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Hyperspectral and Machine Learning-Based Evaluation of Orange Quality and Environmental Impacts

Saif Al-Hinai[1*], Amal Al-Balushi[1], Mohammed Al-Maskari[2], Sultan Al-Mahruqi[3]

Abstract

Emerging non-invasive technologies for determining fruit characteristics represent an innovative and compelling direction for researchers and technical experts. Concurrently, these investigators are progressively examining the broader consequences of such technologies for diagnostic accuracy. A primary consequence of interest is the environmental burden associated with the non-destructive assessment of fruit. Navel oranges are among the most widely appreciated and frequently consumed fruits worldwide, and maturity indicators, including soluble solids content (SSC) and acidity levels, serve as critical quality benchmarks. The present work utilized hyperspectral sensing across the vis-NIR spectrum to quantify SSC and acidity in navel oranges. Building on this, the environmental consequences of evaluating these two quality parameters were explored using life-cycle assessment methodology. The Impact2002+ framework was used to assess the life-cycle inventory results. According to the outcomes, the endpoint environmental burdens linked to SSC determination surpass those associated with pH determination by approximately 40, 42, 20, and 18 percent within the Human Health, Ecosystem quality, climate change, and resources damage categories, respectively. Random forest algorithm outputs revealed a satisfactory and reliable correlation exceeding 90% between the spectral bands isolated during the feature selection phase and the environmental impact indicators.

Keywords Precision agriculture, Machine learning, Environmental assessment, Non-destructive method, Navel orange, Life cycle assessment

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Introduction

Orange is among the most widely consumed fruits in Iran, with a leading presence in the nation's fruit baskets [1, 2]. Accordingly, evaluating the physical attributes and qualitative properties of orange produce is one of the most commonly used methods for assessing fruit quality in the country [3]. Near-infrared spectroscopy (NIRS) is well-suited for non-destructive analysis of internal fruit constituents, such as soluble solids, acidity, and other traits [4]. Investigating non-destructive sensing of orange characteristics has the potential to markedly enhance the reliability of quality assessment platforms for this strategically important fruit in Iran. Meanwhile, progress in non-destructive detection and sensor-based systems can yield economic benefits in both temporal efficiency and analytical expenses [5]. Numerous investigations have addressed the non-destructive determination of orange properties. This section summarizes several noteworthy recent contributions. Shang *et al.* [6] unveiled an online hyperspectral sorting apparatus targeting whole-surface defect identification on oranges. By reducing the dimensionality of hyperspectral data, their strategy achieved notable improvements in fault-detection sensitivity and operational throughput [6]. Jie *et al.* [7] used fluorescence hyperspectral

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imaging to distinguish varying levels of chlorpyrifos and carbendazim residues on the surfaces of orange peels. Leveraging two-dimensional correlation spectroscopy (2D-COS), they developed discriminative models based on optimal characteristic wavelengths, thereby providing a pathway toward swift, non-destructive classification of pesticide contamination levels in navel oranges [7]. Li *et al.* [4] turned to hyperspectral imaging for the identification of unblemished fruit exteriors, canker lesions, Penicillium fungal spores, and hyphae present on oranges. Their dimensionality-reduction approach dramatically reduced the inspection interval from 46.21 to 1.26 seconds in an online detection configuration. Furthermore, they formulated a high-precision deep learning neural network model capable of accurately distinguishing four surface pixel categories [4]. Yet another pivotal, yet largely unexplored and unilluminated, dimension of such inquiries lies in the comparative environmental footprint of conventional and non-destructive analytical approaches. A variety of studies have placed side-by-side non-destructive detection and traditional methods from standpoints of functional performance and economic expenditure. Casson *et al.* [8] conducted an investigation comparing the environmental repercussions of classical ripening assays with those of an optical technique applied to olive fruits. Reference points included moisture, oil, and phenol content obtained via conventional analyses. Life cycle assessment was used to assess environmental effects, incorporating resource flows such as machinery operation and energy demand for both procedural routes [8]. In a subsequent study by Casson *et al.* [9], non-destructive optical modalities based on visible/near-infrared (vis/NIR) spectroscopy offer an accessible and expeditious approach for predicting olive oil yield and quality parameters. Their follow-up inquiry focused on measuring the environmental footprint of vis/NIR technologies relative to wet-chemistry analyses of olive oil using the Life Cycle Assessment (LCA) methodology [9]. A designated functional unit underwent scrutiny under a comprehensive “cradle to grave” system boundary. In the end, vis/NIR spectroscopy produced robust findings, securing its status as an environmentally preferable analytical option with minimal ecological impact. Judging by the published record within the Scopus database, scholarly attention to this subject remains notably sparse. Consequently, a deeper exploration appears imperative, given that traditional procedures for assessing the attributes of fruits such as citrus oranges often demand considerable resources and exacerbate ecological strains. Anchored in the research literature review, the methodological proposition advanced here harnesses hyperspectral imaging technology to acquire high-fidelity spectral information, thereby facilitating a holistic evaluation of citrus quality traits. Machine learning algorithms are subsequently used to couple hyperspectral outputs with conventional measurement data, thereby amplifying the system’s predictive performance [6, 10]. Hyperspectral imaging technology integrates spectral analysis with image-based inspection, enabling the assessment of external fruit appearance and the detection of concealed quality issues [11, 12]. Such an approach marks a foundational advancement in fruit evaluation, capitalizing on discriminating wavelengths to conduct an all-encompassing quality assessment [13, 14]. The current study investigates the chemical properties of orange products, namely sugar content and acidity level. The core objective is to measure the relative environmental burden difference between outcomes from hyperspectral imaging and those from traditional analytical pathways, using life-cycle assessment and defined scenarios. This comparative framework accounts for energy expenditure, time efficiency, and the potential for waste generation.

Beyond this, the research focuses on developing machine learning models to forecast orange quality parameters from hyperspectral data streams, highlighting opportunities for resource optimization in agricultural operations. These predictive models are trained and validated on a dataset capturing fluctuations in environmental conditions, enabling a detailed understanding of the interplay between external environmental drivers and citrus fruit properties. The findings from this study offer meaningful insights into the ecological sustainability of methodologies for evaluating orange quality. By delineating the relative merits and drawbacks inherent to both traditional and hyperspectral strategies, this work informs agricultural practice towards pathways that emphasize efficiency gains while mitigating environmental degradation. Such an integrated outlook contributes to the evolving discourse on sustainable agriculture, delivering practical solutions to streamline citrus production cycles while safeguarding ecological assets.

