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Modeling the corrosivity and scaling of drinking water distributed in Morocco using multiple linear regression

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ABSTRACT

The present study concentrates on the modeling of water corrosivity and calcocarbonic balance of the drinking water distribution in Fez, Morocco. Utilising a range of linear regression techniques by Statistica 12. The study analyses twelve physicochemical parameters to formulate predictive models for the indices of water corrosivity (Larson and Leroy). A total of 156 water samples were collected from six different points over the duration of six months, and the samples analysed show that the means of the parameters are CAT (4.89±0.39) meq/l, CATs (4.60±0.37) meq/l, TH (5.86±0.71) meq/l, dissolved oxygen (8.53±0.22) mg/l, chloride (1.13±0.57) meq/l, oxidability (1.56±0.71) mg(O_2/l), residual chlorine (0.59±0.16) meq/l, LSI (0.02±0.15), conductivity (0.83±0.17) mS/cm, temperature (17.25±1.02) °C, turbidity (0.58±0.17) NTU and sulfate (0.69±0.35) meq/l. The means value of the water indices are Larson index (0.18±0.16) and Leroy index (0.85±0.12). The models achieved good predictive accuracy, with R^2 values of 92.02% and 98.76%, and a low standard error 0.04 and 0.01 for the Larson and Leroy indices, respectively. The findings underscore the inverse correlation between corrosivity and calco-carbonic balance, emphasizing the significance of maintaining water quality within acceptable standards to prevent corrosion and scaling in water distribution systems. The results of the study provide valuable insights for the management of water quality, particularly in regions exhibiting similar environmental conditions. The aim of this study is to identify the parameters responsible for this phenomena.

Keywords: calcocarbonic balance, corrosivity index, drinking water, mathematical modelling, water distribution network, water quality.

INTRODUCTION

Water is an essential resource for human survival, but its quality can be compromised by various forms of contamination, making it unsafe for consumption and potentially leading to waterborne diseases (WHO, 2011). Ensuring proper water treatment is a key priority to protect public health (Rhajaoui, 2019). In areas where water quality control is inadequate, inappropriate treatment methods often lead to significant problems such as corrosion and scaling within water distribution systems, with detrimental consequences for both infrastructure and public health (Gholizadeh et al., 2017), and the water quality still be affected throughout the distribution process.

In the case of Fes City, Morocco, the drinking water distribution systems are primarily made of galvanized steel, ductile iron and cast iron which are particularly susceptible to corrosion and scaling. They can represent more than half of water distribution network (Gonzaleza et al., 2013). These phenomena can significantly degrade the water quality and shorten the lifespan of the distribution systems. Corrosion occurs when the water's physicochemical properties cause the dissolution of the pipe materials while scaling results from the precipitation of minerals like calcium carbonate, which can clog pipes and reduce flow efficiency. The water distribution system, often described as a dynamic reactor, experiences constant physicochemical interactions between water and the materials forming the pipes. This interaction causes the release of iron or ferrous ions into the water, resulting in a metallic taste and red water (Zhang et al., 2022). As a result, the quality of the water delivered to households can differ significantly from the quality of the water at the treatment station. The conditions influencing water quality within distribution networks are complex, and understanding these factors has become the subject of extensive scientific inquiry (Bensoltane et al., 2018). For Fes City, the corrosion and scaling potential of the drinking water are critical concerns for operational teams working to maintain the integrity of the water supply system.

A major challenge in water distribution systems, especially those constructed with galvanized steel pipes, is the corrosive nature of water. Corrosive water can degrade the pipe infrastructure by dissolving metal components, which not only reduces the pipes' lifespan but also contaminates the drinking water with leaches metals, such as lead, cadmium, chromium, and aluminum (El Baroudi et al., 2024). This type of water, often referred to as "corrosive water," poses indirect risks to human health due to the presence of dissolved pipe materials (Kumar et al., 2023). Furthermore, scaling caused by the deposition of minerals can lead to flow restrictions and increased maintenance costs, thereby affecting the efficiency and safety of the water distribution system.

