VARIABILITY AND INTERDEPENDENCIES BETWEEN FRACTAL GEOMETRY PARAMETERS IN GRAPEVINE LEAVES

Alin DOBREI[1], Florin SALA[1,2,*]
[2]University of Life Sciences "King Mihai I" from Timisoara, Timisoara, Calea Aradului, 300645, Romania
[2]Agricultural Research and Development Station Lovrin, Lovrin, 307250, Romania
[*]Corresponding author: florin_sala@usvt.ro

Abstract. *The grapevine leaves was analyzed based on fractal geometry, and the study evaluated interdependencies between parameters specific to fractal geometry. The grape varieties considered in the study were represented by Chasselas (Ch), Cabernet Sauvignon (CS), Muscat Hamburg (MH), Muscat Iantarnîi (MI), Muscat Ottonel (MO), Perlă de Csaba (PC), and Victoria (Vi). Fresh leaves were taken from each variety. The leaves were herborized to preserve the integrity of the leaves, and were scanned. Imaging analysis and fractal analysis were used to generate fractal geometry parameters: foreground pixels (FP), fractal dimensions D1 (MEE = 0.5), D2 (MEE = 0.2), BW parameter (black and white pixels), B+BW parameter (black + black and white pixels), W+BW parameter (white + black and white pixels). The descriptive statistical analysis generated the analysis report based on a number of 15 samples for each grapevine variety. Correlation analysis was used to evaluate the interdependence between fractal geometry parameters, for each grape variety. Correlations with different levels of intensity were recorded between the parameters of the fractal geometry, in relation to the vine variety. The values of the correlation coefficient showed some matches and differences of the parameters of the fractal geometry in the seven grape varieties studied. In all cases, a very strong positive correlation was recorded between D1 and D2. Also, a negative correlation was recorded between W+BW and B+BW parameters, but of variable intensity.*

Keywords*: correlations, descriptive statistics, fractal geometry, vine leaves, variability*

INTRODUCTION

Leaves are important plant organs in relation to the reception of light energy and the process of photosynthesis (Terashima et al., 2011; Li et al., 2022; Roth-Nebelsick and Krause, 2023).

The structure and functions of the leaves were analyzed from the perspective of some "key modules", such as light capture, water and nutrient flow, respectively gas exchange (Li et al., 2017). Plant leaves have been studied as integrated systems, modeled evolutionarily in relation to mimetic adaptations and carbon fixation, with new perspectives on the economic aspects of leaf functionality (Roth-Nebelsick and Krause, 2023).

The leaves show different typologies of shapes, with intraspecific and interspecific variability, as a result of adaptation to environmental conditions (Nakayama et al., 2024). The diversity and complexity of leaf shape have been explained on the basis of some molecular mechanisms involved, but there are still some questions about plant leaves (Nakayama et al., 2024). Morpho-anatomical features (foliar parameters) of plant leaves play an important role in relation to the ability of plants to adapt to environmental conditions (Liu et al., 2020). Studies of the leaves based on specific indices (e.g. LAI, LAD, LOP) were made in relation to the absorption of light radiation inside the crown of the trees (Plekhanova et al., 2021).

Plant leaves were analyzed in some studies from the perspective of anatomical compromises and ecological strategies (Pierce et al., 2022). The authors of the study analyzed the "compromise" at the level of the leaves between the economic spectrum and the mechanical constraints, associated with the size of the leaves and their mechanical support

The way of allocating leaf biomass was considered as an economic and ecological strategy of plants (Guo et al., 2023). Correlation tests were applied in studies of some parameters in relation to the age of the leaves (Guo et al., 2023).

Different neural networks have been developed for the study of leaf morphology, systematics and classification of plant species (Azlah et al., 2019; Abdulazeez, et al., 2021; Wagle et al., 2022). Specific parameters of plant leaves are of interest in such studies for the realization of working algorithms, and the quality of leaf images is very important (Azlah et al., 2019). The morphological variation of plant leaves was associated with the differences present in the geometry of the edges (Runions and Tsiantis, 2017).

Analysis of leaf geometry was done by different methods, and fractal analysis was reported in many studies (Sala et al., 2017; Cândea-Crăciun et al., 2018; Agapie et al., 2020; Vishnu and Jaishanker, 2023; Vishnu et al., 2023).

