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INVESTIGATING THE EFFECTS OF SPECTROSCOPIC METHOD IN ESTIMATING SOLUBLE SOLID CONTENT VALUES AND FIRMNESS OF CHERRIES FROM AN ENVIRONMENTAL POINT OF VIEW: PREDICTION OF ENVIRONMENTAL PARAMETERS WITH MACHINE LEARNING METHOD

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In this study, 60 cherry samples with native varieties were selected from the Hir region in Ardabil province. They were classified into four growth stages, including before the optimal harvest date, the day before the optimal harvest time, the optimal harvest time, and after the optimal harvest date, by a panel of human experts. Next, by combining the feature selection method (relief) and the spectrometry method (vis-NIR), the effective wavelengths were extracted to estimate the soluble solid content (SSC) values and firmness of the cherry product. In the continuation of the process of this method, a list of inputs was formed, and by applying the life cycle assessment method, the environmental effects of the process of estimating SSC values and cherry hardness in the presence of tests and obtained data was performed. In the final stage, with the help of the radial basis function neural network method, a relationship was established between the reflection intensity values in the effective wavelengths and the endpoint effects of the life cycle assessment to estimate the environmental effects. It was found that the radial basis function neural network could estimate the environmental effects of the experimental process with an acceptable accuracy (over 95% on average).

Keywords: non-destructive evaluation; soft computing; computational intelligence; ensemble learning; fruit

Cherries are a seasonal fruit that is very customer-friendly and has many fans when they are fresh, ripe, and sweet (Szabo et al., 2023; Momeny et al., 2020). Generally, ripening indicators such as tissue firmness and water-soluble solids (SSC) are measured by experimental and destructive methods and indicators by producers and fruit products (Nowakowski and Nowakowski, 2018; Szabo et al., 2023; Aslantas et al., 2016). Today, the stakeholders of fruit production and industries commonly use non-destructive methods such as spectroscopy and the chemical properties of agriculture.

Recent research has focused on non-destructive methods for evaluating fruit ripeness using visible and near-infrared (vis-NIR) spectroscopy (Ziosi et al., 2008; Infante et al., 2011). These technologies enable real-time monitoring of ripening progress and physiological changes in fruits with high accuracy (Bonora et al., 2013). In today's agricultural industry, there is a need for quantitative information to be used by independent harvesting systems in post-harvest sorting and storage (Ayebazibwe, 2023; Florkowski et al., 2022). In order to achieve this goal, in recent years, the integration of machine learning methods and non-destructive diagnostic tools such as spectroscopy has paved the way for creating intelligent and non-destructive diagnostic systems for obtaining physical and chemical information for all types of agricultural products (Munawar et al., 2022).

Visible-NIR spectroscopy is a non-destructive technique that is very suitable for measuring quality characteristics in fruits: it is fast, requires little sample preparation, and allows the simultaneous determination of several parameters using a single measurement (Liu et al., 2005). The use of this technique both by the producers in the field and by the fruit consumers in the production and packaging line, the uniformity of fruit bunches not only in terms of external appearance but also in terms of internal quality parameters such as firmness, dissolved solid content, and acidity, also guarantees that both dominate the taste of the fruit.

Several studies in this field have been conducted on cherries. In this section, some studies are presented. Visible and near-infrared reflectance (vis-NIR) spectroscopy (350–2500 nm) was used by Shao et al. (2019) to evaluate cherry bruising levels. They identified optimal wavelengths using principal component analysis (PCA) loadings and sequential projection algorithm (SPA). The LS-SVM model, based on the five optimal wavelengths (603, 633, 679, 1083, and 1803 nm), showed superior qualitative discrimination of bruising and achieved a classification accuracy of 93.3%. This study showed the relationship between cherry colour, firmness, soluble solids content (SSC), and vis-NIR reflectance (Shao et al., 2019).

Lafuente et al. (2019) developed models using vis-NIR spectroscopy to estimate the dissolved solids content (SSC) in cherry trees. They applied this spectroscopy to the fruit of *Prunus avium* 'Chelan' ($n = 360$) in the range of 400–2420 nm. The linear (PLS) and non-linear (LSSVM) regression methods were used to create prediction models. Both methods yielded comparable results (correlation coefficient $CC = 0.97$ and $CC = 0.98$, respectively). The 700–1060 nm range better predicted SSC in different seasons. A variable selection procedure identified forty variables that achieved a CC value of 0.97, similar to the full range (Lafuente et al., 2019).