The calcocarbonic balance, also known as the calcium-carbonate balance, in drinking water, plays a critical role in water quality control, especially within distribution networks. Effective management of this balance is necessary to prevent both corrosion and scaling, which can compromise the water supply infrastructure (Hachemi and Zeroual, 2021). Controlling this balance not only preserves the structural integrity of the network but also reduces scaling in both public and private installations (Machkor, 2011). Indices such as the Langelier, Leroy, and Larson indices are commonly used to assess a water system's corrosiveness by analyzing its physicochemical parameters.

In our study, we analyzed the physicochemical parameters of the drinking water in Fes City, including Langelier index (LSI), CAT, CAT saturation, chloride, sulfate, dissolved oxygen, residual chlorine, conductivity, turbidity, TH, oxidability and temperature. These parameters are crucial in understanding the water's potential for corrosion and scaling within the distribution network. Multiple linear regression modeling by software Statistica 12 and Excel was employed to identify the key parameters influencing water quality, providing valuable insights to help water producers take corrective actions to mitigate corrosion and scaling (Kumar et al., 2023).

The main objective of this study is to assess the corrosion and scaling potential of the drinking water distribution systems in Fez, It is imperative to consider the multitude of health risks to the population and the economic losses incurred due to corrosion and scaling of drinking water (Yousefi et al., 2016). By focusing on water parameter data from the city of Fez water treatment plant, this research offers a novel application of mathematical techniques to better understand and manage water quality. Specifically, we use linear models to determine the relationships between the calcocarbonic balance and water corrosivity (Li, 2014), providing a framework for improving the management of drinking water distribution systems and the water quality.

MATERIALS AND METHODS

Study zone

Fez is located in the northeastern region of Morocco and constitutes one of the nine provinces of the Fes-Meknes region. It is the second-largest city in the country, with a population of 1,365,000 as reported in the 2022 Moroccan census. The prevailing climate is semi-arid continental, with distinct seasonal patterns. Summers are characterized by high temperatures and low humidity, while winters are cold and wet (Bouizrou et al., 2021). It is located between parallels 34° 03′ 00″ North and meridians 4° 58′ 59″ West, covering an area of 424 km².

The study was conducted at the National Office of Electricity and Drinking Water in Fes, which forms part of the Direction Regional Centre Nord Fes-Meknes (DR5). That is mentioned in the Figure 1.

Sampling and physicochemical water analysis

Water sample collection for physiochemical analysis is a process that needs to be done with great

