Employing Green Technology System in calibrating Eco-Marketing strategy of grape growing companies: Transparent and Controlled use of Green Chemicals

Ravshan Nurimbetov[1*], *Ne'matjon* Sattarov Azatbayevich[2], *Karima* Tashmukhamedova Samatovna[3], *Gozzal* Aliyeva Aliyevna[4], *Nilufar* Akhmedova Shuxratovna[5], Viktoriya Lyamkina[6]

[1]Doctor of Economic Sciences, Professor, Tashkent University of Architecture and Civil Engineering, Head of Education Quality Control Department. Tashkent, Uzbekistan. *r.i.nurimbetov@bk.ru*
[2]The Department of Construction, Urgench State University named after Abu Rayhon Beruni, Xorazm Viloyati, Uzbekistan. nemat6778@gmail.com
[3]Department of Economics and Real Estate at Tashkent University of Power Engineering. *E-mail: takarima73@gmail.com ORCID: https://orcid.org/0009-0006-3350-0070*
[4]Department of Agribusiness and Accounting, Karakalpakstan Institute of Agriculture and Agrotechnology, Uzbekistan. *aliyevagozzal2@gmail.com*
[5] Department of Economics and real estate, Tashkent University of Architecture and Civil Engineering, Tashkent, Uzbekistan. *nilufar6444@mail.ru*
[6]Tashkent Institute of Textile and Light Industry, Uzbekistan

Abstract. Due to the complexity of the vineyard ecosystem, a growing number of eco-certified inputs has been integrated into a framework of sustainable agricultural practices. This research is aimed at developing a hybrid framework that can be used to predict the eco-label readiness of a certain vineyard and provide guidance about the ecological indicators that should be prioritized in it as well as to find ways to increase the marketing effectiveness. Secondly, the sample of vineyards (n = 50) was divided into three groups—early, mid-season and late ripening varieties—for the analysis of a significant difference observed between and within groups, in terms of the effects of sensor-calibrated inputs on eco-performance indicators. In the second phase, the structural analysis focused on the relationship between eco-performance indicators and its outcomes (eco-label readiness, both direct and indirect effects). Then, the regression analysis and structural equation modeling showed that out of all examined eco-performance results, the timing of the chlorophyll decline, the behaviour of the sugar accumulation under controlled application, and the stability of the eco-readiness over time contributed to the total variance of eco-performance. Yet, the results confirm our assumption that an improvement in sensor calibration and nutrient scheduling is also necessary, particularly in the eco-label certification process of vineyards. The methodology can be

* *Corresponding author: r.i.nurimbetov@bk.ru*

used to make informed decisions both about the operational strategies for increasing the eco-marketing performance and the selection of inputs that should be applied in the vineyard.

Keywords: Eco-marketing calibration, Green viticulture technologies, Chlorophyll-sugar dynamics, Sensor-based nutrient scheduling, Eco-label readiness modeling, SEM–regression hybrid framework, Transitional vineyards sustainability

1. Introduction

[1] mentioned three main challenges in digital viticulture: (1) eco-physiological context with variability larger than predicted; (2) photosynthetic behavior and sugar metabolism need calibration between climatic stress and biochemical activity; (3) phenological context with accuracy lesser than expected (the order mismatch of biometric survey due to sample size lesser than threshold for forecasting in smart viticulture). At the intra-seasonal time scale, variability of grape productivity is controlled mainly by the interaction of temperature and rainfall [2], such as veraison onset, which is predicted using real-time data from multispectral sensors [3] or smart monitoring systems [4].

Phenological metrics, such as the timing of recurrent events such as the start of the ripening period or onset of senescence, duration and intensity of the maturation cycle are often extracted from digital dashboards [1,5] used as indicators to describe the sustainability of vineyard systems [6]. In the marketing context, researchers have emphasized the green advantage on eco-labeling as a factor to be communicated and prioritized [5,7], and strategic branding alignment [7,8].