Siedliska et al. (2017) conducted a study using hyperspectral transmission imaging to distinguish between seedless and healthy cherries of three cultivars ('Lutówka', 'Pandy 103', and 'Groniasta') with different soluble solid content (SSC). The vis-NIR ranges (450–1000 nm) were used for image acquisition. They used a correlation-based feature selection (CFS) algorithm and second derivative pretreatment of hyperspectral data to build supervised classification models. The discrimination accuracy between pitted and intact cherries exceeded 87% for fresh and frozen cherries. These findings indicate that transmission-mode hyperspectral imaging is an accurate and objective method for pit detection in cherries, suitable for integration into online sorting systems. In the study of Nagpala et al. (2017), the ripening evolution of cherry fruits was followed by evaluating parameters such as chroma (skin colour intensity), fruit anthocyanin content, and soluble solids content (SSC). Below, vis-NIR spectroscopy was used to obtain the required wavelengths.

According to database reviews, one of the main aspects of experimental studies can be their environmental effects. Environmental issues still need to be addressed in the studies conducted to evaluate the quality and properties of fruits using the spectrometry method (Casson et al., 2019, 2020). In this study, the main innovation is presented by applying combined non-destructive methods of vis-NIR spectroscopy with machine learning method to predict the environmental parameters obtained from the life cycle assessment method of detecting the SSC values and firmness of the cherry product.

In the present study, cherry product quality is evaluated regarding firmness and soluble solids content (SSC). A vis-NIR spectrometer (in the range of 400–1000 nm) is used to obtain the cherry product spectrum. The effective wavelengths are obtained by applying the machine learning method, and a model is developed to predict and estimate the environmental parameters obtained from the life cycle assessment of the non-destructive experimental testing process.

Material and Methods

Figure 1 shows the proposed non-destructive prediction system, which includes the five steps required to generate input data, train, and evaluate the system. These steps will be discussed in detail below.

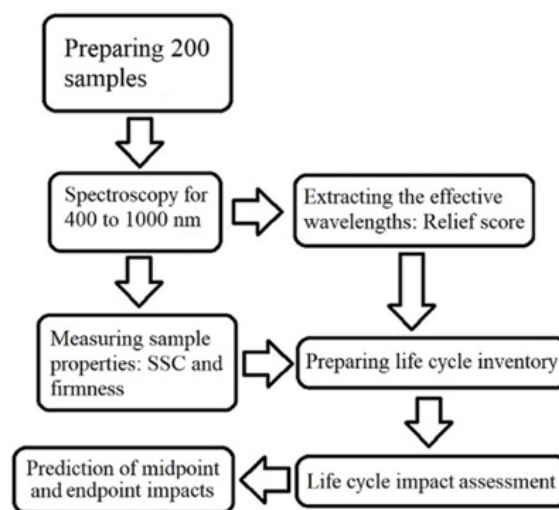


Fig. 1 The steps of the procedure

Sample preparation

Collecting different samples was the first step in creating the proposed prediction system. The samples were prepared from Hir city in Ardabil province (geographical coordination: 38° 04' 50" N, 48° 30' 22" E). In the first step, human experts determined the approximate time of cherry picking. A total of 60 samples were selected and classified in four growth stages, including before the optimal harvest date, the day before the optimal harvest time, the optimal harvest time, and after the optimal harvest date by a human expert panel.

Spectral data extraction

A spectrophotometer (StellarNet, Tampa, EPP200NIR Vis-NIR, USA, equipped with an indium-gallium-arsenide (InGaAs) photodetector) was used to obtain reflectance spectral data. This system was illuminated using a 10 W tungsten lamp. For processing, most of the obtained data were transferred to a laptop computer (Corei7, 1000 M at 3.2 GHz, 8 GB RAM, Windows 10, MatLab 2016a (Mathwork, Las Vegas)).

Measurement of physicochemical properties

Table 1 presents a statistical summary of cherry samples' physicochemical properties (measured), including firmness, acidity, and SSC.

Table 1 Values related to physical-chemical properties

Property	Unit	Maximum	Minimum	Mean	STD deviation
Firmness	100 kg·m ⁻¹	7.55	2.25	4.33	0.86
SSC	%	28.71	12.62	17.76	3.31

The method presented in the study of Pourdarbani et al. (2021) was used to measure firmness. In this method, a manual penetrometer with a special probe (diameter 3 mm and height 10 mm) was used, and the probes were placed on both sides of the cherry. Probes were pressed into the samples to record the force applied, measured in $100 \text{ kg}\cdot\text{m}^{-1}$. The average force applied on both sides of the cherry was considered a measure of stiffness. A spectrophotometer was used to extract SSC. In this method, the product is first dehydrated. Then, the amount of water obtained was measured using a dropper in a spectrophotometer (Optizen 2120 UVplus).

