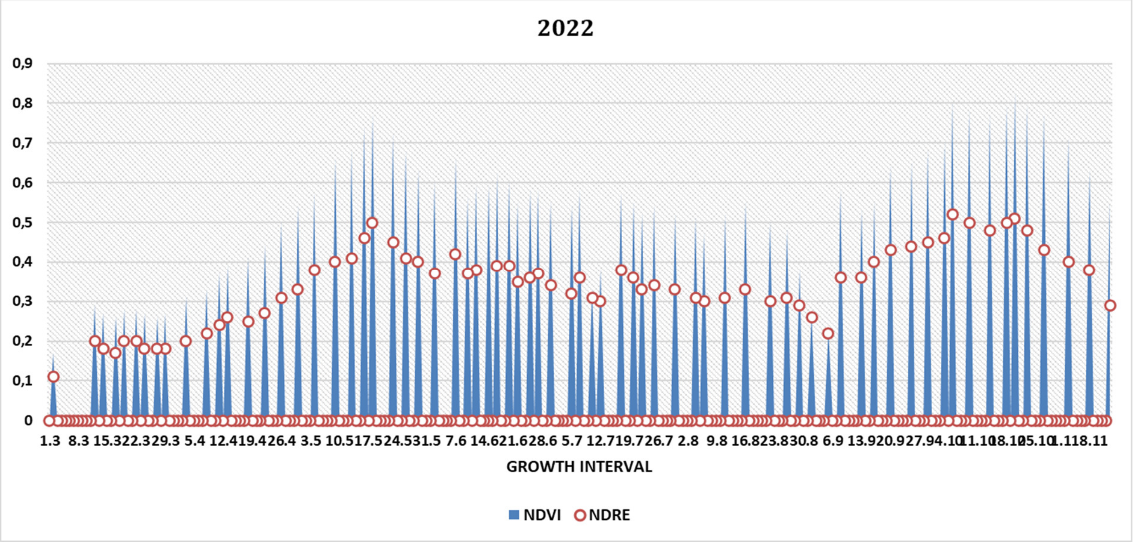


Figure10. Comparative representation of VI's values in the experimental year 2022 at the quince plantation affected by fire blight

In 2022, the same trend observed in periods of strong disease manifestation was evident: the NDRE value was either equal to or even higher than the NDVI value. The low-stress conditions have led to the previously explained trend that the recorded NDRE values are approximately 30% lower compared to the NDVI. The strong manifestation of fire blight in late August and early September can be attributed to a rich rainfall regime superimposed over this period, which also generated high values of atmospheric humidity. This factor was decisive in the manifestation of the disease with increased intensity.

According to the data and quadratic regression presented in Figure 11, it is observed that NDVI contributes 93.12% to the variability of NDRE, against the background of a positive and strongly statistically significant correlation between the two parameters.