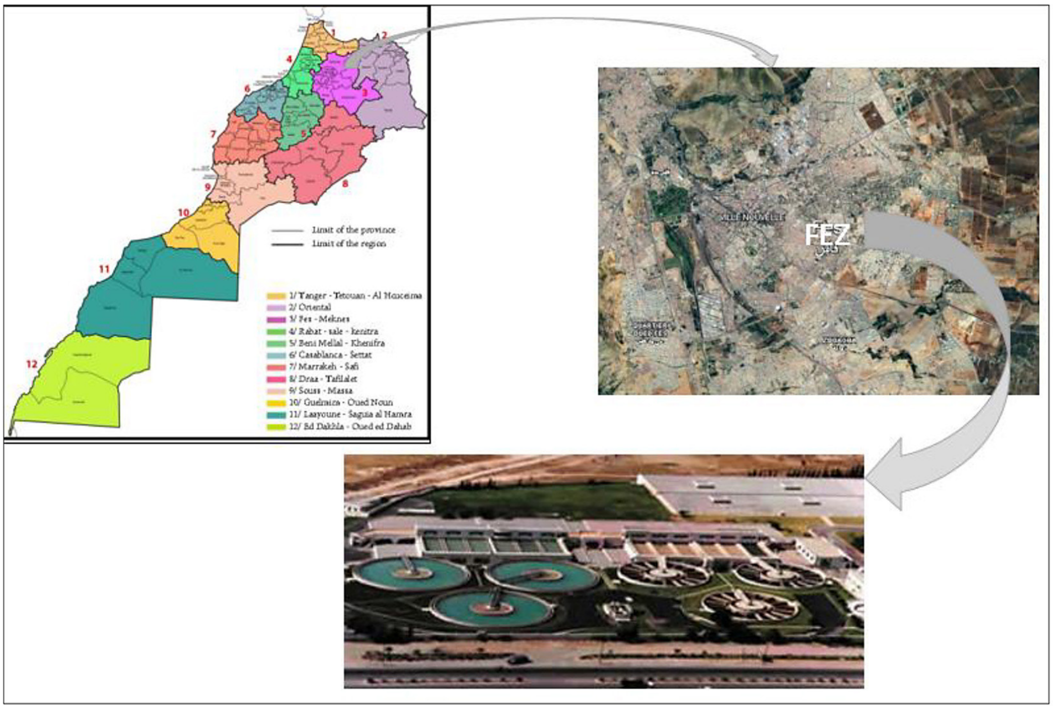

Figure 1. Geographical location of the city of FEZ (Google Earth and ONEE official website)

care. Using 2.5 L bottles, samples of the treated water were collected from the tap after distribution once a week for 6 months (April 2021 and September 2021), coming from various Fez sources (6 points). The physicochemical analyses, including temperature, dissolved oxygen, LSI, conductivity, turbidity, oxidability, dissolved oxygen (O_2), TH, sulfate (SO_4^{2-}), chloride (Cl^-), complete alkalinity title (CAT), complete alkalinity title saturation (CATs) and residual chlorine (Cl_2) and temperature were all measured using the techniques outlined by (Rodier et al., 2009). The analytical methods employed are presented in Table 1. A total of 156 samples were collected between April 2021 and September 2021. Two indices were employed to assess the corrosivity of the water: the Larson index and the Leroy index (Leroy, 2012).

Evaluation of corrosion/scaling indices

Langelier saturation index

Concerning the calcium carbonate equilibrium theory, the Langelier saturation index model

Table 1. Analysis methods for physicochemical parameters

Parameters	Analysis method	Unites
Conductivity	Electrochemical (conductivity meter)	mS/cm
Turbidity	Electrochemical (turbidity meter)	NTU
pH/ pHs (LSI)	Electrochemical (pH-meter)	---
Dissolved oxygen	Electrochemical	mg/l
Residual chlorine	*DPD test	meq/l
Total dissolved solids (TDS)	Electrochemical (conductometric)	mg/l
Chloride	Titrimetric dosing	meq/l
Sulfate	Nephelometry	meq/l
CAT / CATs	Titrimetric dosing	meq/l
TH	Titrimetric dosing	meq/l
Oxidability	Titrimetric dosing	mg(O_2)/l
Temperature	Electrometric / thermometer	°C

Note: *diethyl paraphenylene diamine.

was employed to ascertain the quality of the water in question. The phenomenon currently under investigation is the impact of the pH on the equilibrium solubility of calcium carbonate. The pH value at which water is saturated with calcium carbonate is known as the saturation pH or pHs (Alvarez-Bastida et al., 2013) (Agatemor and Okolo 2008).

The LSI is defined by the Equation 1 (Lestari et al., 2023):

$$LSI = pHi - pHs \quad (1)$$

where:

$$pHs = (9.3 + A + B) - (C + D) \quad (2)$$

(El Baroudi et al., 2024)

The following equation is valid if the pHs is higher than 9.3 (Nalivan et al., 2019).

$$A = \frac{(Log10\ (TDS) - 1)}{10} \quad (3)$$

(When TDS < 10.000 mg/L)

$$B = -13.12 \times Log10\ (°C + 273) + 34.55 \quad (4)$$

$$C = Log10\ (Ca^{2+} \text{ as } CaCO_3) - 0.4 \quad (5)$$

$$D = Log10\ (alkalinity\ as\ CaCO_3) \quad (6)$$

The Langelier index is a useful indicator of water quality. When the index is below -0.3, the water is considered aggressive and tends to corrode. Conversely, when the index is above 0.3, the water is scaling. In the case of water in equilibrium, the Langelier index value is 0 (Yousefi et al., 2016).