Selection of the effective wavelength

The relief feature selection method was used to select the effective wavelength. The relief algorithm is a feature selection method commonly used in machine learning and data mining (Urbanowicz et al., 2018). It evaluates the relevance of each feature by considering their contribution to classification accuracy. The relief score measures the importance of features by calculating the difference in feature values between samples that are close to each other in the feature space (Kira and Rendell, 1992). This algorithm assigns higher scores to features with significant value differences for samples belonging to different classes, indicating their relevance to classification.

To implement this algorithm, the characteristics obtained from the experimental test were selected as dependent variables and wavelengths as independent variables in the MATLAB software library. Based on this, a series of scores for wavelengths were obtained, and five effective wavelengths were selected as influential independent variables.

Life cycle assessment

At this stage, the life cycle assessment of measuring SSC and product hardness was carried out based on the list prepared by the focus group consisting of laboratory experts. Simapro 9.0.0.48 (PRé Sustainability, Netherland) software was used to perform life cycle assessment. Life cycle impact assessment was done with the help of the IMPACT 2002+ method. The IMPACT 2002+ life cycle impact assessment method is a standard and common method for modelling and quantifying the relationship between environmental inputs and outputs of a life cycle inventory. This method proposes a hybrid midpoint/harm approach, which categorises primary flows and other interventions through 15 midpoint categories into four damage categories. This impact evaluation method categorises into two groups, intermediate effects and final effects (Joliet et al., 2003). According to Table 2, the middle effects have fifteen evaluation parameters.

These impacts are summarised in four final impact groups: human health, ecosystem quality, climate change, and resources.

Next, based on the method presented by Casson et al. (2020), an allocation factor of 0 to 1% is specified for each entry in the process log, considering the time of use and multiple uses of the input for different reference parameters. Next, the value of each analysis (Apa) was calculated for each input and output with the help of Eq. 1 (Casson et al., 2020):

$$\text{amount per analysis} = \frac{\text{quantity} \cdot \text{allocation factor}}{\text{number of the analysis}} \quad (1)$$

Table 2 Parameters of intermediate effects

Mid-point impact category	Unit	End-point impact category	Unit
Carcinogens	kg C ₂ H ₃ Cl eq	human health	DALY (disability-adjusted life years)
Non-carcinogens	kg C ₂ H ₃ Cl eq		
Respiratory inorganics	kg PM _{2.5} eq		
Ionising radiation	Bq C-14 eq		
Ozone layer depletion	kg CFC-11 eq		
Respiratory organics	kg C ₂ H ₄ eq		
Aquatic ecotoxicity	kg TEG water	ecosystem quality	PDF·m ² ·year (potentially disappeared fraction of species in a square meter within a year)
Terrestrial ecotoxicity	kg TEG soil		
Terrestrial acid/nutri	kg SO ₂ eq		
Land occupation	m ² org.arable		
Aquatic acidification	kg SO ₂ eq		
Aquatic eutrophication	kg PO ₄ P-lim		
Global warming	kg CO ₂ eq	climate change	kg CO ₂ eq (equivalent to the effect of one kg CO ₂)
Non-renewable energy	MJ primary	resources	MJ primary (primary energy intensity)
Mineral extraction	MJ surplus		

Table 3 Life cycle inventory

Inputs	Quantity	Allocation factor	Year (lifetime)	Number of analyses	Amount per analysis
Spectroscopy	200	0.18	5	10000	0.0036 (kg)
Preprocessing	200	0.09	-	15000	0.0012 (kg)
Modelling	25	0.23	-	10000	0.000575 (kg)
Firmness analysis	100	0.16	10	15000	0.001066667 (kg)
SSC analysis	200	0.15	5	15000	0.002 (kg)
Juicer	200	0.19	15	10000	0.0038 (kg)
Energy	5.2	1	-	1	5.2 (kWh)
Water	2.5	1	-	1	2.5 (kg)
Outputs					
Experimental data	-	-	-	-	according to the scenario required
Waste material	0.65				0.65 (kg)

Table 3 presents the list of evaluations in different stages for the present study.