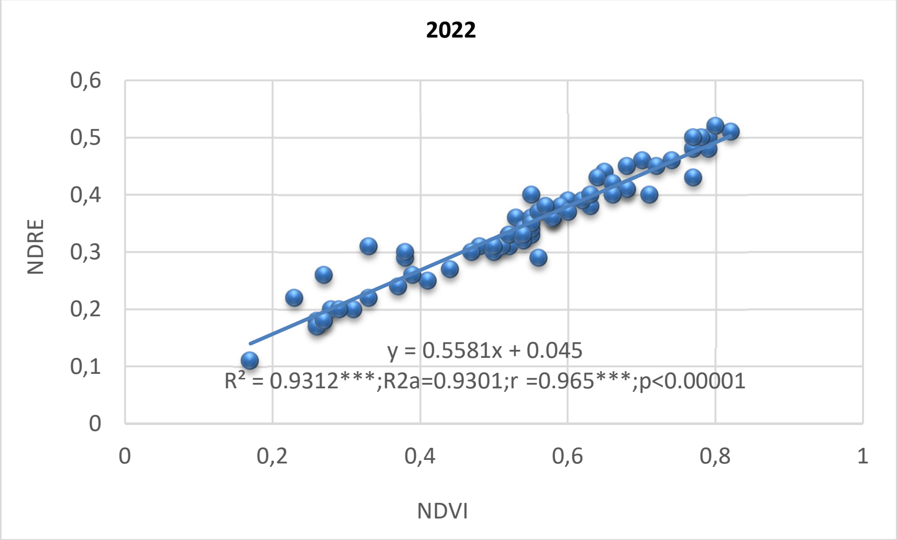
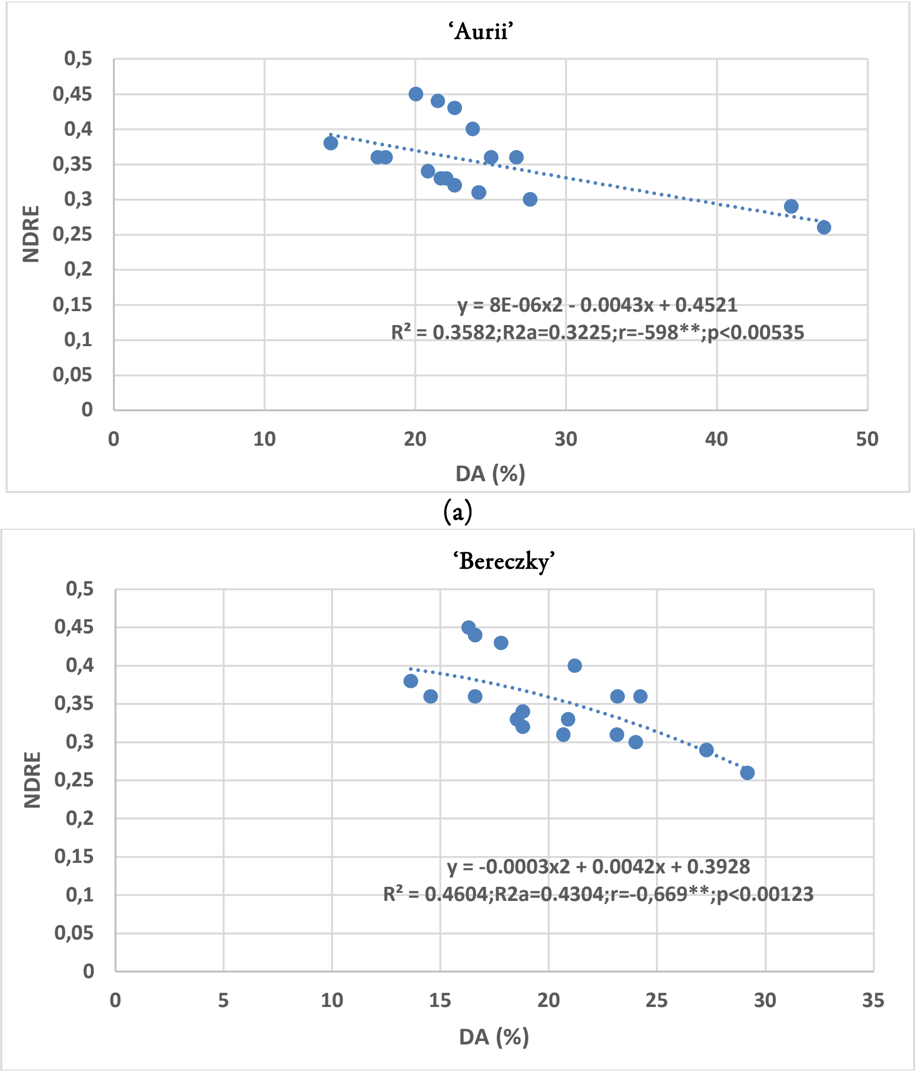


Figure 11. Regression between NDVI and NDRE in the experimental year 2022 at the quince plantation affected by fire blight

As regards the relationship between NDRE and DA in Figure 12 the positive correlation between the two parameters is only apparent considering that only 35.82% (cv. 'Aurii') and 46.04% (cv. 'Bereczky') of the NDRE variation can be explained based on the influence of DA., against the background of considerable influences from the other sources of variation. It should be noted that these values of the correlation between NDRE and DA are specific to 2022, as previous years have shown much higher correlation values, reaching 90.07% for 'Aurii' in 2021.