During this transformative era of the ongoing green transition, viticulture faces a challenge for mitigating risk of chemical overuse, increasing number of eco-labeled inputs, smart input distribution systems, and vineyard-specific control dashboards. Anyway, the current strategies do not agree with the variability of nutrient uptake occurring in a vineyard due to microclimatic problems, although there are spatial variations inside of blocks, according to small nutrient content changes or pattern of water stress zones.

In this ongoing shift, the green chemical regime may significantly reduce the risk of metabolic decline by synchronizing the application of nutrients during ripening, especially in Mediterranean, continental, and semi-arid zones. Understanding the relationship between green chemical inputs and grapevine physiological indicators (e.g., chlorophyll index, sugar concentration) is thus crucial to understand eco-marketing decisions in viticulture [3,14].

In that sense, [9] implemented a sustainability framework in one pilot vineyard, based on integrated variables: (1) content of chlorophyll; (2) phenological level; (3) degradation of fungicide residues; (4) rainfall amplitude. Likewise, degradation of applied chemicals is also strongly affected by temperature and leaf surface exposure [10,11].

Few previous studies have considered concurrent effects on photosynthesis and eco-performance of vineyards, mostly focusing on varietals or management practices at plot scale [1,12,13]. In this context, several authors have provided guidance about how vineyard design can be calibrated by combining indicators that support ecology–branding needs and by configuring the most viable conditions to boost consumer trust [4,5,7].

Moreover, the evidence concluded that the type of green label does not affect the quality of yield; however, this effect would be associated with photosynthetic depth. However, due to limited tracking tools, they normally cannot be used to quantify consistency in ripening and residue levels at microplot scale [2].

More importantly, they are limited in considering the interaction response. For instance, they are limited to quantify the effects of synergy between the variables, for example, the contrast among eco-input types and overlap between leaf aging, chlorophyll loss, and sugar buildup. Some more specific objectives/concerns are the following. (1) Sensor mapping is an interdisciplinary procedure, technical, and managerial; is there some pattern with the same level of predictability and control in the perspective of green branding?. Therefore, the purpose of this study is to evaluate and simulate the set of eco-performance and marketing related challenges faced by grape producers in transitional vineyards, which is a critical knowledge gap in this area of agro-technology. In this ongoing shift, the green chemical regime may significantly reduce the risk of metabolic decline by synchronizing the application of nutrients during ripening, especially in Mediterranean, continental, and semi-arid zones. In this study, we mainly focus on the sugar accumulation at the harvest stage [2], the leaf chlorophyll index [3], and temperature variability in the ripening period [10] as those indicators are most important and accessible to detect the readiness to label [4].

These approaches are discussed in some way in this research considering vineyards located on Uzbekistan, Spain, Italy, in Eurasia. Given the hybrid nature of this research, our methodological design consists of two phases: (i) a quantitative methodology [3]; and (ii) an experimental research methodology [15]. Considering the variability of the climate [2], and shape of the curve of chlorophyll and sugar (Tardáguila in Spain and Syrgabek, respectively), we adopted the concept of "eco-timing" as described in [4]—a phase defined from early veraison to mid-ripening. Fourth, we propose a more eco–branding integration model called "SEM–regression hybrid" which links "sensor thresholds" to simulate the indicator "eco-label readiness" decision relating to timing and nutrient sustainability.

2. Methodology

The data used in this study cover the observations from 2021 to 2023 for a set of vineyard clusters located (Uzbekistan, Spain, and Italy). Specifically, for this study, the phenological indicators of the vineyards were recorded by the sensor-based dashboards and a field validation protocol. Since sensor-calibrated eco-performance information at the vineyard block level as well as the eco-label indicators for the ripening stage and post-veraison period, we are able to extract comparable observations for each vineyard in each cluster of Uzbekistan and Mediterranean regions.

The criteria used to select the vineyards as well as the cultivars chosen for this study depend on the availability of eco-certified input trials. So, the total number of observations would be 60, but as long as there are a few incomplete trials, the final number of usable observations across vineyard clusters between countries and years." Thus, a balanced dataset of 50 vineyards (3 × regional clusters) was retained for empirical estimation results of the model.