Modelling procedure

The radial basis function neural network method was used for modelling. The theory of this method is presented by Ardabili et al. (2016). In this study, the effective wavelengths were considered as the input of the model, and the values of the end effects were the output of the model. MATLAB software and hardware with Intel(R) Core(TM) i7-8550U CPU @ 1.80 GHz and 16 GB RAM were used to perform the modelling process. In this study, the modelling process was carried out in two stages, including network training and network testing. Network training started with 70% of the total data. The optimal network model should be obtained to train the network. For this purpose, the number of neurons in the hidden layer was considered the primary variable, and the training process was implemented. It was observed that increasing the number of neurons in the hidden layer increases the accuracy of the network. This increase in the number of neurons in the hidden layer continued until the error became a smooth line. Finally, the number of 32 neurons in the hidden layer was chosen as the optimal number of neurons. The root mean square error measures and correlation coefficient were used to evaluate the model error in the network training stage. The next step was to test the network with the remaining 30% of the data.

For this purpose, the selected network from the network training stage was tested with 30% of the remaining data, and the performance parameters of the network were extracted according to Eq. 2 and Eq. 3 for root mean square error and correlation coefficient.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \hat{x}_i)^2} \quad (2)$$

$$CC = \frac{Cov(x, \hat{x}) \cdot 100}{\sigma_x \sigma_{\hat{x}}} \quad (3)$$

Results and Discussion

This section presents the main findings of the feature selection process for choosing the most effective wavelengths on firmness and SSC

values of the product. Figure 2 presents the wavelengths of 10 samples during the spectroscopy analysis (labelled as S1 to S10). According to Figure 2, the wavelengths of 617, 622, 627, 632, and 637 nm have the highest impact on firmness, and the wavelengths of 657, 667, 662, 672, and 677 nm have the highest impact on SSC values. Shao et al. (2019) also claimed the wavelengths of 603, 633, and 679 nm as the effective ones on detecting bruise degree for cherry which had a direct relation with its firmness and soluble solids content. Accordingly, the intensity of these wavelengths has been selected as the input values of the modelling process with radial basis function for predicting the firmness and SSC values.

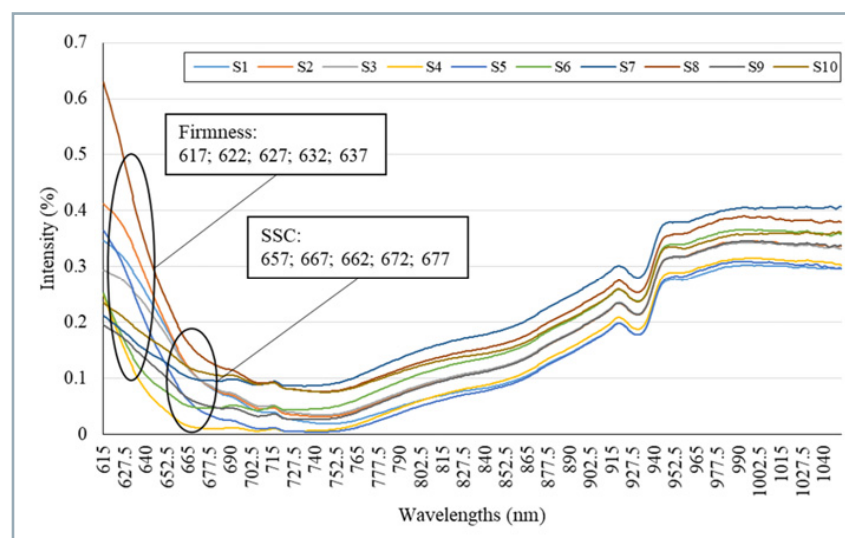


Fig. 2 Sample wavelengths extracted from hyperspectral imaging

In the study by Pappas et al. (2011), the correlation of chemical properties in higher wavelengths between 1560 and 1700 nm was emphasised, while in the current study, one of the conditions of experiments was the investigation of wavelengths below 1000 nm. This discussion can clarify an important limitation of the research. This also can emphasise and encourage on additional studies for future curiosities and be an opportunity for further research. The similar discussion was also emphasised by Nakanishi (1962).

Life cycle assessment

According to Fig. 3, the energy followed by the laboratory procedure has the highest share on the midpoint environmental impact of firmness and SSC analysis.

The high share of energy in the midpoint environmental impact of firmness and SSC analysis reflects the energy-intensive nature of laboratory operations. In labs, a considerable amount of energy is consumed for various activities, including the operation of analytical equipment, heating, ventilation, and air conditioning (HVAC) systems, and general lighting. In the context of firmness and SSC analysis, specialised instruments like penetrometers and SSC require consistent power. The energy needed to maintain