(a)

(b)

Figure 12. Regression between NDRE and GA in the two quince varieties (a-'Aurii'; b- 'Bereczki') affected by fire blight (2022)

Other factors that contribute to the reduction of NDRE values can be the loss of foliage and chlorophyll content. The loss of chlorophyll pigments can also be due to natural leaf senescence, diseases or other types of biotic and abiotic stress, which can contribute up to 31.5% to the link between the two properties. However, the recording of low NDRE values in the middle of the growing season, after periods of precipitation, overlapped with the determinations in the field, where high values of the degree of fire attack were recorded.

Recent studies (Naguib and Daliman, 2022, Voitik, 2023) have shown that the lower layers of vegetation show little influence on NDVI values. This effect is amplified in plants with several layers of leaves. NDRE offers a better perspective for perennial crops and in advanced development phenophases, such as fruit and forest species, because it evaluates the vegetation in depth of the canopy, not just its surface. Thus, the NDRE can provide more accurate values as long as the NDVI remains constant.

This is explained by the fact that NDVI saturates in dense vegetation, since the visible red light is almost completely absorbed by the upper layers of the foliage, causing the index to stabilize at a high leaf area value. NDRE's use of the red-edged band reduces this saturation effect, preserving a wider dynamic range that remains receptive to chlorophyll changes even in mature, fully enclosed orchards. Therefore, our results demonstrate that modern, non-destructive methods for identifying and monitoring natural fire blight infections in quinces, involving the use of hyperspectral spectroscopy technologies, are valuable alternatives that can be successfully employed at a low cost.

Changes in the physical, biochemical, and physiological properties of host plants caused by the attack of pathogenic diseases result in significant alterations in certain optical and metabolic parameters in plant organs and tissues. The vegetation indices used, calculated with the help of multispectral devices, can detect these changes, together with the monitoring of the spatio-temporal model of disease evolution. Still, for the verification and validation of the results, evaluations of the disease's impact in the field are also necessary to identify the most efficient and accurate vegetation indices.

Conclusions

Fire blight is influenced by several factors that make this complex disease difficult to study and manage.

The degree of E. *amylovora attack* is strongly determined by environmental conditions, such as humidity and temperature, which also influence the effectiveness of control strategies. These variables cannot be controlled, and the increase in extreme weather events due to global warming makes it essential to evaluate new technologies under challenging climate conditions.

The use of satellite-determined NDVI and NDRE vegetation indices is a viable method for determining the dynamics and intensity of the *E. amylovora* quince attack. Although we have determined a strong positive correlation between VI's, NDRE showed a higher accuracy, compared to the determinations regarding the degree of attack on plants, due to the ability to evaluate the interior of the plant canopy.

According to the dynamic data recorded over the three years analyzed, the quince plantation has consistently suffered from stress caused by the disease, as evidenced by NDRE values typically ranging from 0.2 to 0.5. In the conditions of intense disease attack, achieved during the vegetation cycle, the NDRE values were most often between 0.2 and 0.3.

The intensity of the disease is decisively determined by climatic conditions, especially precipitation and atmospheric humidity. Still, it manifests itself with a delay of 10-14 days compared to periods of heavy rainfall. The 10-14 day delay occurs because *Erwinia amylovora* requires high humidity to infect flowers and spread to shoots, then takes about two weeks to multiply in tissue before necrosis appears.Therefore, the NDRE thresholds of 0.5-0.6 for early warning of *E. amylovora* attack and those of 0.2-0.3 for high-intensity attacks of the bacterial pathogen can be validated.

Authors' Contributions

Conceptualization: RLS, SC; Data curation: C.B, C.B; Formal analysis: C.B, RMS; Funding acquisition: CB, RLS; Investigation: CB, RLS; Methodology: RMS, SC; Project administration: RLS;

Resources: CB; Software: SC; Supervision: RLS; Validation: SC; Visualization: CB; Writing - original draft: CB; Writing - review and editing: RLS, RMS, SC.

All authors read and approved the final manuscript.

Ethical approval (for researches involving animals or humans)

Not applicable.

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Conflict of Interests

The authors declare that there are no conflicts of interest related to this article.

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