The present study evaluated the interdependence between the parameters of the fractal geometry of the leaves of seven grape varieties.

MATERIAL AND METHODS

In relation to the purpose of the study, vine leaves were used to obtain digital images and apply imaging and fractal analysis.

The biological material was represented by seven grape varieties: Chasselas (Ch), Cabernet Sauvignon (CS), Muscat Hamburg (MG), Muscat Iantarnîi (MI), Muscat Ottonel (MO), Perlă de Csaba (PC) and Victoria (Vi). The leaves were scanned, 1:1 ratio. Digital images (e.g. Figure 1) were analyzed to obtain fractal geometry parameters. The following elements were determined: foreground pixels (FP), fractal dimensions D1 (MEE = 0.5), D2 (MEE = 0.2), parameters BW (black and white pixels), B+BW (black + black and white pixels), W+BW (white + black and white pixels). The fractal analysis was done by the box counting method (Voss, 1985; Rasband, 1997). The statistical certainty was ensured in the fractal analysis, according to the regression coefficient $R^2 = 0.999$, and the regression line with Slope = 1.863, figure 2.



Figure 1. Scanned vine leaf, example of the Muscat Ottonel variety
(Original figure, scanned and processed by Florin Sala)

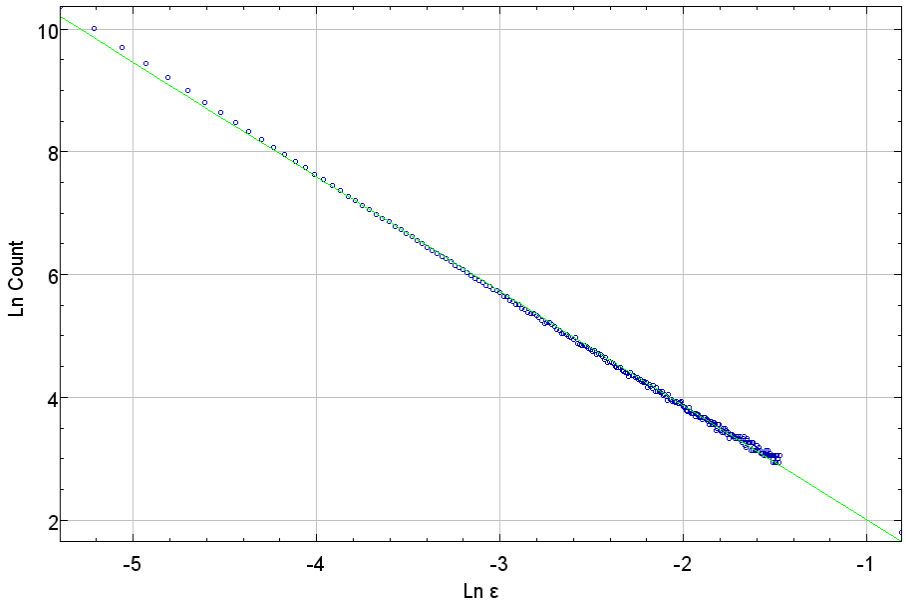


Figure 2. Regression line in fractal analysis, vine leaf, Muscat Ottonel variety
(Original figure, result of the analysis)

The data series were analyzed to assess the variability within each grape variety. The interdependence between the fractal geometry parameters was evaluated by correlation analysis. Appropriate statistical methods were used (Hammer et al., 2001).

RESULTS AND DISCUSSIONS

Fractal analysis of grapevine leaves, seven varieties, found out the values of fractal geometry parameters of grapevine leaves (FP; D1; D2; BW; B+BW; W+BW). Descriptive statistical analysis of the data series led to tables 1 - 6.

In the case of the studied parameters, variations of the values were recorded within each variety, as well as between the grape varieties. The FP parameter registered variations Min – Max, FP = 792164 – 1119576 (Cs), FP = 395044 – 527986 (CS), FP = 471948 – 1339954 (MH), FP = 923908 – 1443555 (MI), FP = 637018 – 1338704 (MO), FP = 539866 – 1126587 (PC), and respectively FP = 899315 – 1389590 (Vi), table 1.