Larson index

The Larson index model defines the index as follows in Equation.7 (Al-Qurnawi et al., 2022):

$$Larson\ index = \frac{[Cl^-] + [SO_4^{2-}]}{[HCO_3^-]} \quad (7)$$

The concentrations of chloride (Cl^-), sulfate (SO_4^{2-}), and bicarbonate (HCO_3^-) are expressed in mill equivalents per liter (meq/l) (Song et al, 2019). The water classification can be determined by calculating the index, with the following categorization:

The Larson index is a useful tool for determining the corrosivity of water. Values below 0.8 are considered to be slightly corrosive, while those between 0.8 and 1.2 are corrosive, and values above 1.2 are highly corrosive (Al-Qurnawi et al, 2022).

Leroy index

To determine the corrosivity of water, another index has been calculated which can be used to estimate it. This index, designated the Leroy index, is defined by the following Equation 8. (Hassani et al., 2024):

$$Leroy\ index = \frac{CAT}{TH} \quad (8)$$

The *Leroy index* is defined as the ratio between the CAT and the total hardness concentration (TH). This test can be used to determine whether a given water is prone to corrosion. The results are expressed in mill equivalents per liter (meq/l). The water in question is considered slightly corrosive at concentrations between 0.7 and 1.3, and highly corrosive at concentrations above 1.3 (Bakouan et al., 2017).

Modeling

The multiple linear regression model is one of the most commonly used statistical techniques to analyze multifactorial effects. A multiple linear regression (MLR) model is a statistical technique used to study and model the relationship between variables (Mata, 2011). This statistical technique employs several explanatory variables to predict the outcome of a response variable (Salhi et al., 2013) (John et al., 2021).

The MLR analysis establishes a correlation between the factors (parameters) and the response, which is the corrosivity index in this case. The MLR model can be expressed in mathematical terms as the following Equation 9 (Laajine et al., 2022):

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + ... + \beta_n X_n + \varepsilon \quad (9)$$

where: Y the predicted response, Xi the independent variables, β_0, β_i, and β_n, the regression coefficients, k the number of variables studied.

Model coefficients are calculated using Statistica 12 and Excel software.

Graphical analysis

To ascertain the veracity of the model, several different graphs are employed for the purposes of graphical analysis. The Statistica software provides three graphs: Henry's line of residual values, histogram of residual values, and analysis of relationships between residuals and predicted values (Bezazi et al., 2015).

RESULTS

Constitution of the database

The database was constructed through physicochemical analyses collected weekly for six months of samples derived from 6 sources. The above analyses yielded 156 samples, which are presented in Table 2. The values present in this table are real and unaltered.

The nature of surface water and groundwater can be determined by various indices, which are classified as aggressive, neutral, or incrusting. The objective of these tools is to provide those responsible for water treatment with indications of the behavior of water in the distribution network, particularly concerning the formation of the carbonate layer (Langelier saturation index) and the interaction between water and all oxidable metals (Larson and Leroy index). Table 3 presents the results of the analysis. The dependent variables are calculated according to the formulas presented above.

The results presented in Table 3 indicate that the quality of the waters under investigation meets the established standards, as the values observed fall within the expected range for each index.

Data analysis

We propose linear models for analyzing the relationships between a quantitative explanatory dependent variable and several quantitative explanatory independent variables (Nakamura et al., 2023). These models will then be used to predict the behavior of each index relating to corrosivity and calcocarbonic equilibrium as a function of the physicochemical parameters influencing it. Tables 4 and 5 present the results of the multiple linear regression analysis.