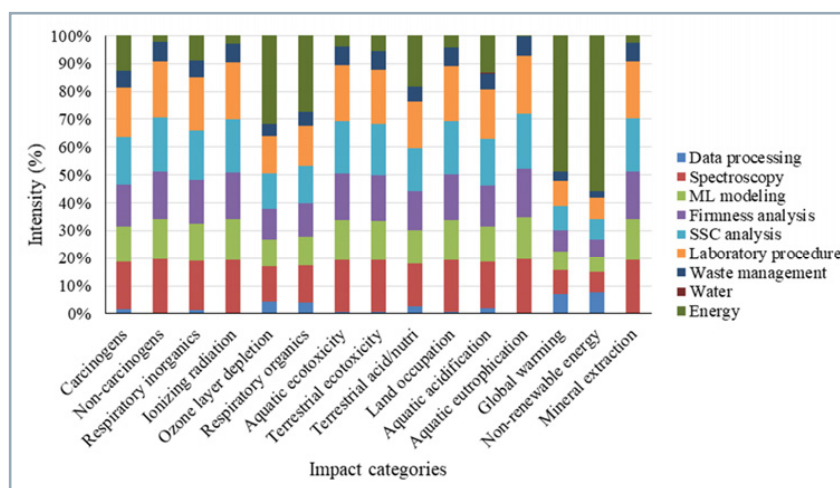


Fig. 3 The environmental impacts of the inputs for firmness and SSC analysis

stable environmental conditions in a laboratory, such as controlled temperatures and humidity, also adds to the overall energy use. This high energy consumption can contribute to a significant environmental impact, especially if non-renewable sources are predominantly used.

Laboratory procedures also play a substantial role in the environmental impact due to their reliance on consumables and chemical reagents. These procedures might involve the use of disposable items like plastic pipettes, gloves, and other single-use materials, which generate waste. In addition, some tests require chemical reagents or buffers, which can have

adverse environmental effects if not properly managed or disposed of. As these procedures are integral to ensuring accurate firmness and SSC measurements, their contribution to the environmental footprint is significant. The combination of high energy use and waste generation from laboratory procedures explains why these factors lead to the highest share of midpoint environmental impact in firmness and SSC analysis.

As discussed before, limited studies have been conducted on evaluating one of the important aspects (environmental aspect) of non-destructive monitoring systems on fruit. However, the highest effective

Table 4 Comparing the firmness and SSC analysis in terms of midpoint environmental impacts

Impact category	Unit	Firmness analysis	SSC analysis
Carcinogens	kg C ₂ H ₃ Cl eq	0.018963	0.033621
Non-carcinogens	kg C ₂ H ₃ Cl eq	0.067925	0.125065
Respiratory inorganics	kg PM _{2.5} eq	0.002007	0.003612
Ionising radiation	Bq C-14 eq	14.13252	25.96966
Ozone layer depletion	kg CFC-11 eq	1.72E-07	2.85E-07
Respiratory organics	kg C ₂ H ₄ eq	0.0004	0.000671
Aquatic ecotoxicity	kg TEG water	517.0828	947.4349
Terrestrial ecotoxicity	kg TEG soil	85.92825	156.263
Terrestrial acid/nutri	kg SO ₂ eq	0.027931	0.04867
Land occupation	m ² org.arable	0.028372	0.051273
Aquatic acidification	kg SO ₂ eq	0.006513	0.011539
Aquatic eutrophication	kg PO ₄ P-lim	0.004492	0.008334
Global warming	kg CO ₂ eq	2.012365	3.083968
Non-renewable energy	MJ primary	34.8189	51.59452
Mineral extraction	MJ surplus	0.178439	0.326695