The parameter D1 registered variations of the data series, D1 = 1.837 – 1.892 (Ch), D1 = 1.841 – 1.852 (CS), D1 = 1.800 – 1.901 (MH), D1 = 1.842 – 1.898 (MI), D1 = 1.822 – 1.898 (MO), D1 = 1.846 – 1.902 (PC), respectively D1 = 1.846 – 1.902 (Vi), table 2.

Table 1. Statistical values for the FP parameter

Statistica parameters	Ch	CS	MH	MI	MO	PC	Vi
N	15	15	15	15	15	15	15
Min	792164	395044	471948	923908	637018	539866	899315
Max	1119576	527986	1339954	1443555	1338704	1126587	1389590
Sum	1.45E+07	7219316	1.65E+07	1.75E+07	1.25E+07	1.39E+07	1.69E+07
Mean	964190.3	481287.7	1097376	1163422	836453.3	927814	1127430
Std. error	28835.17	7832.219	58507.3	46902.39	43370.07	47295.24	35834.41
Variance	1.25E+10	9.20E+08	5.13E+10	3.30E+10	2.82E+10	3.36E+10	1.93E+10
Stand. dev	111678.1	30334.05	226597.8	181652.2	167971.6	183173.7	138786.1
Median	953186	485795	1172328	1136008	790820	981618	1162413
25 prcntil	861745	473556	1007874	991247	733980	769789	982286
75 prcntil	1074422	492780	1254868	1357820	859178	1087878	1185269
Skewness	-0.00569	-1.43665	-1.61235	0.171656	2.075258	-0.81048	-0.09464
Kurtosis	-1.43366	4.435712	3.236743	-1.67519	5.479902	-0.35348	-0.32009
Geom. mean	958107.7	480339	1067909	1150250	823271.5	908581.6	1119296
Coeff. var	11.5826	6.3027	20.6491	15.6136	20.0814	19.7425	12.3100

Table 2. Statistical values for D1 parameter

Statistica parameters	Ch	CS	MH	MI	MO	PC	Vi
N	15	15	15	15	15	15	15
Min	1.837	1.841	1.800	1.842	1.822	1.846	1.846
Max	1.892	1.852	1.901	1.898	1.898	1.902	1.907
Sum	27.917	27.690	28.123	28.102	28.123	28.048	28.149
Mean	1.861	1.846	1.875	1.873	1.875	1.870	1.877
Std. error	0.004	0.001	0.007	0.005	0.006	0.004	0.005
Variance	0.0002	1.04E-05	0.0007	0.0004	0.0005	0.0002	0.0003
Stand. dev	0.016	0.003	0.027	0.019	0.023	0.014	0.018
Median	1.862	1.846	1.885	1.871	1.880	1.873	1.882
25 prcntil	1.852	1.843	1.867	1.856	1.865	1.857	1.860
75 prcntil	1.876	1.848	1.894	1.891	1.892	1.879	1.887
Skewness	0.241	0.191	-1.745	-0.095	-1.146	0.233	-0.338
Kurtosis	-0.413	-0.530	3.390	-1.509	0.559	0.483	-0.664
Geom. mean	1.861	1.846	1.875	1.873	1.875	1.870	1.877
Coeff. var	0.8390	0.1749	1.4450	1.0127	1.2214	0.7728	0.9562

In the case of the D2 parameter, there were variations in the data series, D2 = 1.794 – 1.862 (Ch), D2 = 1.814 – 1.828 (CS), D2 = 1.765 – 1.849 (MH), D2 = 1.799 – 1.850 (MI), D2 = 1.755 – 1.868 (MO), D2 = 1.798

– 1.875 (PC), respectively D2 = 1.802 – 1.865 (Vi), table 3.

In the case of the BW parameter, the data series within each vine variety showed variations, such as BW = 1.106 – 1.175 (Ch), BW = 1.132 – 1.464 (CS), BW = 1.139 – 1.270 (MH), BW = 1.180 – 1.308 (MI), BW = 1.254 – 1.678 (MO), BW = 1.121 – 1.367 (PC), respectively BW = 1.071 – 1.391 (Vi), table 4.