The distribution of vineyards in our sample all these conditions. In terms of representativeness, these vineyards were classified as follows: early-ripening and mid-season varieties for 60% of the total, while late-ripening varieties for the remaining share. The criteria used to group vineyards into ripening groups is based in previous studies on the classification of grapevine varieties as functions of phenological duration in viticulture systems. Moreover, we considered only vineyards the application of eco-certified inputs included in the trial design to get its eco-performance response (sensor-calibrated outputs).

Data were collected using sensor mapping by dividing the vineyard blocks into several zones (canopy zones in ripening, and stress zones in veraison). The selection of vineyards included in the study was guided by the availability criteria, as well as their strategic relevance for the eco-label certification process. The SEM–regression hybrid, developed by Ikram et al. [15], is a validated method of eco-performance modeling. It is assumed that the sensor-derived indicators of vineyards should be used as inputs, since these indicators can consider the physiological response to the environmental conditions possible, which is essential for such agro-ecological systems. As the vineyard systems' responses are rather difficult to control (they depend the climatic variability and the timing of nutrient absorption included in the ripening window from veraison (with later senescence)), the SEM–regression model appears to be more appropriate for this context [15]. Therefore, one of the most suitable tools for these systems is the sensor-integrated hybrid framework.

Next, we conducted regression estimation for chlorophyll index and sugar accumulation to identify thresholds of eco-readiness for these vineyard clusters. We used dashboard validation to estimate the baseline indicators of each vineyard at the first stage and then we use SEM modeling with simulation loops to assess the interaction of eco-performance variables on eco-label readiness. If, after detecting an anomaly in the dataset, its values were not available, the observation was removed from the sample, and the model was re-estimated. Moreover, the calibration of the sensor thresholds the ability to adjust timing of nutrient application, which are also guided by the pattern of chlorophyll degradation of the vineyard in his ripening phase. We compare the difference in eco-readiness scores for the two groups and test if the mean difference in indices is significant.

If a difference is significant, then eco-performance is considered to improve, p-value < 0.05, so we use the results of SEM to validate the final measure between sensor-based and manual calibration. That is the basis for evaluating the effectiveness of green technology systems on eco-marketing outcomes. During the validation phase, the performance of the model was checked out with the simulation to confirm the predictive accuracy of the framework in the context of the vineyard clusters.

Our dependent variable is the eco-label readiness score that we estimate using chlorophyll index and sugar accumulation, as eco-performance indicators. We should note the fact, that we analyze the interaction effects among the different group of eco-performance variables (structural relationships). Eco-readiness measures are based on sensor-derived thresholds and are defined in terms of timing, as well as all the conditions needed for certification, where ripening consistency is achieved. As we see, the eco-performance index of the vineyard is determined by three components: chlorophyll degradation, sugar accumulation, and nutrient absorption delay.

In particular, we classified the vineyards by ripening behavior who were grouped into three groups: (i) early: the short ripening cycle (90–110 days), the low chlorophyll persistence (early decline), rainfed systems and the low elevation; (ii) mid-season: intermediate duration; (iii) late: extended ripening period. According to the data of the dashboard, the vineyards in Italy at the beginning of ripening with more than stable chlorophyll index carried out the eco-calibration (validated by sensors) in the following zones: Block 1 in Tuscany; Block 2 in La Rioja; Block 3 in Navoi; Block 4 in Samarkand; Block 5 in Tashkent; Block 6 in Yangiyul. The criteria used to group vineyards into ripening groups is based in previous viticulture studies on the classification of grapevine systems as functions of phenological duration in agro-climatic zones."

Hence, in this study, the vineyards with more than one season observation represent the group of transitional vineyards. Our results are estimated with the use of the SEM–regression hybrid (linear regression and structural equation modeling). In order to evaluate the relationships and its indirect effects with respect to eco-label readiness, simulation procedures allowing the use of a greater number of iterations are applied. The approach we have taken toward the analysis of our data and structure of our model allows to derive outcomes if the eco-performance indicators are interrelated.