As demonstrated in Table 4, the coefficient of determination R^2 is equal to 92.02%, indicating a high degree of explanatory power of the dependent variable Y (Larson index) by the independent variables Xi (parameters). Moreover, the standard deviation, (σ_{err} = 0.047), is notably low. It can be concluded that the model is both explanatory and predictive, at least in terms of the standard error.

Table 2. Results of physicochemical parameters with Moroccan MAV water standards

Parameters	Minimum value	Maximum value	Mean (of 156 samples)	MAV**
Temperature (°C)	15	19.5	17.25	<25
TH (meq/l)	4.28	7.6	5.86	2<TH<6 *
O_2 dissolved (mg/l)	7.98	8.5	7.61	5<O_2<8
LSI	-0.37	0.34	0.02	-0.3<LSI<0.3 *
TDS (mg/l)	436.15	911.87	593.45	< 2000
CAT (meq/l)	4.23	5.82	4.89	< 4.2 *
CATs (meq/l)	3.82	5.4	4.60	---
Chloride Cl^- (meq/l)	0.05	2.14	1.13	< 7.05
Sulfate SO_4^{2-} (meq/l)	0.12	1.42	0.69	< 5.21
Cl_2 residual (meq/l)	0.3	0.9	0.59	< 1
Conductivity (mS/cm)	0.61	1.203	0.83	< 2.5
Oxidability (mg(O_2)/l)	0.72	3.22	1.56	< 5
Turbidity (NTU)	0.3	0.95	058	< 0.5

Note: *rule of good practice, **maximum admissible value.

Table 3. Maximum and minimum index values

Indices	Minimum value	Maximum value	Mean (of 156 samples)	RGP*
Larson index (meq/l)	0.002	0.679	0.18	0.8 to 1.2
Leroy index (meq/l)	0.622	1.173	0.85	0.7 to 1.3

Table 4. Multiple linear regression for the LARSON index

Parameter	(SO_4^{2-})	Turbidity	Temperature	Conductivity	LSI	Cl_2 residual	Oxidability	Cl^-	O_2 (dissolved)	TH	CATs	CAT	β_0
βi	0.2889	-0.0185	0.0013	0.0823	-0.0113	-0.0032	-0.00014	0.1567	-0.0491	-0.0265	0.0025	-0.0350	0.4458
$S_{\beta i}$	0.0312	0.0356	0.0044	0.0611	0.0332	0.0354	0.0101	0.0076	0.0296	0.0094	0.0138	0.0139	0.2918
				R^2	σerr	F	ddl	SCEm	SCEr				
				0.920=92.02%	0.047	137.4312	143	3.6557	0.3169				

Note: Sai is the standard deviation of the coefficients, F: Fischer-Snedecor number, ddl: the degree of freedom (n-p-1) / n=number of trials; p=number of parameters, SCEm: squared sum of total deviations and SCEr: squared sum of residual deviations.

The results of the linear regression, presented in Table 5, indicate that the coefficient of determination for this model is close to 1 (R^2 = 0.9876), suggesting a good fit. Moreover, the error is minimal.

Mathematical analysis of results

To test whether there is a statistically significant association between the response and each descriptor, the p-value associated with the descriptor is compared to the 0.05 level of significance (Cordero-Ahiman et al., 2021). This comparison indicates the risk of falsely concluding that an association exists at the 5% level, which is the level of significance commonly used in statistical hypothesis testing. The results presented in Table 6 indicate a statistically significant association between the response, Larson index, and the factors influencing it. This conclusion is supported by the p-value, which indicates a significant difference at α = 0.05 level (Laajine et al., 2022). From Table 6 we conclude that there are seven significant parameters, namely CAT, TH, DO, Chloride, LSI, Conductivity and Sulfate, as demonstrated in Figure 2. The Larson index is positively influenced by chloride, sulfate, and conductivity concentration, which is consistent with its role as an indicator of water ionic corrosivity.