Table 3. Statistical values for parameter D2

Statistical prameters	Ch	CS	MH	MI	MO	PC	Vi
N	15	15	15	15	15	15	15
Min	1.794	1.814	1.765	1.799	1.775	1.798	1.802
Max	1.862	1.828	1.849	1.850	1.868	1.875	1.865
Sum	27.215	27.307	27.426	27.387	27.590	27.426	27.434
Mean	1.814	1.820	1.828	1.826	1.839	1.828	1.829
Std. error	0.004	0.001	0.006	0.004	0.008	0.005	0.005
Variance	0.0003	1.97E-05	0.0005	0.0003	0.0009	0.0004	0.0003
Stand. dev	0.017	0.004	0.023	0.016	0.030	0.019	0.018
Median	1.814	1.820	1.835	1.827	1.849	1.826	1.827
25 prcntil	1.805	1.816	1.818	1.811	1.819	1.814	1.814
75 prcntil	1.820	1.824	1.846	1.843	1.864	1.843	1.839
Skewness	1.529	-0.059	-1.749	0.043	-0.986	0.833	0.412
Kurtosis	3.729	-1.077	3.050	-1.339	-0.171	1.233	-0.220
Geom. mean	1.814	1.820	1.828	1.826	1.839	1.828	1.829
Coeff. var	0.9371	0.2438	1.2793	0.8849	1.6138	1.0536	0.9908

Table 4. Statistical values for the BW parameter

Statistical parameters	Ch	CS	MH	MI	MO	PC	Vi
N	15	15	15	15	15	15	15
Min	1.106	1.132	1.139	1.180	1.254	1.121	1.071
Max	1.175	1.464	1.270	1.308	1.678	1.367	1.391
Sum	17.078	19.426	17.693	18.441	20.814	18.762	17.969
Mean	1.139	1.295	1.180	1.229	1.388	1.251	1.198
Std. error	0.005	0.020	0.009	0.009	0.026	0.017	0.023
Variance	0.0004	0.0062	0.0013	0.0012	0.0105	0.0043	0.0078
Stand. dev	0.019	0.079	0.036	0.035	0.103	0.065	0.088
Median	1.136	1.299	1.174	1.226	1.366	1.237	1.180
25 prcntil	1.128	1.269	1.152	1.211	1.306	1.208	1.146
75 prcntil	1.153	1.305	1.199	1.250	1.443	1.300	1.268
Skewness	0.030	-0.027	1.192	0.779	1.673	0.035	0.531
Kurtosis	-0.561	1.533	1.394	0.657	3.904	-0.076	0.194
Geom. mean	1.138	1.293	1.179	1.229	1.384	1.249	1.195
Coeff. var	1.7076	6.0926	3.0473	2.8219	7.3964	5.2286	7.3589

In the case of the B+BW parameter, the data series within each grape variety showed variations, such as B+BW = 1.723 – 1.776 (Ch), B+BW = 1.584 – 1.804 (CS), B+BW = 1.739 – 1.843 (MH), B+BW = 1.721 – 1.805 (MI), B+BW = 1.723 – 1.778 (MO), B+BW = 1.639 – 1.771 (PC), respectively B+BW = 1.731 – 1.802 (Vi), table 5.

In the case of the W+BW parameter, the data series within each grape variety showed variations, such as W+BW = 1.874 – 1.915 (Ch), W+BW = 1.960 – 1.980 (CS), W+BW = 1.805 – 1.916 (MH), W+BW = 1.838 – 1.908 (MI), W+BW = 1.909 – 1.981 (MO), W+BW = 1.887 – 1.958 (PC), respectively W+BW = 1.834 – 1.918 (Vi), table 6.