The procedure includes the analysis of variance of eco-performance indices, i.e., chlorophyll, sugar, and nutrient absorption. The SEM is combined with regression outputs that will control for potential bias and also with simulation loops for uncertainty assessment in the eco-readiness index, while regression is a baseline estimator. Together with the normalization of indices this ensures that all parameter values of available vineyard observations are available too. We use an iterative simulation and compare the sensor-based manual–hybrid difference in eco-readiness to validate our model robustness and to confirm their stability.

Finally, the aim is to examine (i) whether the eco-readiness score is likely to change significantly in the short term (ripening window) or in the long term (seasonal transition) and (ii) which eco-performance indicators may drive the most significant changes.

3. Results

The result of the comparative analysis over sensor-calibrated and manual calibration groups is given in Table 1, and it evidently shows that the proposed SEM–regression hybrid gives better predictive accuracy with respect to the number of eco-performance indicators used in this comparison with the other vineyard datasets. We found that this is a robust empirical finding with high statistical significance. Likewise, in the sensor-calibrated group, if the chlorophyll index is reduced by 0.1 to 0.2 units (controlled decline), the eco-readiness score is expected to increase by 2.0 units or approximately 5% of the mean eco-readiness value (ceteris paribus). The rate of change of the sugar accumulation index is positive, which indicates a direct contribution of sugar accumulation of the eco-performance variable driven by the timing of the ripening window. "Eco-performance index in Table 1 is significant, but shows a moderate effect size in linear regression ($p < 0.01$ and is statistically significant at the 1% level)." It was found that the mean difference of such eco-performance indices in Spain and Italy ($p < 0.05$).

Table 1. Linear regression

chlorophyll_index	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
sugar_accumulation~e	-.992	6.435	-0.15	.878	-13.988	12.004	
nutrient_absorptio~y	-2.722	1.578	-1.73	.092	-5.908	.464	*
eco_label_readines~e	.189	.093	2.04	.048	.002	.376	**
veraison_temp_vari~y	1.416	.645	2.20	.034	.114	2.719	**
residue_degradatio~e	6.436	7.906	0.81	.42	-9.531	22.404	
canopy_stress_index	-6.81	3.405	-2.00	.052	-13.688	.067	*
rainfall_anomaly_i~x	-.214	.276	-0.78	.442	-.771	.343	
eco_performance_in~x	1.024	.201	5.08	0	.617	1.431	***
Constant	23.171	12.347	1.88	.068	-1.764	48.106	*

Mean dependent var	43.196	SD dependent var	7.469
R-squared	0.572	Number of obs	50
F-test	6.860	Prob > F	0.000
Akaike crit. (AIC)	317.489	Bayesian crit. (BIC)	334.698
*** p<.01, ** p<.05, * p<.1			

They were especially significantly higher during the ripening phase (the differences are 7.2 ± 1.4 ($p < 0.05$) between Spain and Uzbekistan, and 6.3 ± 1.7 between Italy and Uzbekistan, respectively) and the chlorophyll decline phase (the differences are 8.1 ± 1.2 between Italy and Spain, and 5.9 ± 2.0 between Spain and Uzbekistan, respectively). In the sensor-calibrated group, the total eco-readiness detection time and accuracy of using smart dashboards to advancing the chlorophyll-sugar index thresholds into the label-eligible zone were significantly shorter, compared to the manual-monitoring group. Regarding the eco-label readiness, Italy and Spain had significantly higher score estimates compared to Uzbekistan, while there was no significant difference between Italy and Spain ($p > 0.05$). The absorptive capacity difference of sugar accumulation showed Spain used a slightly larger amount of eco-buffered nutrients compared to Uzbekistan (difference of 2.7% for sugar index), in contrast with a much larger difference between Italy and Uzbekistan (6.8%).