Table 5. Multiple linear regression for the LEROY index

Parameter	(SO_4^{2-})	Turbidity	Temperature	Conductivity	LSI	Cl_2 residual	Oxidability	Cl^-	O_2 (Dissolved)	TH	CATs	CAT	β_0
βi	-0.0597	-0.0165	0.00102	0.1148	-0.0141	-0.0195	-0.0196	-0.00052	-0.0172	-0.1436	0.0015	0.1712	0.9725
$S_{\beta i}$	0.0094	0.0107	0.0013	0.0184	0.0099	0.0106	0.0031	0.0023	0.0089	0.0028	0.0042	0.0041	0.0876
				R^2	σerr	F	ddl	SCEm	SCEr				
				0.987=98.76%	0.014	956.371	143	2.2967	0.0286				

Table 6. Main results p-value, coefficients for Larson Index

Predictor	Coefficient	SE coef	t(143)	p–Value
Constant	0.445884551	0.291828252	1.52790056	0.128746
CAT	-0.0350106144	0.0138356061	-2.53047204	0.012474
CATs	0.00253025383	0.0139255417	0.181698772	0.856076
TH	-0.0265440491	0.00941839705	-2.81831919	0.005512
Dissolved O_2	-0.0490943704	0.0296197413	-1.65748816	0.009961
Chloride	0.156780741	0.00763835536	20.5254579	0.000000
Oxidability	-0.0001376880	0.0101808515	-0.01352421	0.989228
Chlorine residual	-0.0031612386	0.0354971128	-0.08905622	0.929162
LSI	-0.0113444477	0.0332351252	-0.34133909	0.007333
Conductivity	0.0823959764	0.0611252603	1.34798569	0.0179794
Temperature	0.00130607531	0.00440006798	0.296830711	0.767026
Turbidity	-0.0185487192	0.0356884756	-0.51973974	0.604049
Sulfate	0.288941242	0.0312008763	9.26067716	0.000000

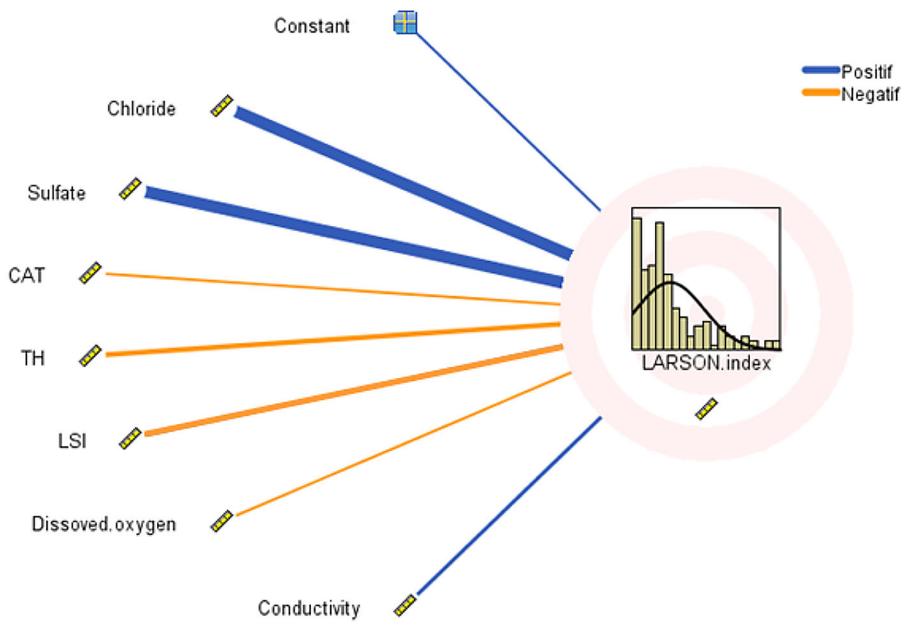

Figure 2. The diagram below illustrates the factors that determine the corrosiveness of water according to Larson's index

Conversely, an increase in LSI, higher hardness or better oxygenation of the water seems to attenuate this corrosivity.