Table 5. Statistical values for the B+BW parameter

Statistical parameters	Ch	CS	MH	MI	MO	PC	Vi
N	15	15	15	15	15	15	15
Min	1.723	1.584	1.739	1.721	1.723	1.639	1.731
Max	1.776	1.804	1.843	1.805	1.778	1.771	1.802
Sum	26.182	25.207	26.615	26.396	26.184	26.091	26.436
Mean	1.745	1.680	1.774	1.760	1.746	1.739	1.762
Std. error	0.004	0.012	0.007	0.007	0.004	0.008	0.004
Variance	0.0002	0.0020	0.0007	0.0008	0.0002	0.0010	0.0003
Stand. dev	0.014	0.045	0.026	0.029	0.015	0.032	0.017
Median	1.743	1.676	1.773	1.756	1.749	1.750	1.761
25 prcntil	1.738	1.667	1.753	1.732	1.734	1.730	1.753
75 prcntil	1.750	1.696	1.788	1.791	1.752	1.760	1.769
Skewness	0.666	0.860	1.276	0.293	0.498	-2.346	0.651
Kurtosis	0.685	4.906	2.734	-1.503	0.457	6.973	1.773
Geom. mean	1.745	1.680	1.774	1.760	1.746	1.739	1.762
Coeff. var	0.7900	2.6748	1.4458	1.6316	0.8310	1.8466	0.9455

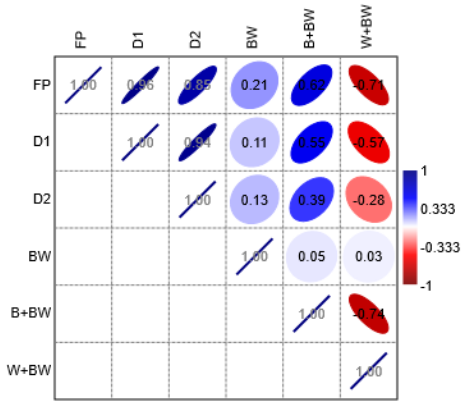
Table 6. Statistical values for the W+BW parameter

Statistical parameters	Ch	CS	MH	MI	MO	PC	Vi
N	15	15	15	15	15	15	15
Min	1.874	1.960	1.805	1.838	1.909	1.887	1.834
Max	1.915	1.980	1.916	1.908	1.981	1.958	1.918
Sum	28.444	29.513	28.047	28.165	29.177	28.744	28.290
Mean	1.896	1.968	1.870	1.878	1.945	1.916	1.886
Std. error	0.004	0.001	0.007	0.007	0.004	0.005	0.007
Variance	0.0002	2.74E-05	0.0007	0.0008	0.0003	0.0004	0.0007
Stand. dev	0.014	0.005	0.027	0.028	0.017	0.019	0.026
Median	1.898	1.968	1.869	1.886	1.947	1.908	1.896
25 prcntil	1.881	1.963	1.852	1.847	1.938	1.901	1.864
75 prcntil	1.907	1.969	1.888	1.905	1.954	1.936	1.905
Skewness	-0.247	0.760	-0.699	-0.264	-0.171	0.681	-0.577
Kurtosis	-1.231	0.918	1.486	-1.851	1.711	-0.087	-0.811
Geom. mean	1.896	1.968	1.870	1.877	1.945	1.916	1.886
Coeff. var	0.7541	0.2661	1.4278	1.4992	0.8496	0.9996	1.3663

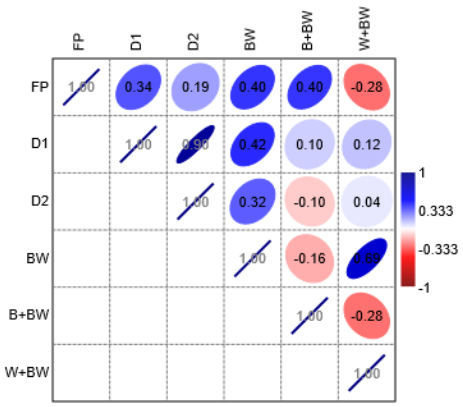
Within the data series, for each parameter considered in the study, different variability was recorded. Within the FP parameter, the variability was between CV = 6.2037 (CS) and CV = 20.6491 (MH). Within parameter D1, the variability was between CV = 0.1749 (CS) and CV = 1.4450 (MH). Within the D2 parameter, the variability was between CV = CV = 0.2438 (CS) and CV = 1.6138 (MO). In the case of the BW parameter, the variability was comprised between CV = 1.7076 (Ch), and CV = 7.3964 (MO). In the case of B+BW parameters, the variability was between CV = 0.7900 (Ch) and CV = 2.6748 (CS). In the case of the W+BW parameter, the variability was between CV = 0.2661 (CS) and CV = 1.4992 (MI).