Materials and Methods

Figure 1 depicts the operational workflow adopted in the current investigation as a proposed predictive framework for estimating the environmental repercussions of non-destructive quantification of sugar content and acidity in navel

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oranges. The schematic lays out seven sequential stages for producing input data and training and appraising the system. These stages encompass: preparation of navel orange specimens, laboratory extraction of acidity and soluble solids contents (SSC) values, deployment of the hyperspectral methodology to capture reflectance spectra across multiple wavebands, compilation of the life cycle inventory dataset, impact assessment of the life cycle inventory, model construction via the random forest algorithm, and prediction of impact categories: Midpoint and Endpoint Impact evaluation method 2002+.

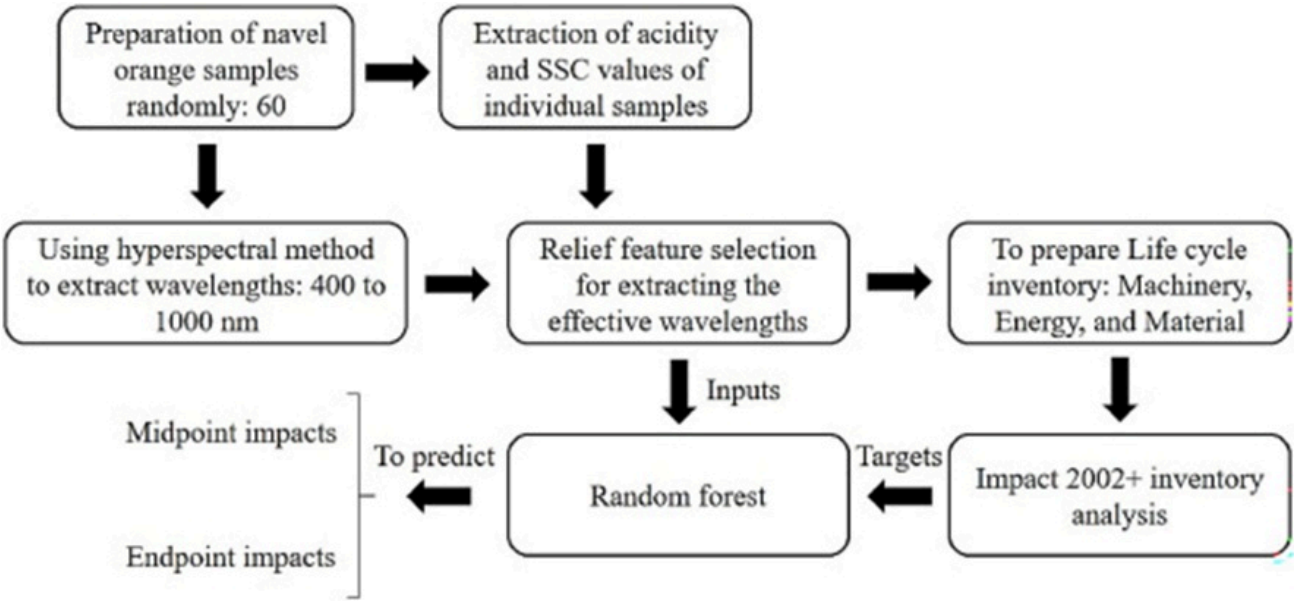

Figure 1. The flowchart of the study's procedure.

Preparing the samples

The navel orange cultivar served as the biological material for this study. A batch of 60 specimens, drawn entirely at random, was employed in the experimental campaign. Assembling a diverse collection of samples represented the inaugural step in constructing the proposed predictive platform. The fruit specimens were sourced from Sari, situated within Mazandaran province. Initially, a panel of human assessors pinpointed the approximate harvest window for the Thomson variety. All 60 samples were subsequently allocated into four distinct maturity stages by the expert panel, following the sampling protocol outlined in the work of Pourdarbani *et al.* [15]: twenty days before the optimal harvest date, ten days before the optimal harvest point, at the optimal harvest point, and ten days beyond the optimal harvest date. Every ripening category contained 60 individual samples. Immediately upon collection, the fruit samples underwent scanning to record their spectral signatures.

Hyperspectral imaging

Figure 2 portrays the hyperspectral imaging apparatus. The configuration incorporates a custom-fabricated light-sealed enclosure that accommodates an image sensor, a charge-coupled device (CCD) camera, an illumination module, and the sample, all interfaced with an external computer running an information and control suite (SpectrometerOPTC-1000, IRAN). The line-scan camera acquires image frames measuring up to 720 × 440 mm at a spatial resolution of 0.2 mm, with integration times ranging from 10 to 110 ms. It registers electromagnetic radiation from 190 to 115 nm at a spectral resolution of 1 nm, though the analysis focuses on the 400 to 1000 nm interval to ensure imaging stability and reduce noise.

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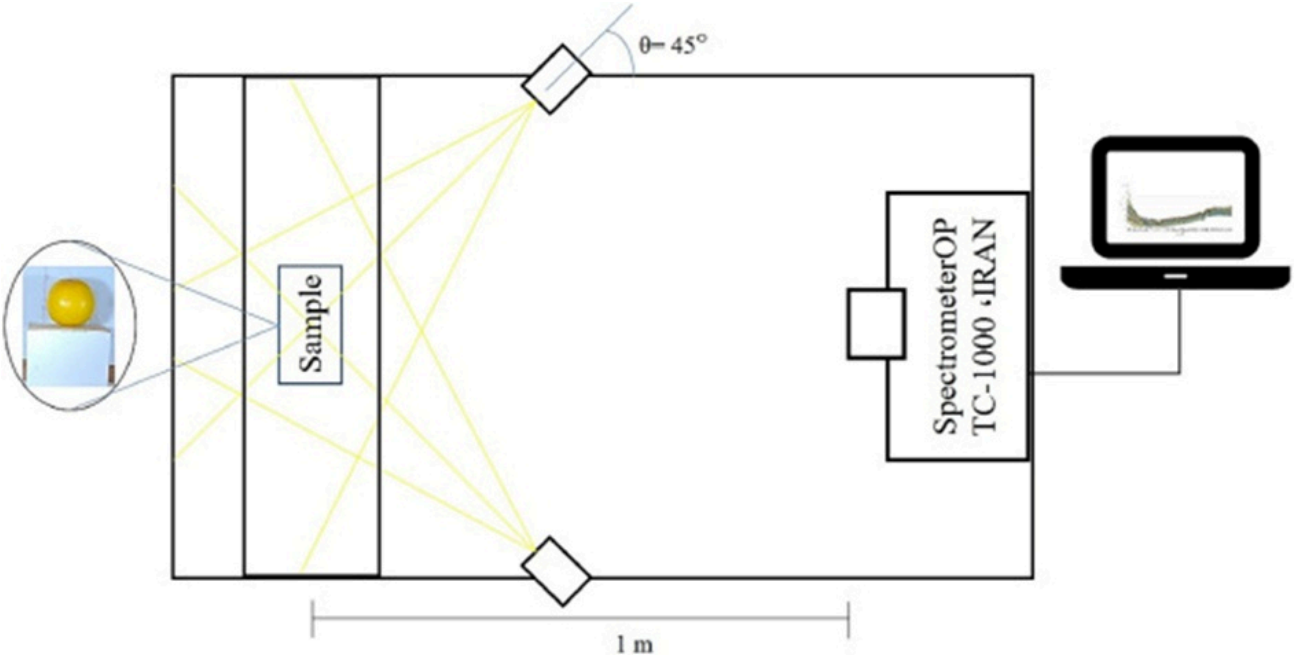