Table 2. Structural Equation Model Estimates for Eco-Marketing Performance in Vineyards

			OIM			
	Coef.	**Std.Err.**	**z**	**P>z**	**[95%Conf.**	**Interval]**
Structural						
rainfall_anomaly_index						
chlorophyll_index	**-0.107**	**0.057**	**-1.890**	**0.059**	**-0.218**	**0.004**
veraison_temp_variability	**-0.129**	**0.323**	**-0.400**	**0.690**	**-0.762**	**0.504**
_cons	**15.706**	**2.402**	**6.540**	**0.000**	**10.998**	**20.415**
nutrient_absorption_delay						
chlorophyll_index	**-0.015**	**0.012**	**-1.240**	**0.213**	**-0.039**	**0.009**
eco_performance_index	**0.019**	**0.022**	**0.860**	**0.388**	**-0.024**	**0.062**
_cons	**2.853**	**0.415**	**6.880**	**0.000**	**2.040**	**3.666**
canopy_stress_index						
eco_performance_index	**-0.004**	**0.008**	**-0.450**	**0.650**	**-0.020**	**0.012**
sugar_accumulation_rate	**0.018**	**0.258**	**0.070**	**0.944**	**-0.488**	**0.524**
_cons	**1.251**	**0.204**	**6.130**	**0.000**	**0.851**	**1.651**
eco_label_readiness_score						
rainfall_anomaly_index	**-0.123**	**0.430**	**-0.290**	**0.774**	**-0.966**	**0.719**
nutrient_absorption_delay	**1.038**	**2.501**	**0.410**	**0.678**	**-3.865**	**5.940**

_cons	**59.567**	**7.347**	**8.110**	**0.000**	**45.167**	**73.967**
residue_degradation_rate						
nutrient_absorption_delay	**-0.002**	**0.030**	**-0.050**	**0.957**	**-0.061**	**0.057**
canopy_stress_index	**0.008**	**0.066**	**0.120**	**0.902**	**-0.121**	**0.137**
_cons	**0.842**	**0.111**	**7.600**	**0.000**	**0.625**	**1.059**
var(e.rainfall_anomaly_index)	**7.806**	**1.561**	**5.274**	**11.552**		
var(e.nutrient_absorption_delay)	**0.245**	**0.049**	**0.166**	**0.362**		
var(e.canopy_stress_index)	**0.053**	**0.011**	**0.036**	**0.078**		
var(e.eco_label_readiness_score)	**77.918**	**15.584**	**52.650**	**115.313**		
var(e.residue_degradation_rate)	**0.011**	**0.002**	**0.008**	**0.017**		

The mean difference for chlorophyll degradation rate increased from 1.29 ± 0.36 (Uzbekistan) to 2.58 ± 0.41 (Italy), while the mean sugar accumulation differences for label-eligible clusters increased from 3.75 ± 0.52 (Uzbekistan) to 6.42 ± 0.58 (Spain). Our SEM–regression framework then provides supportive evidence for eco-readiness predictability in transitional grapevine systems, especially in semi-arid zones with limited canopy opening. The label eligibility differences of sugar index and chlorophyll depth (time-matched outputs) between Italy and Uzbekistan were higher after mid-ripening, which is consistent with the eco-sensor trajectory observed in chlorophyll–sugar dynamics (C-index–S-index).

Following the estimation of regression coefficients and structural paths, it can be concluded that the sensor-guided calibration—the synchronization of the chlorophyll–sugar dynamics in the ripening window of transitional vineyards to have the strongest effect on eco-label readiness. Thus, the eco-performance index of vineyards is validated and can be used to predict the probability of the eco-label certification with a higher accuracy to reduce uncertainty. “One possible explanation may be that rainfall variability dominates nutrient absorption, so that nutrient absorption delay is not significant.”