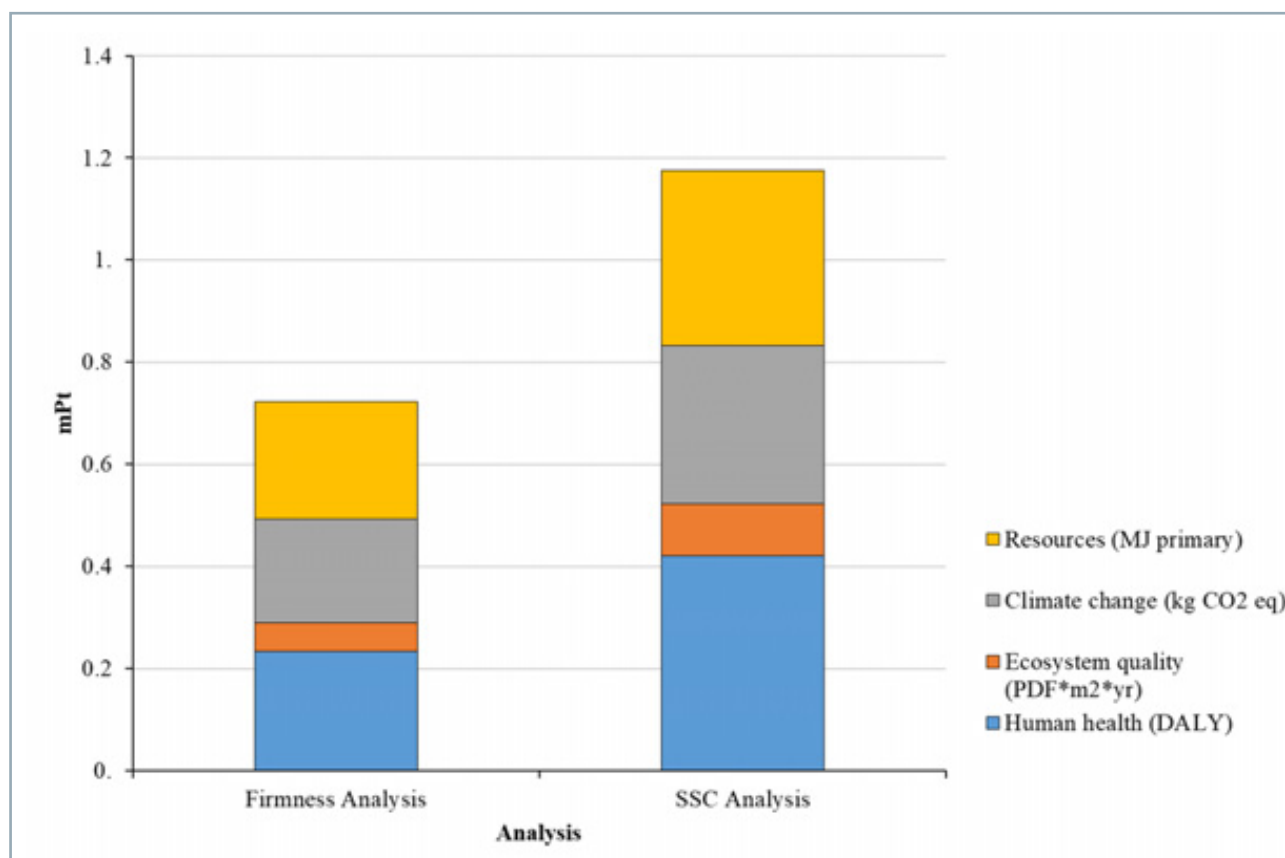


Fig. 4 A comparison between the firmness and SSC analysis in terms of midpoint environmental impacts

input on environmental emissions belonged to energy (Casson et al., 2020).

Energy was identified as the most important input in environmental publications on the analysis of olive oil (Casson et al., 2019). This shows that in the analyses related to non-destructive detection with spectroscopy, regardless of the type of the product being tested, the limiting input from the environmental point of view is energy. The solution seems to be the use of renewable energy sources in energy supply. Because the use of energy in these processes is undeniable, hardware optimisation for modelling in instrumentation and control systems can only reduce consumption by 5–10% (Hashemi, 2021; Ardabili, 2014). According to the results obtained from this research, the impact of energy input on environmental emissions is numerically higher than 30%. To cover the difference beyond 20%, it is necessary to use another solution such as changing the source of energy production. In order to solve this problem, it is emphasised to use

carbon-free energy supply sources or low-carbon energy supply sources, or sources that do not create additional carbon in the environmental carbon cycle.

Table 4 and Fig. 4 present a comparison between the firmness analysis and SSC analysis in terms of midpoint environmental impacts. According to the results, the SSC analysis has owned the most share of midpoint environmental impacts in comparison with the firmness analysis.

Modelling

This section has been categorised into two main processes including training and testing processes. According to Table 5, it is clear that the accuracy values of predicting the environmental impacts of the firmness analysis is higher than that of the SSC analysis. This can be due to the high reliability in measuring the firmness values compared to the SSC values of the product. Figure 5A–B presents the testing results.

Table 5 The results of the training process of radial basis function

	Parameter	RMSE	CC (%)
SSC	human health	3.21E-07 (DALY)	93
	ecosystem quality	0.173 (PDF·m ² ·year)	94
	climate change	0.223 (kg CO ₂ eq)	91
	resources	3.87 (MJ primary)	92
Firmness	human health	7.65E-08 (DALY)	95
	ecosystem quality	0.057 (PDF·m ² ·year)	96
	climate change	0.129 (kg CO ₂ eq)	93
	resources	0.399 (MJ primary)	94