Figure 2. Hyperspectral imaging system.

Each aggregated sample was subjected to 450 individual scanning operations, each lasting 300 ms, during which 1279 spectral bands were logged per hyperspectral reflectance image. Following the imaging routine, 50 fruit nuclei were randomly selected and weighed using a digital analytical balance. **Figure 3** presents a representative view of the data-acquisition interface used throughout the hyperspectral measurement sequence.

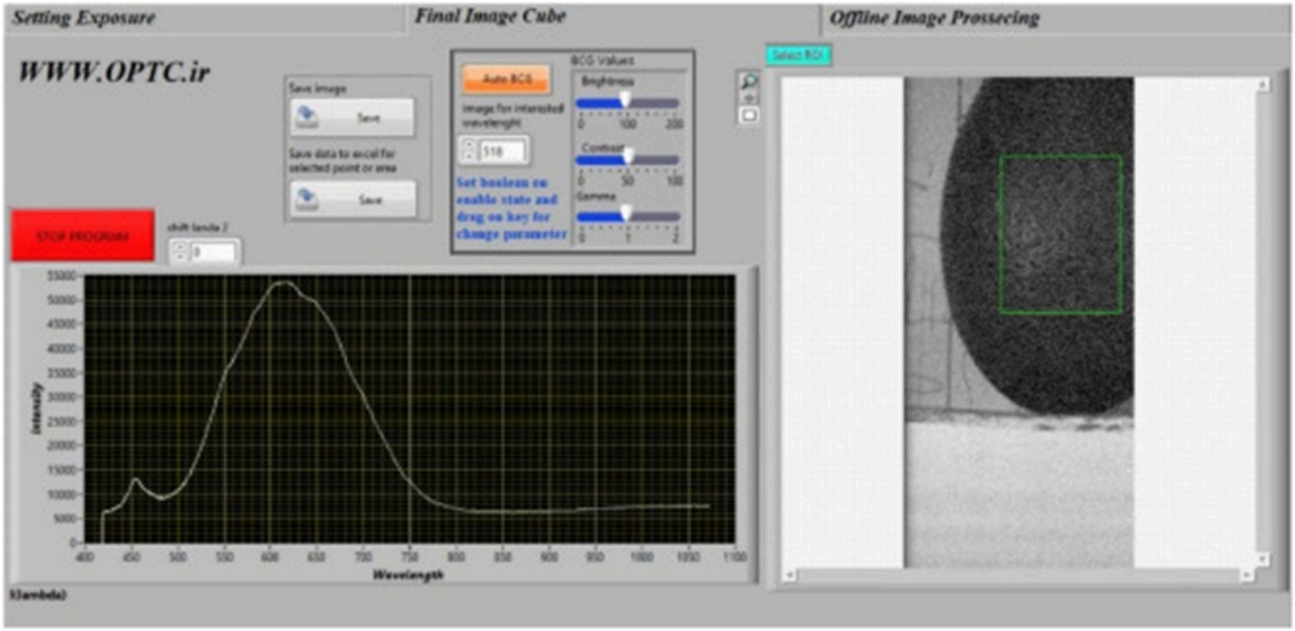

Figure 3. An example of hyperspectral data collection.

Navel orange properties measurement

Table 1 summarizes the physicochemical characteristics determined for the navel orange specimens, encompassing mass, acidity, and SSC. As **Table 1** reveals, the relative standard deviation, also termed the coefficient of variation, for

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SSC content (3.3) is greater than that recorded for acidity and firmness.

Table 1. Values related to physical-chemical properties.

Property	STD deviation	Min	Mean	Unit
Weight	15.25	232.9	250.5	g
Acidity	0.21	3.13	3.48	pH
SSC	0.27	8	8.3	%

A digital laboratory scale with 0.1 g precision was used to measure weight. A spectrophotometer was used for SSC extraction. In this approach, the sample is first dehydrated. The resulting aqueous values were then analyzed using a dropper within a spectrophotometer (Optizen 2120 UVplus). An acidity meter offering ±0.01 accuracy was utilized to continue recording pH readings.

Feature selection technique

The Relief feature selection method was used to identify influential wavelengths. The Relief algorithm represents a feature selection strategy routinely applied across machine learning and data mining disciplines [16]. It assesses the relevance of each feature by evaluating its impact on classification accuracy. The Relief score quantifies feature significance by computing differences in feature values between samples situated near one another in the feature space [17]. The algorithm assigns higher scores to features that exhibit marked dissimilarities. It focuses on value patterns in samples from separate classes, indicating their relevance to the classification outcome. To put this algorithm into practice, characteristics derived from the experimental testing were designated as dependent variables, while wavelengths were set as independent variables within the MATLAB software library. Based on this, a collection of wavelength scores was generated, and five highly effective wavelengths were selected as influential independent variables.