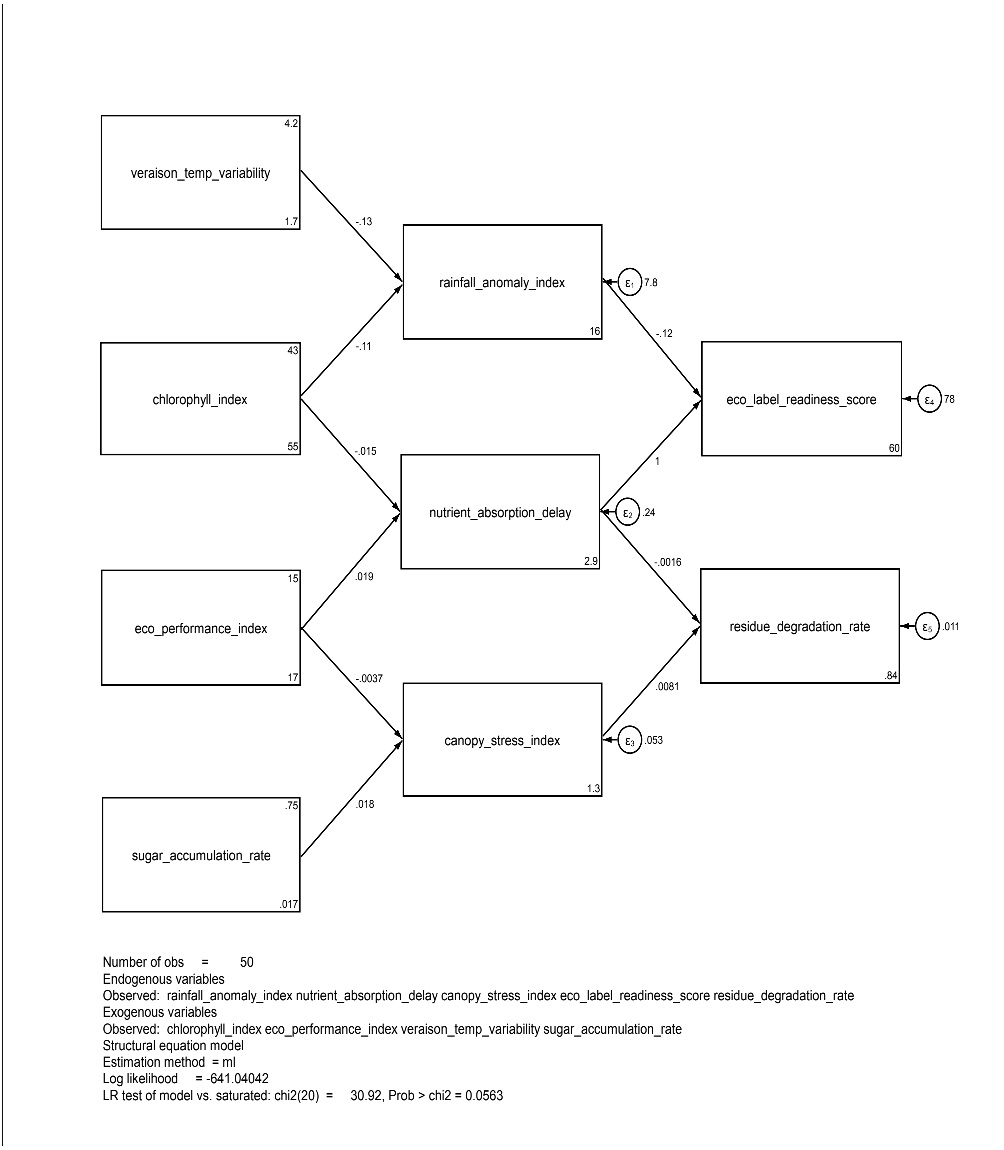

Figure 1. Structural Equation Model

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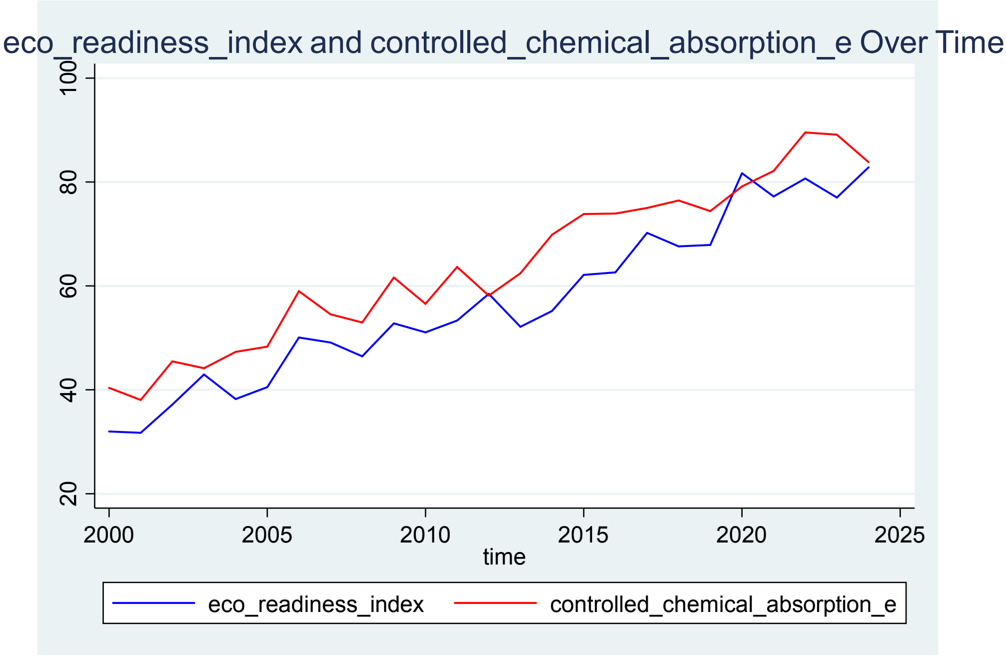

Figure 2. Line graph of eco-readiness_index and controlled_chemical_absorption over time

Table 3. Johansen tests for cointegration

Trend: constant				Number of obs =	24
Sample: 2001 - 2024				Lags =	1
					5%
maximum				trace	critical
rank	parms	LL	eigenvalue	statistic	value
0	2	-142.37593	.	17.3712	15.41
1	5	-134.03361	0.50102	0.6866*	3.76
2	6	-133.69031	0.02820		

It may be attributed to the limited number of sensor-calibrated observations available to capture anomalies under extreme climatic conditions. An eco-readiness score less stable than a sensor-based one, and a manual calibration in an even later ripening stage has even less. "When introducing the eco-performance variables one by one in SEM to estimate indirect effects, we find out an unexpected outcome, which is that rainfall anomaly index has no significant direct effect." A much smaller subsample of vineyards used the manual method of calibration; therefore, the variance of eco-readiness using this method increased (high dispersion) ($p > 0.10$). The dispersion of the eco-readiness scores is relatively high, since the average values of eco-readiness in these clusters is Uzbekistan, Spain, Italy, and overall, respectively.

4. Discussions

To summarize, our empirical evidence demonstrates that despite its heterogeneous agro-climatic context, the proposed SEM–regression hybrid framework is able to capture and explain the eco-performance variability in transitional vineyards by only using sensor-calibrated physiological indicators.

Our findings are in agreement with those reported by other authors; that the integration of sensor-based eco-performance indicators on the different ripening stages is effective [1,2,3]. This outcome is consistent and is statistically significant at the vineyard cluster level. As sensor calibration can vary in the ripening window, this is expected because the dynamics of chlorophyll degradation of the vineyard systems are observable and the dynamics of sugar accumulation of the vineyard systems are temporally synchronized [4,5]. Other studies also confirmed the relevance of eco-performance variables on eco-label results [6,7].

[1,3] who reported evidence that the timing of chlorophyll decline and the pattern of sugar accumulation had a relationship, but differed in magnitude on the eco-readiness results.