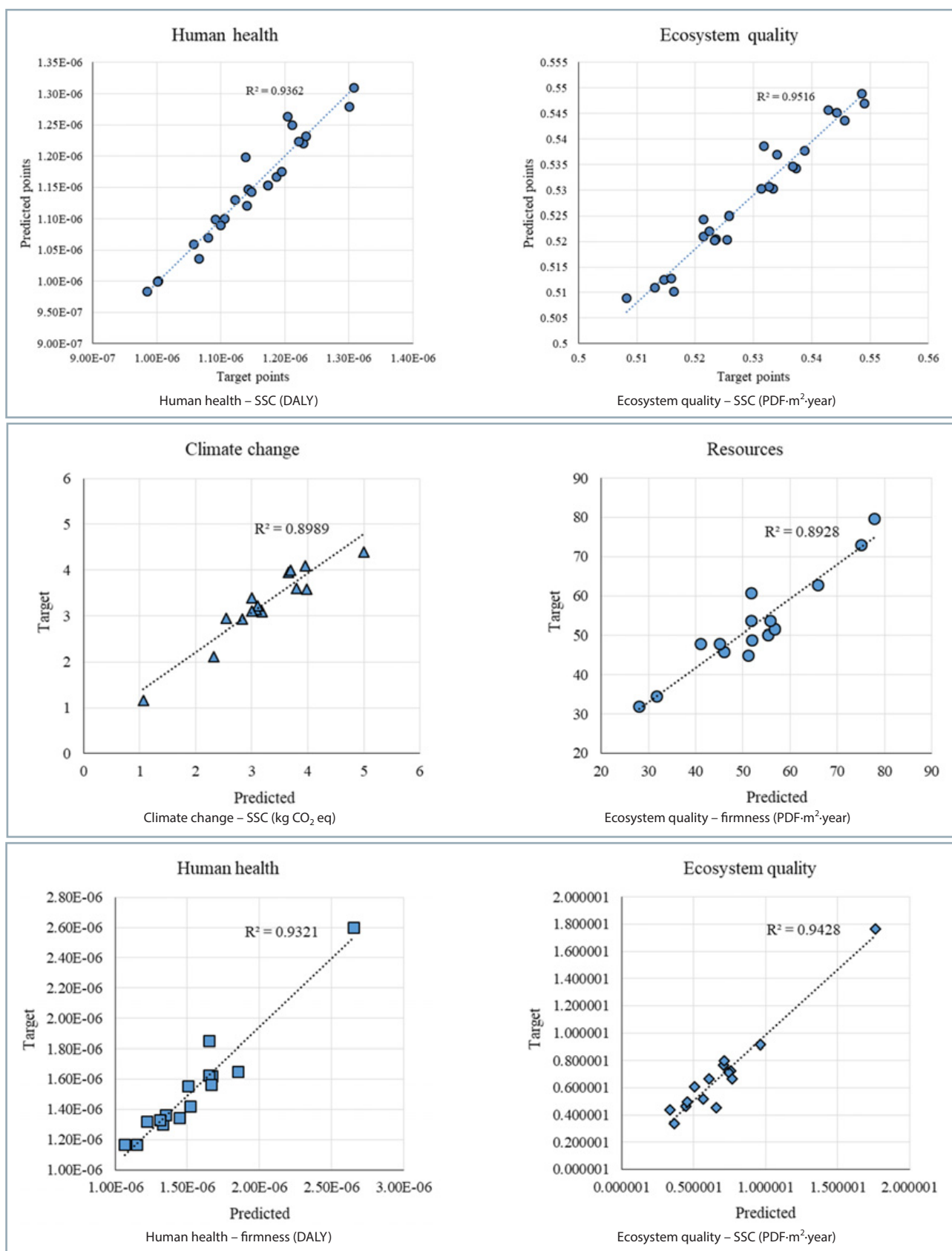


Fig. 5A Testing results of the radial basis function model

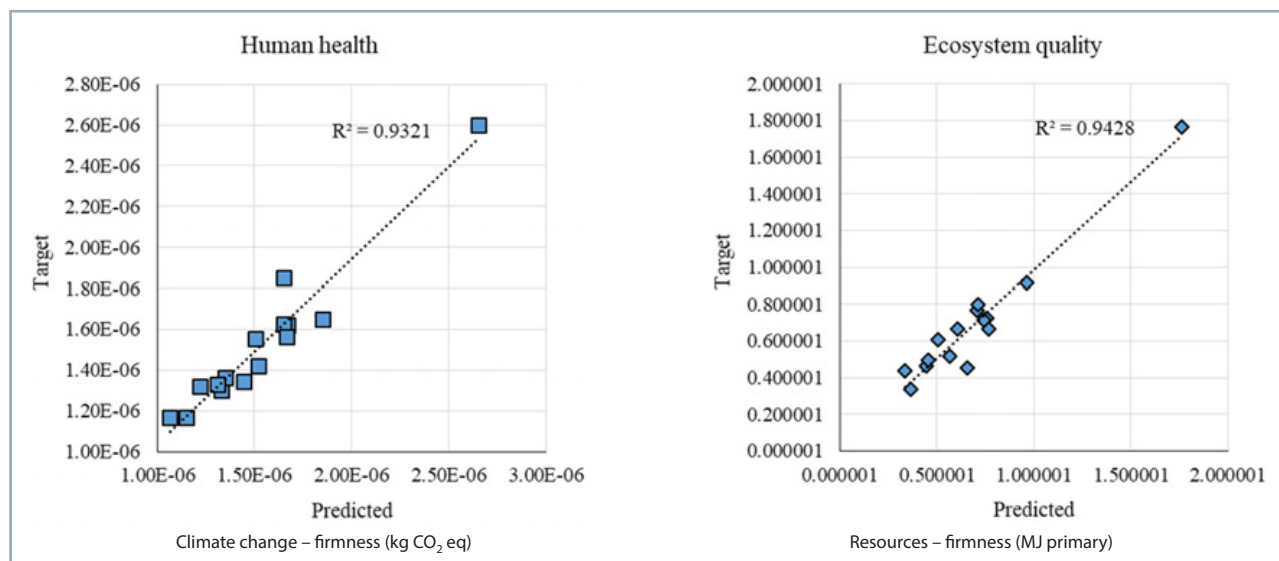


Fig. 5B Testing results of the radial basis function model

According to Table 5, it can be concluded that the developed model could successfully cope with the modelling process of the environmental impacts of the firmness and SSC analysis.

In the present study, the highest prediction accuracy by the machine learning method reached almost 96%, while the prediction accuracy in different studies for predicting the parameters extracted from the non-destructive method was slightly different. In the study of Shao et al. (2019), the prediction accuracy by modelling with the support vector machine integrated method reached 93%, which was about 3% less than the accuracy obtained from the present study. Even in the study by Xing and Guyer (2008), in order to check the classification accuracy of cherry samples, the total accuracy was between 82% and 87%, which was about 9% to 15% less than the results obtained for the present study. Suhandy and Yulia (2021) achieved the maximum accuracy of 91% in Lampung robusta specialty coffee category with partial least squares method.

It should be kept in mind that the method presented in the present study, in addition to creating a network with higher accuracy, has provided the ability to predict and model more outputs (output of environmental impacts) from the non-destructive evaluation method and is a more complementary step towards the future in the direction of the application of machine learning methods in the science of precision agriculture. The integration of these methods, in addition to completing the puzzle of the efficiency of machine learning methods in various sciences, reveals the capabilities of these methods and takes an effective step in industrialisation and a technological look at these sciences. But it still struggles with some limitations. One of the existing limitations is the lack of databases and studies in this field, which requires the activity of researchers in these fields in order to provide the most accurate and up-to-date architectures of different machine learning networks.