Life cycle assessment (LCA)

Life cycle assessment constitutes a dedicated framework for examining the resources, operations, and services involved over the entirety of a production cycle, from raw material extraction and production phases through to various production systems and the associated potential environmental consequences. This investigation follows the ISO 14040 and 14044 LCA guidelines, which include defining the goal and scope, performing life cycle inventory analysis, evaluating LCA impacts, and interpreting the results [18]. An attributional LCA was conducted to examine the significant environmental flows entering and exiting the studied systems [19]. Here, the life cycle assessment aims to examine the environmental implications of measuring and evaluating navel orange properties—namely, SSC and acidity—using hyperspectral imaging combined with machine learning-based prediction.

In this work, the procedure outlined by Casson *et al.* [8] was adopted to establish the functional unit. Consistent with the investigation by Casson *et al.* [8], the functional unit was built around the laboratory's analytical services, delivering two analyzed parameters along with a non-destructive analysis. The life cycle assessment inventory was compiled from a questionnaire completed by the laboratory's core group. The questionnaire covered details such as equipment mass, the nature of the devices under examination, their operational lifespan, the usage duration per test, and the energy draw of each apparatus. Following the methodology described by Casson *et al.* [8], an allocation coefficient ranging from 0 to 1 percent of the total allocation is assigned to each inventory entry, taking into account the usage time and the multiple roles of that entry across different reference parameters. Next, the value for each analysis (Apa) was determined for every input and output by means of **Eq. 1** [8]:

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$$Amount\ per\ analysis = \frac{\text{Quantity} \times \text{Allocation factor}}{number\ of\ \text{the}\ analysis} \quad (1)$$

Tables 2 and 3 supply the compositions and specifications of the instruments and apparatus used throughout this research, together with the inventory of evaluations performed at various stages of the current study.

Table 2. Specifications of devices and tools used.

Equipment	Material composition	Electricity consumption (W)	Weight (kg)
Hyperspectral CCD Camera	85% electronic components; 10% steel; 5% glass	144	2.8
Spectrophotometer box	95% wood; 3% electrical components; 1% glass; 1% plastic	10	15
Computer	97% electrical components; 3% aluminium	64.98	1.1
pH meter	60% plastic; 40% electrical components	24	1.5
SSC spectrophotometer	55% plastic; 45% electrical components	12	1.2
Juicer	30% electrical components; 25% steel; 25% plastic; 20% aluminum	800	3.5

Table 3. Life cycle inventory.

Category	Process/Item	Amount per analysis	Number of analyses	Lifetime (Years)	Allocation factor	Quantity	Unit
Inputs	Hyper spectroscopy	0.0024	10,000	5	0.16	150	Kg
Inputs	Computer vision	0.0008	15,000	12	0.24	50	Kg
Inputs	Modeling	0.00019	5,000	–	0.19	5	Kg
Inputs	pH analysis	0.001	7,500	5	0.15	50	Kg
Inputs	SSC analysis	0.000566667	15,000	5	0.17	50	Kg
Inputs	Juicer	0.00045	10,000	15	0.09	50	Kg
Inputs	Electricity	4.8	1	–	1	4.8	kWh
Inputs	Water	3	1	–	1	3	Kg
Outputs	Experimental data	According to the scenario	–	–	–	–	–
Outputs	Waste material	1.25	–	–	–	1.25	Kg

The IMPACT 2002+ model was used to evaluate the life-cycle impact of the experimental method. To implement this model, SimaPro 9.3 software was used to perform a life-cycle impact assessment and assess the environmental

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consequences. This model computes environmental impacts at both intermediate and final stages, separating outcomes into fifteen Midpoint and four Endpoint impact groupings. The Endpoint impact categories included human health (HH), environmental quality (EQ), climate change (CC), and resources (R), each of which was deployed for the contribution analysis. These impact classifications were chosen as midpoint impacts, constituting merely a subset of the endpoint impacts.

Modeling

The random forest approach was applied for modeling purposes in this study. The theoretical basis of the random forest technique is detailed by Breiman [20]. Thanks to these strengths and its inherent robustness, random forests have broad application across diverse machine learning contexts, including classification, regression, and feature selection. This investigation employed the random forest algorithm to estimate and non-destructively model endpoint impacts from the life-cycle assessment associated with measuring pH and SSC values in navel oranges. In this manner, the wavelengths isolated during the feature selection process were assigned as independent variables, and the endpoint environmental impacts were designated as dependent variables. Subsequently, the network configuration was fine-tuned to train the optimal network for predicting the measured outputs. Root mean square error (RMSE) and correlation coefficient (CC) figures were used to judge network performance.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_i - \widehat{x_i}\right)^2} \quad (2)$$

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

In these formulas, x^ stands for the predicted values, x i,s represents the actual values, and N denotes the sample count.

Results and Discussion

This portion delivers the research outcomes and discoveries. The findings are organized into three subsections: the first covers spectroscopy outcomes, the second covers life-cycle assessment outcomes, and the third covers modeling outcomes. **Figure 4** presents the hyperspectral method's output as reflection intensity across various spectral ranges. This diagram illustrates reflectance spectra in a single figure. Using a feature selection technique, wavelengths influencing each dependent variable (i.e., SSC and pH) were identified. According to the results, wavelengths 577, 580, 584, 588, and 592 were identified as effective for SSC, while wavelengths 916, 931, 963, 978, and 998 were identified as effective for pH. This indicates that wavelengths affecting SSC lie within the visible range, whereas the wavelength affecting acidity lies in the infrared range. Visible light (wavelengths spanning approximately 400-700 nm) can be sufficient for sensing SSC. One possibility lies in its interaction with fruit pigments, chiefly chlorophyll and carotenoids.

Meanwhile, these pigments may absorb light at specific wavelengths in the visible spectrum, allowing a spectrophotometer to measure the intensity of the absorbed light. Light absorption by such pigments can be linked to the concentration of dissolved solids like sugar within the fruit. Based on the findings, it can be concluded that visible light can be used effectively for SSC evaluation. The data indicated that, for acidity detection, effective wavelengths lie in the infrared region beyond 700 nm, which helps distinguish distinct chemical signatures of oranges. The fruit tissue allows infrared rays to penetrate, with the absorption intensity being modifiable to a large degree by the water and organic acid composition within the orange. At the same time, specific organic acids present in orange samples can uniquely absorb radiation in the infrared region, thereby revealing their acidity.