The results of the second index in Table 7 demonstrate a statistically significant relationship between the response variable, Leroy index, and the specified terms. This can be observed by the fact that the p-value is below the threshold for statistical significance (Nakamura et al., 2023). Moreover, the Table 7 parameters exhibited equivalent numerical values, including CAT, TH, oxidability, chlorine residual, LSI, conductivity and sulfate. As shown in Figure 3, the Leroy index is found to be significantly impacted by water hardness (TH) and LSI (in a negative manner), followed by CAT and conductivity (in a positive manner). It has been demonstrated that parameters such as sulfates, oxidability, and residual chlorine have a mitigating effect on the index.

Determining model fit

In order to ascertain whether the model is an accurate representation of the data, it is necessary to examine the fit statistics presented in the table 8.

Table 7. Main results p-value, coefficients for Leroy index

Predictor	Coefficient	SE coef	t(143)	p-value
Constant	0.972546777	0.0876852552	11.0913377	0.000000
CAT	0.171184607	0.00418418941	40.9122508	0.000000
CATs	0.0015408449	0.00415716656	0.370647861	0.711448
TH	-0.143673805	0.00282993351	-50.7693218	0.000000
Dissolved O_2	-0.017288947	0.00889980514	-1.94262085	0.054027
Chloride	-0.000521411	0.0022950867	-0.227185824	0.820604
Oxidability	-0.019675879	0.00305902719	-6.43207089	0.000000
Chlorine residual	-0.019524559	0.0106657713	-1.8305811	0.049245
LSI	-0.014157013	0.00998611482	-1.41766981	0.015846
Conductivity	0.114889299	0.0183662275	6.25546532	0.000000
Temperature	0.0010287655	0.0013220827	0.778140053	0.437772
Turbidity	-0.016566208	0.0107232698	-1.54488408	0.124584
Sulfate	-0.059779201	0.0093748867	-6.37652524	0.000000

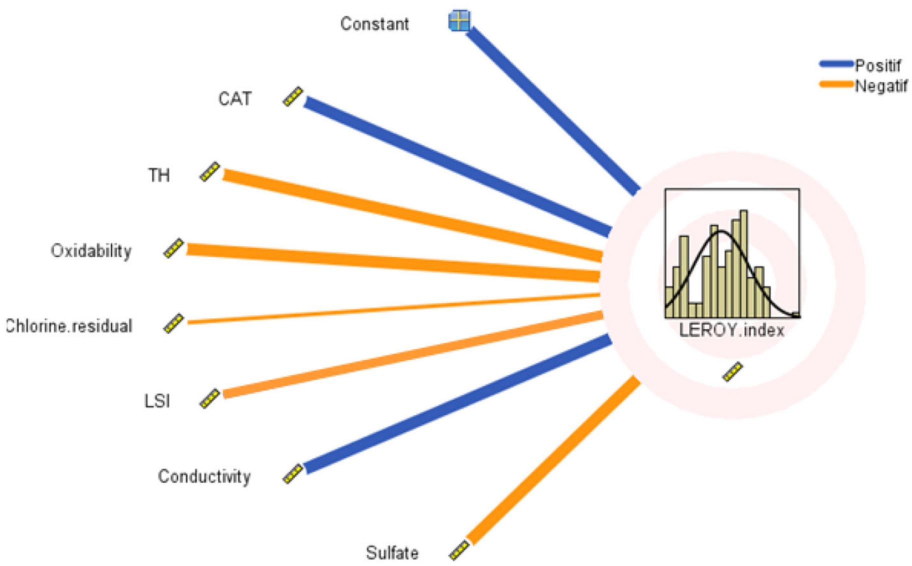

Figure 3. The diagram below illustrates the factors that determine the corrosiveness of water according to Leroy's index