The interdependence between the characterization parameters of the fractal geometry was analyzed for each type of vine. The results were the correlation diagrams shown in figure 3.

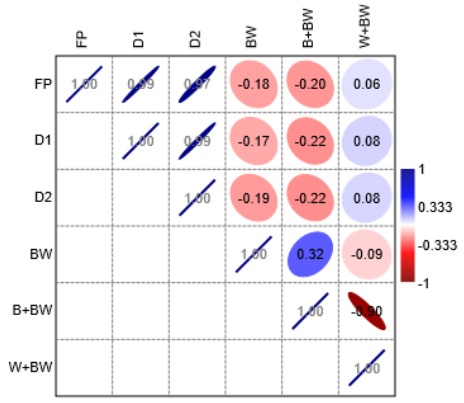
In the case of the Chasselas variety (Ch), a very strong correlation was identified between D1 and FP (r = 0.963) and between D1 and D2 (r = 0.944). Strong correlation was recorded between D2 and FP (r = 0.849). Moderate negative correlation was recorded between W+BW and FP (r = -0.705) and between W+BW and B+BW (r = -0.740). Other correlations were also recorded, but of low intensity.



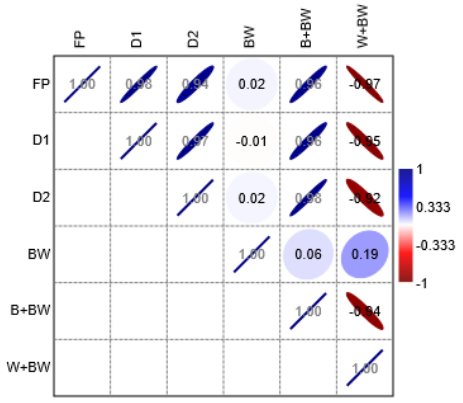
(a) Chasslas (Ch)



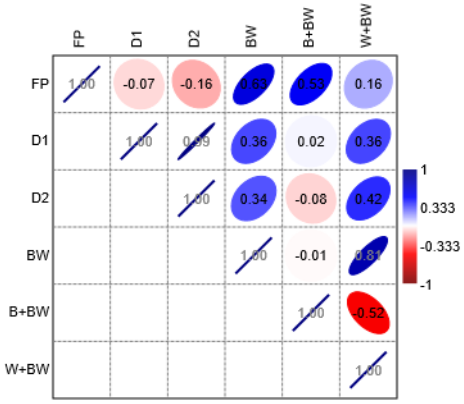
(b) Cabernet Sauvignon (CS)



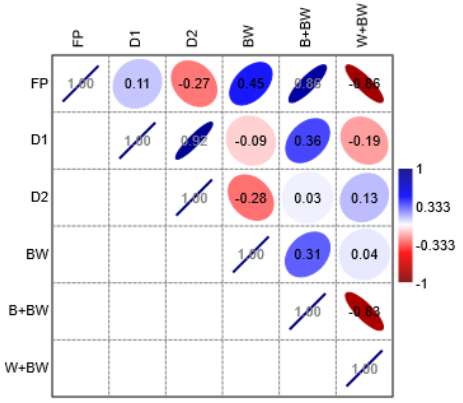
(c) Muscat Hamburg (MH)



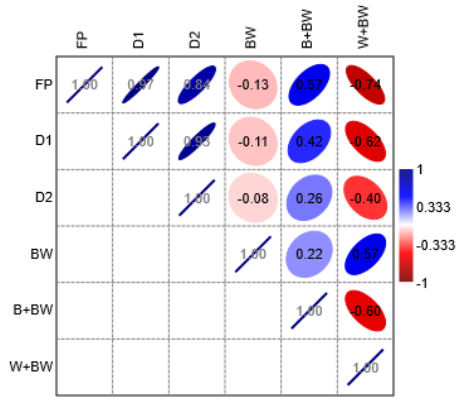
(d) Muscat Iantarnîi (MI)



(e) Muscat Ottonel (MO)



(f) Perla de Chaba (PC)



(g) Victoria (Vi)

Figure 3. Correlation diagrams between the leaves fractal geometry parameters at the grape varieties studied

In the case of the Cabernet Sauvignon (CS) variety, a very strong correlation was recorded between D1 and D2 (r = 0.902). At the level of the other parameters, low intensity correlations were recorded.