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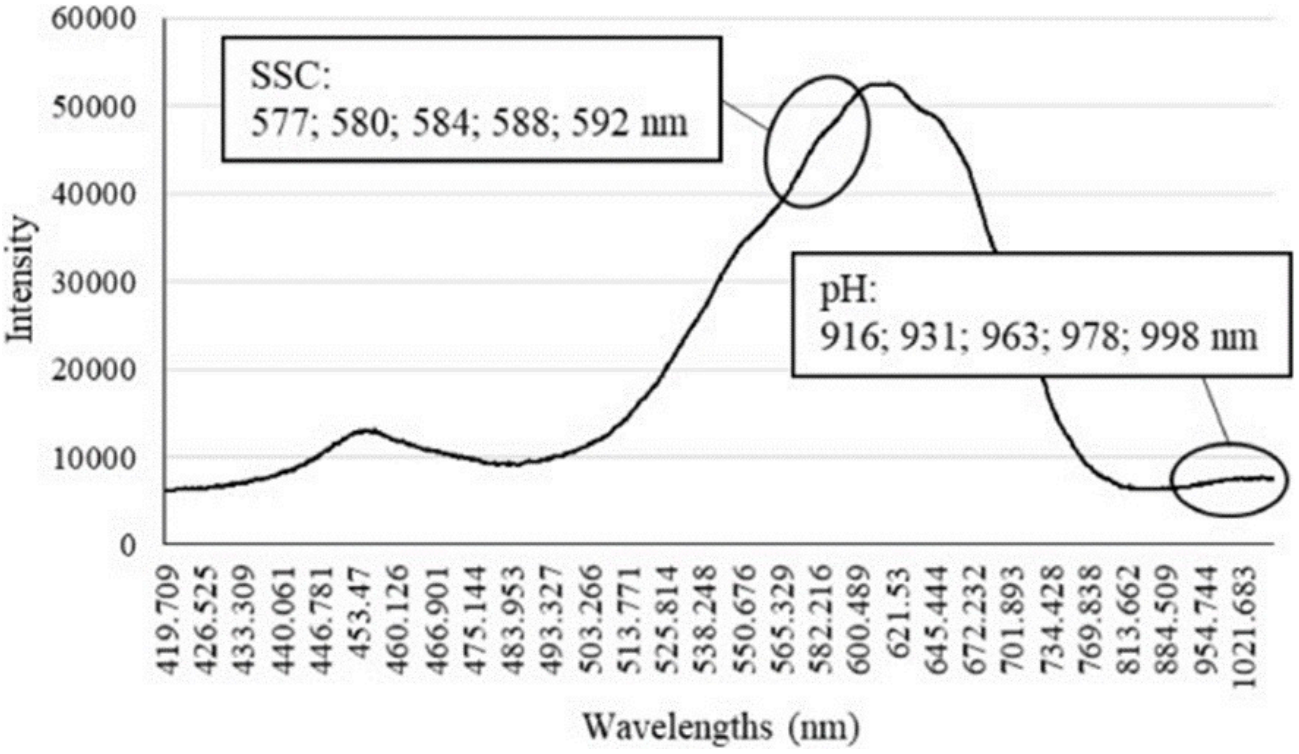

Figure 4. The output results of the hyperspectral method for measuring the reflection intensity.

Results of life cycle assessment

Figure 5 shows the life-cycle assessment results for Midpoint indicators under the Impact2002+ methodology. This graphic organizes environmental impact outputs by process type. As shown in **Figure 5**, the greatest environmental load among the midpoint indicators is in the energy consumption category, followed by SSC detection. Energy consumption exerts the dominant effect on impact indices tied to non-renewable energy usage and global warming. In keeping with earlier statements, the foremost environmental impact at the Midpoint level stems from energy consumption. This observation suggests that the non-destructive detection workflow is heavily dependent on energy-intensive components. These components can increase energy consumption during data collection, instrument operation, hardware deployment, and even modeling. Rising energy consumption translates into higher energy input requirements, which, in turn, widens the environmental footprint. A large fraction of global energy production draws from non-renewable sources. Non-renewable energy generation results in higher greenhouse gas and other pollutant emissions. Therefore, one can assert that adopting energy-efficient practices and shifting to renewable energy sources to reduce the environmental impacts of energy consumption is a viable solution. The SSC detection pathway represents another factor shaping environmental emissions. It can be suggested that the techniques deployed for SSC detection rely predominantly on energy-powered technologies. Accordingly, the combined burden of SSC detection and elevated energy demand worsens the environmental load. By understanding these dynamics, policies can be crafted to optimize energy use in SSC detection workflows, thereby lessening overall environmental impacts and advancing sustainability in the smart agriculture technology sector. According to the results, the lowest impact is in the execution stage of the laboratory procedure, followed by waste management. The effects linked to the machine learning component are also considerable. This component involves computer, hardware, and software infrastructure, all of which consume significant energy, hardware capacity, and time throughout the modeling network's training and testing cycles.

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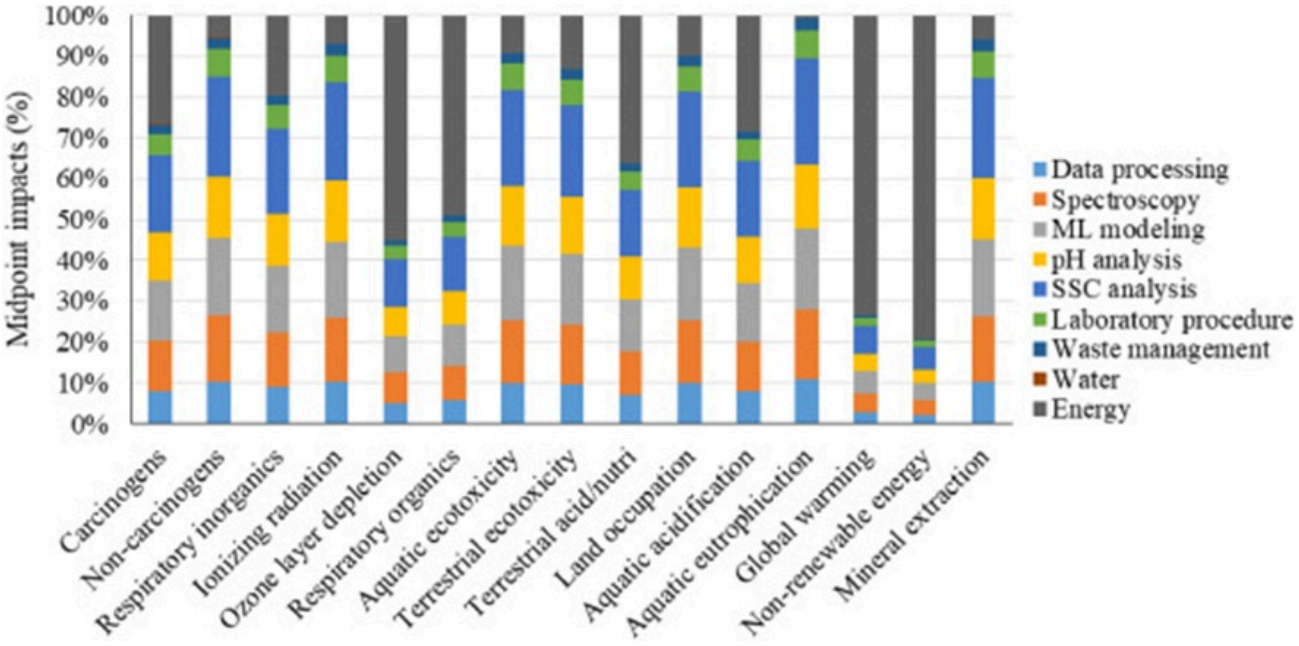