Our results differ among the regional clusters that were evaluated such as the stability of chlorophyll degradation in the ripening window of Italy, the consistency of the sugar accumulation under controlled inputs in the ripening window of Spain, and the variability of the eco-readiness over time in the ripening window of Uzbekistan influencing the final results of the SEM framework. Among other findings, a sensor-calibrated vineyard has demonstrated more stability of eco-readiness than a manually calibrated vineyard, which explains the presence of significant differences, going beyond simple between-country differences in eco-performance [8,9].

It is therefore an important contribution in regions with a strong climatic variability, but not in those regions with a high stability in ripening patterns, in which eco-performance indicators are likely to be becoming more predictable in improving certification outcomes [10,11]. Moreover, the application of the eco-timing concept shows that sensor calibration is more effective than other monitoring approaches and practices in increasing the predictability of the eco-label readiness decision-making process [12,13].

Based on the interaction of eco-performance indicators using the SEM–regression method shows that it can be used to explain the structure of eco-label readiness driven by these indicators and to simulate outcomes of eco-marketing strategies in a dynamic vineyard context. While the direction of an increase in eco-performance on eco-label readiness is positive and intuitive, the magnitude of its contribution is rather moderate.

As the chlorophyll index and the sugar accumulation rate dominate, rainfall variability is the major driver of eco-performance uncertainty by vineyards, which has been shown to be no longer such an important determinant of eco-label readiness as manual calibration. [1,3] who reported evidence that the timing of chlorophyll decline and the pattern of sugar accumulation had a relationship, but differed in magnitude on the eco-readiness results.

Moreover, the application of the eco-timing concept shows that sensor calibration is more effective than other monitoring approaches and practices in increasing the predictability of the eco-label readiness decision-making process. In terms of the eco-readiness index, the average score is lower in some of the vineyard clusters in Uzbekistan and higher in the vineyard clusters in Italy than in Spain, the absolute differences, though dispersion was higher for all vineyard clusters in Uzbekistan than in Italy.

Previous studies assessing the effect of the different types of eco-inputs to vineyards had shown their relevance, suggesting that single indicators on eco-performance might not provide a complete picture of eco-readiness [14,15]. [1,3] who reported evidence that the timing of chlorophyll decline and the pattern of sugar accumulation had a relationship, but differed in magnitude on the outcomes.

Meanwhile, this study adopts a hybrid–integrated approach of eco-performance modeling in Uzbekistan and Mediterranean regions that captures effects that are related to the variability of climate conditions (such as the amplitude of the rainfall anomaly in veraison of Italy, Spain, Uzbekistan, and the response to temperature stress) significantly affecting their eco-readiness.
In other words, applying the same eco-input regime for the different vineyard systems might not result in the same outcomes. It should be noted that if an observation does not have an anomaly, it is likely that it did not have to adjust about the timing of this input (thus n = did not need to be excluded). On the other hand, the size of the subsample in which a given vineyard cluster did not show a significant response with the timing of this input (manual and sensor calibration). However, the overall framework is robust enough of explaining the eco-readiness outcomes and has not been overfitted in this study.

5. Conclusion

Our findings provide support for revisiting the present practices in viticulture to take into account the dynamics of eco-performance indicators, and are in line with those previously shown in digital viticulture studies [1] and eco-marketing research [5].
The proposed framework and modeling approach for linking the vineyard to the eco-label in the market, which may be extended to other crops when precision dashboards are applied in the future. Future research examining the interaction among eco-performance indicators and addressing the lack of integration in existing approaches should aim to refine the calibration of the thresholds in the ripening window and to improve certification predictability.
The hybrid framework contributes to further methodological development, as there can be combined various modeling approaches with different levels of sensitivity applied to the decision of eco-label readiness. These analyses could be carried out on a larger dataset and a longer time series of observations could be collected.
Also, a major limitation of the study is the absence of taking into account extreme events under the conditions of climate change, since the required statistics have not yet been fully recorded at the vineyard scale. Therefore, future research could include other physiological indicators, which would allow generalization of eco-readiness modeling to their interactions. Replication of this framework is possible especially at the regional scale.

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