Conclusion

The present study focused on the intersection of advanced analytical techniques and environmental sustainability in

non-destructive analysis. The use of spectroscopic methods for estimating soluble solids content (SSC) and firmness in cherries offers a non-invasive alternative to traditional assessment methods, which can be resource-intensive and generate waste. By employing spectroscopy, the research highlights a pathway to not only improve the efficiency and accuracy of fruit quality assessments but also reduce the environmental footprint associated with destructive testing methods. The integration of machine learning to predict environmental parameters demonstrates the potential for further innovation in this field. Machine learning models can process large volumes of data and detect patterns that might not be immediately apparent through conventional analysis. In general, the following results were obtained:

- The wavelengths of 617, 622, 627, 632, and 637 nm have the highest impact on firmness.
- The wavelengths of 657, 667, 662, 672, and 677 nm have the highest impact on SSC values.
- Energy followed by the laboratory procedure has the highest share on the midpoint environmental impact of the firmness and SSC analysis.
- The SSC analysis has owned the most share of midpoint environmental impacts in comparison with the firmness analysis.
- The accuracy values of predicting the environmental impacts of the firmness analysis are higher than those of the SSC analysis.
- The developed model could successfully cope with the modelling process of environmental impacts of the firmness and SSC analysis with a high correlation coefficient value.

Future research could focus on optimising these techniques for other crops, exploring additional environmental parameters, and enhancing machine learning models for broader applicability. Ultimately, the study supports the ongoing evolution toward sustainable and technologically advanced practices in agriculture and fruit quality assessment.

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