Figure 5. Midpoint indicators of environmental impacts by process stages.

Table 4 contrasts the pH and SSC analysis stages from the viewpoint of midpoint environmental impacts. Drawing on the findings presented, the environmental consequences of SSC evaluation outstrip those of pH evaluation. This pattern holds because the contribution of inputs utilized in SSC analysis exceeds that for pH analysis. Moreover, SSC analysis is more time-intensive and energy-intensive than pH analysis.

Table 4. Comparison of environmental effects from the point of view of intermediate indicators for SSC and pH analysis.

Impact category	Unit	SSC analysis	pH analysis
Carcinogens	kg C2H3Cl eq	0.014028	0.006328
Non-carcinogens	kg C2H3Cl eq	0.046434	0.016613
Respiratory inorganics	kg PM2.5 eq	0.001443	0.000602
Ionizing radiation	Bq C-14 eq	9.690909	3.516892
Ozone layer depletion	kg CFC-11 eq	1.48E-07	8.76E-08
Respiratory organics	kg C2H4 eq	0.000335	0.000191
Aquatic ecotoxicity	kg TEG water	357.3768	132.7233
Terrestrial ecotoxicity	kg TEG soil	60.14278	23.38816
Terrestrial acid/nutri	kg SO2 eq	0.021637	0.010695
Land occupation	m2org.arable	0.01957	0.007803
Aquatic acidification	kg SO2 eq	0.00486	0.002219
Aquatic eutrophication	kg PO4 P-lim	0.003015	0.001014
Global warming	kg CO2 eq	1.960136	1.371697
Non-renewable energy	MJ primary	35.57144	26.23302

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Mineral extraction	MJ surplus	0.121022	0.043557

On the flip side, this pattern also manifests within the endpoint impact indicators. Per the endpoint indicators, the environmental impacts of SSC measurement exceed those of pH measurement by roughly 40, 42, 20, and 18 percent for Human Health, Ecosystem quality, climate change, and resources, respectively. The finding that environmental loads from measuring soluble solids content (SSC) in navel oranges exceeded those from pH measurements across multiple endpoint indicators highlights the differing environmental implications of these two procedures. As touched on earlier, SSC measurement involves more resource-intensive methods and inputs than pH measurement. In other words, technologies employed for SSC evaluation demand greater energy consumption, more inputs, or more precise instrumentation, all of which can heighten environmental impacts across different groupings.

Additionally, the variations in environmental impacts across endpoint categories underscore the multidimensional character of sustainability evaluations. Though SSC and pH measurements are both essential indicators of navel orange quality, their environmental impacts extend beyond their direct usefulness. Elements such as energy consumption, chemical application, and waste handling associated with each measurement technique can place varying levels of stress on human health, ecosystem quality, climate change, and resource depletion.

Results of modeling

This stage presents the findings from the random forest model. **Table 5** displays the outcomes of the network training process. Judging by the network accuracy metrics, the environmental parameter estimates from acidity measurements are more precise than those from SSC measurements. The greatest estimation accuracy for acidity is for human health, with resource quality ranking second. The stronger correlation between environmental variables and acidity captured by hyperspectral means, rather than by SSC, can be traced to the assignment of specific spectral patterns to acidity levels within the tested specimens. Hyperspectral approaches entail recording light reflectance across a wide span of wavelengths, facilitating accurate characterization of chemical constitution and traits. Acidity, largely determined by organic acid content, may exhibit unique spectral fingerprints that hyperspectral analysis can detect and associate with environmental conditions. In addition, wider environmental drivers—soil health, moisture availability, and farming methods—can modulate acidity concentrations, further cementing this linkage. As a result, a higher correlation coefficient for hyperspectral-based acidity detection has implications for more refined estimates of environmental burden, especially regarding human health and resource valuation. Elements like flavor, nutritional content, and possible health concerns from elevated acid levels—connected to human health—alongside excessive fruit acidity that can degrade resource integrity, particularly soil productivity and water efficiency, illustrate ways in which high fruit acidity may affect human wellness. With accurate identification of soil and water acidity, coupled with an understanding of how these levels interact with other environmental drivers, land managers and decision-makers will gain a stronger foundation for farmland stewardship, resource allocation decisions, and public health programming, thereby fostering sustainable growth and well-being.

Table 5. The output results from the random forest model training.

Indicator	Impact category	CC	RMSE
SSC	Human health	0.95	8.01E-08
SSC	Ecosystem quality	0.97	0.011
SSC	Climate change	0.94	0.021
SSC	Resources	0.96	0.051
pH	Human health	0.98	2.76E-09
pH	Ecosystem quality	0.93	0.008

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pH	Climate change	0.96	0.063
pH	Resources	0.97	0.52

Figure 6 further presents the findings from the testing phase of the model built using the random forest method, using categorized data for network validation. As shown in **Figure 6**, network precision during testing has dipped slightly compared to the training phase. Even so, the overarching trend inferred from the scatter plot interpretation confirms that testing-phase outputs are consistent with those observed during model training.