In the case of the Muscat Hamburg (MH) variety, a very strong correlation was recorded between D1 and FP (r = 0.989), between D2 and FP (r = 0.970), between D1 and D2 (r = 0.987) and between W+BW and B +BW (r = -0.904). In the case of the other parameters, low intensity correlations were identified.

In the case of the Muscat Iantarnîi (MI) variety, a positive correlation was recorded between D1 and FP (r = 0.977), between D2 and FP (r = 0.943), between B+BW and FP (r = 0.963), between W+BW and FP (r = -0.974), between D1 and D2 (r = 0.972), between B+BW and D1 (r = 0.957), between W+BW and D1 (r = -0.951), between B+B2 and D2 (r = 0.975), between W+BW and D2 (r = -0.919), and between W+BW and B+BW (r = -0.938). At the level of the other parameters, weak correlations were recorded.

In the case of the Muscat Ottonel (MO) variety, a very strong correlation was recorded between D1 and D2 (r = 0.991). Strong correlation was recorded between W+BW and BW (r = 0.816). Weak correlation was recorded between BW and FP (r = 0.627), between B+BW and FP (r = 0.539), between W+BW and D2 (r = 0.418), and between W+BW and B+BW (r = -0.512). At the level of the other parameters, low intensity correlations were recorded.

In the case of the Perla de Chaba (PC) variety, a very strong correlation was recorded between D1 and D2 (r = 0.916). Strong correlation was recorded between B+BW and FP (r = 0.856), between W+BW and FP (r = -0.863), and between W+BW and B+BW (r = -0.826). At the level of the other parameters, low intensity correlations were recorded.

In the case of the Victoria (Vi) variety, a very strong correlation was recorded between D1 and FP (r = 0.970), between D1 and D2 (r = 0.933). Strong correlation was recorded between D2 and FP (r = 0.846). Moderate correlation was recorded between W+BW and FP (r = -0.741). Weak correlation was recorded between W+BW and D1 (r = -0.609), between B+BW and FP (r = 0.567), between W+BW and BW (r = 0.567) and between W+BW and B+BW (r = -0.597). At the level of the other parameters, low intensity correlations were recorded. The values of the correlation coefficient showed some matches and differences of the parameters of the fractal geometry in the seven grape varieties studied. In all cases, a positive correlation was recorded between D1 and D2, at a very strong correlation level. Also, a negative correlation was recorded between W+BW and B+BW parameters, but of variable intensity.

Grapevine is an important horticultural plant, and it has been studied in relation to genetic diversity, the relationship with environmental and technological factors (Sala and Blidariu, 2012; Riaz et al., 2018; Kaya et al., 2023). Grapevine leaves have a specific typology, and have been used in different ampelography studies, to discriminate some genotypes through fractal analysis (Mancuso 2001, 2002).

The fractal analysis, used in the present study, facilitated the description of the geometry of the leaves of the seven varieties considered, and the correlation analysis highlighted different levels of interdependence between the parameters of the fractal geometry. The recorded results contribute to the database, related to the vine, which may be of interest for future studies in the characterization of genotypes, the relationship with environmental factors, as well as in ampelographic studies.

CONCLUSIONS

The leaf typology of the seven vine varieties was studied by fractal analysis, and the descriptive statistical analysis generated the data report related to the considered fractal geometry parameters, under statistical safety conditions.

Differentiated variability was recorded for each parameter of the fractal geometry, in relation to the vine variety. The correlation analysis quantified the level of interdependence between the parameters of the fractal geometry, through the values of the recorded correlation coefficient.

Based on the values of the correlation coefficient, different interdependencies of the fractal geometry parameters were identified, in the seven grape varieties studied. A very strong positive correlation was recorded between D1 and D2, in all cases. Negative correlation, of variable intensity, was recorded between W+BW and B+BW parameters, but of variable intensity.

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