There remains a call for even more streamlined and effective approaches to evaluating this method sustainably; yet, reviewing the output suggests that the pH measurement protocol still lags behind the SSC measurement protocol in terms of optimization. These constraints, nonetheless, carry weight for the final results. The input log design, quite possibly a principal research limitation within the examined topic, is structured so that extraneous factors are likewise incorporated—beyond orange acidity and SSC, additional variables can influence environmental parameters. Stronger correlation coefficients might be secured when hyperspectral techniques are used to detect acidity and SSC, but this would further demand an appreciation of environmental impacts shaped by compound interactions, for instance, between soil classifications and weather regimes that shift geographically; investigations into region- and climate-specific soil types, as well as cultivation practices and post-harvest handling procedures, also weigh in heavily. If solely sourness and soluble sugar content are factored in, the interplay between them may be neglected, yielding incomplete or skewed assessments of environmental effects on fruit. For this reason, expanded data collection is needed to build a richer picture of the intricate ties binding fruit production, fruit quality, and the surrounding environment.

Conclusion

Drawing on hyperspectral techniques, the environmental footprint of pH and SSC determination in Navel Oranges was assessed using a life-cycle assessment framework. A secondary aim pursued by this work was to examine the long-term viability of ecologically sound, non-destructive pH and SSC readings in Navel Oranges, a fruit esteemed for its storability. Hyperspectral-based pH detection has been shown to generate stronger responses to environmental challenges than soluble solids content (SSC) quantification. In fact, dynamic acidity concentration metrics align more closely with resource quality appraisals and human health considerations. In contrast, acidity levels remain critical to product formulation and other commercial spheres, as all these dimensions can shape its makeup depending on the end use. This observed tendency underscores the need to treat acidity levels as a key lever for environmental effects in farming systems, providing actionable intelligence for stakeholders seeking to refine agricultural operations, resource distribution, and public health strategies. The results chart a course for refining the SSC analysis pipeline to achieve dependable non-destructive evaluation. Given the existing restrictions and hurdles, subsequent studies are encouraged to extend the system boundary investigation and adopt a cradle-to-grave perspective covering the span from the initial point of orange production through harvest, assessment, and waste handling. Additionally, landfill-centric scenarios could provide a more straightforward route to isolate the driving factors needed to build sustainable, non-destructive detection platforms for gauging orange attributes and quality, as depicted in **Figure 7**.

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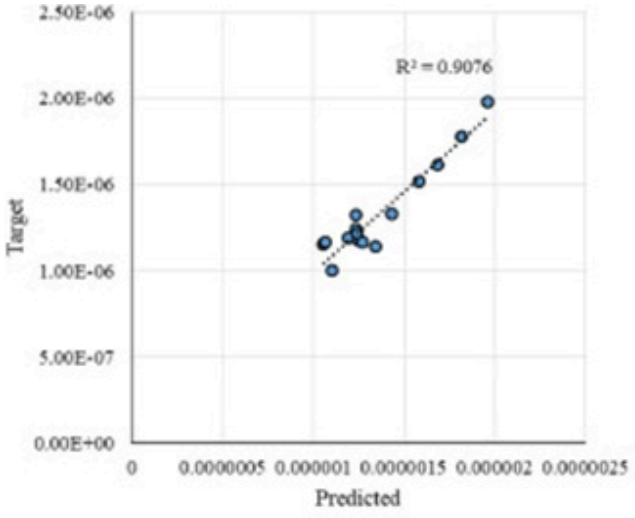

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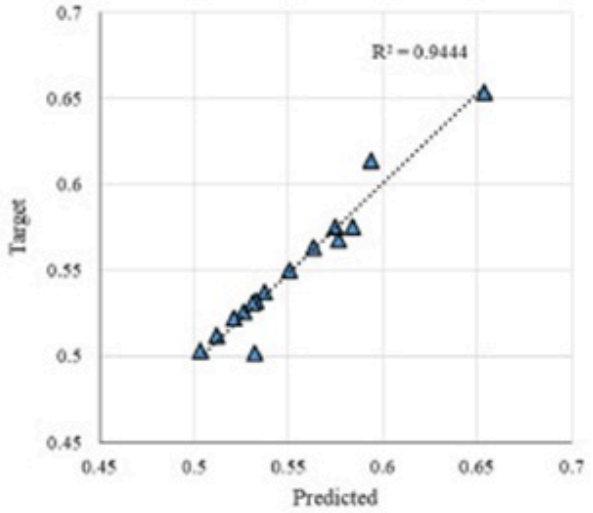

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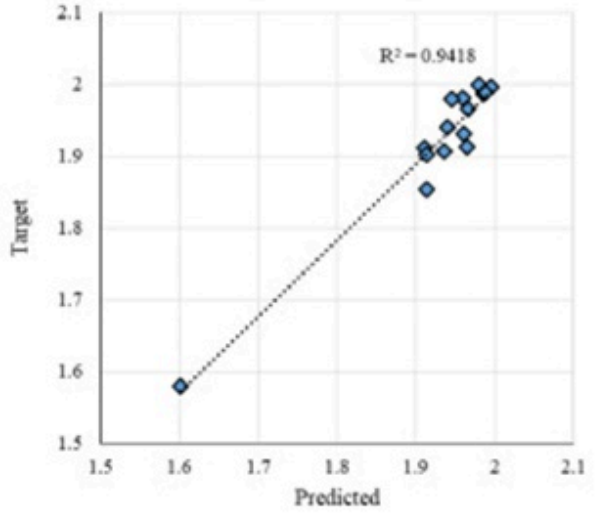

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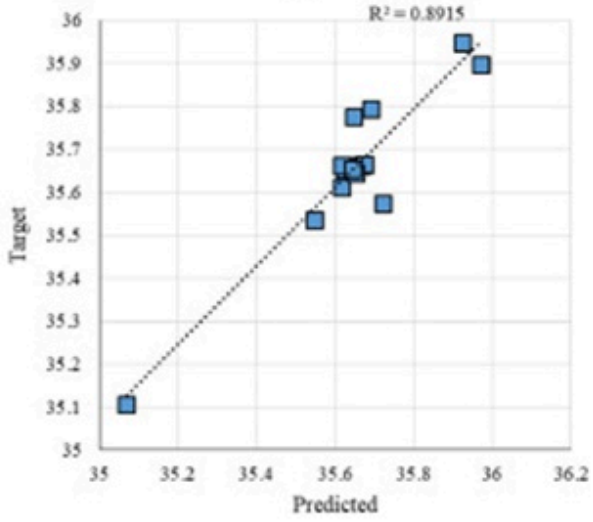

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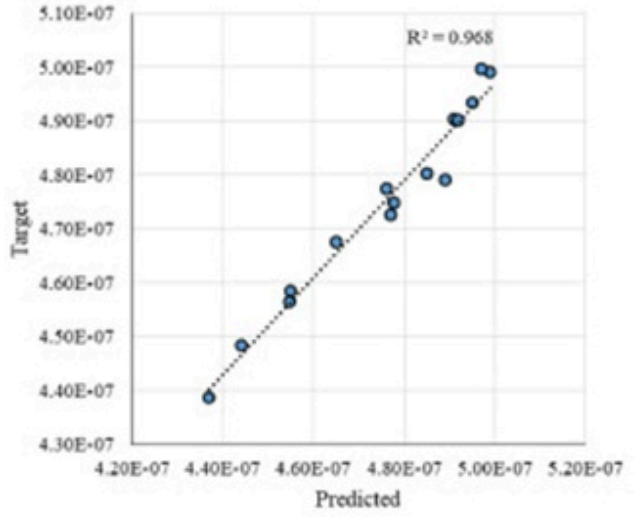
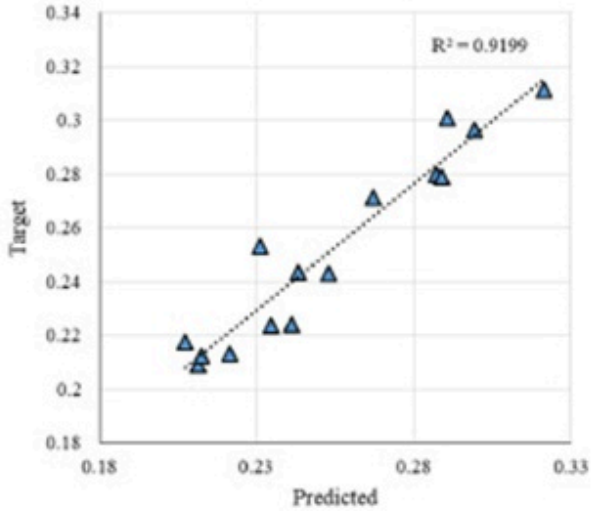


(e)



(f)





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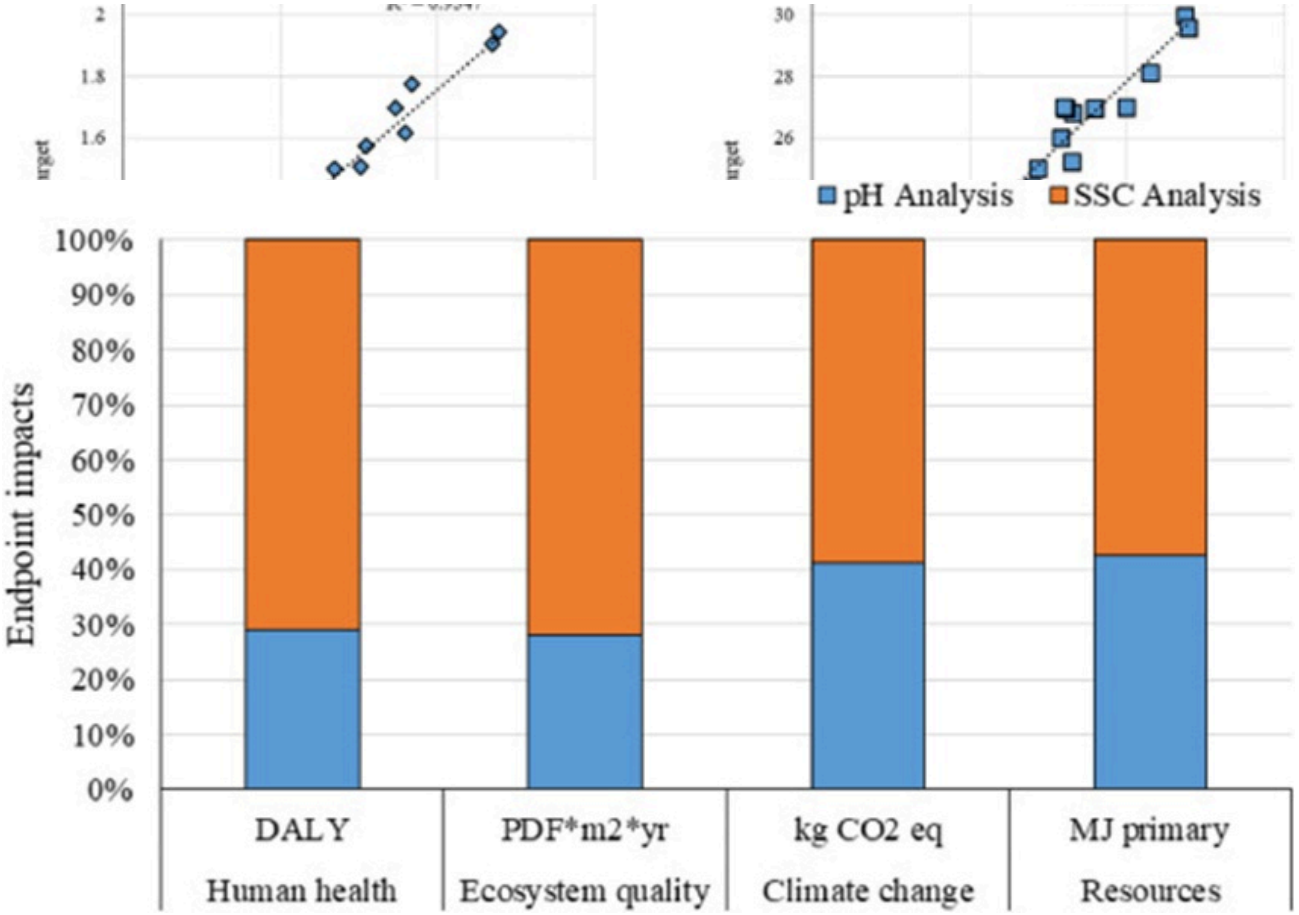

Figure 7. Comparison of environmental effects of SSC and pH analysis from the point of view of final indicators.

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Conflict of interest

None

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Ethics statement

All authors ensure that the manuscript procedures were performed in compliance with relevant laws and institutional guidelines and that the appropriate institutional committee has approved the manuscript.

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