Table 8 demonstrates that the adjusted model, comprising seven variables, has an explanatory power of 92.02% to the Larson index. This high degree of explanatory power is further confirmed by the explanatory power rate of almost 92%. Consequently, our model can be considered highly explanatory (Kwak et al., 2022). Moreover, the R-squared value (pred) of 87.52% indicates that the prediction of the LARSON index by the seven variables is nearly 88%. This evidence demonstrates that our model is capable of making accurate predictions. Furthermore, the R^2 value of 98.76%, as observed in Table 8, indicates that the second index exhibits considerable variability, with 7 variables retained. This rate of nearly 99% suggests that the model is sufficiently explanatory. Also, the R-squared (pred) of 89.21% indicates that the Leroy index predicted from the seven variables is nearly 89%. This evidence supports the assertion that the model in question can make accurate predictions (Booker, 2010). Consequently, we may conclude that the models provide a satisfactory fit to the data.

The mathematical model

The linear mathematical models thus identified are represented by the following equations: Equation 10 and Equation 11. The first mathematical model for MLR:

$$Y(I_{LARSON}) = 0.4458 - 0.0350CAT - 0.0265TH - 0.0491Dissolved\ O_2 + 0.1567Chloride - 0.0113LSI + 0.0823Conductivity + 0.2889Sulfate \quad (10)$$

The second mathematical model for MLR:

$$Y(I_{LEROY}) = 0.9725 + 0.1711\ CAT - 0.1436\ TH - 0.0196\ oxidability - 0.0195\ Cl_2\ residual - 0.0141\ LSI + 0.1148\ conductivity - 0.0597\ sulfate \quad (11)$$

The initial model indicates a negative correlation between the Langelier saturation and Larson index. In particular, as the value of the Langelier saturation index declines, the value of the Larson index rises. This phenomenon increases the probability of pipe degradation and compromise the quality of water. It can be reasonably concluded that the CAT has a negative effect on the Larson index. This is evident, as the higher the concentration of bicarbonates in the water, the less corrosive it is, and the higher the concentration of chloride and sulfate ions, the more accelerated the corrosive process (Song et al., 2019). For the second model, it can be demonstrated that the Leroy index is inversely proportional to the LSI, a

Table 8. Larson and Leroy index model fit

Index	Standard error	Press	Square R^2	Adjusted R^2	Predicted R^2
Larson index	0.0470819	0.000610	92.02%	91.35%	87.52%
Leroy index	0.0141466	0.000120	98.76%	98.66%	89.21%

relationship that is also observed for the first index. The model indicates that the ratio between CAT and TH exerts a negative influence on the Leroy index, whereas conductivity exerts a positive influence on this index. When the water is mineralized, with an increased calcium and magnesium ion content, corrosion is not pronounced. This is due to the acceleration of the scaling process (Sunardi et al., 2020). Conversely, when the solution contains high concentrations of chloride and sulfate ions, the corrosive process is accelerated (Nakamura et al., 2023).

Graphical analysis of results

Henry's law of residual values

The normality test developed by Statistica 12 gives the following results. Figure 4a represents the normality test for the Larson index. It depicts a normal probability plot of the residuals. The residuals are plotted against the expected normal values, and a straight line indicates the expected normal distribution (Machkor and Messaoudi, 2015). The residuals are distributed around this line, allowing the deviation from normality to be visualized. The majority of residuals lie close to the line, indicating relative normality, although a few extreme residuals show a slight disturbance.

The probability plot (Figure 4b) for the Leroy index also indicates that the majority of residuals are situated close to the straight line, suggesting a normal distribution of residuals (Fellak, 2020). As with the Larson index, a few extreme residuals deviate from the line, indicating anomalies or variations not captured by the model. Overall, the results are satisfactory, but attention should be paid to the deviations at the extremes to improve model accuracy.

Histogram of residual values.

The distribution of the residues is plotted in Figures 5a and 5b in order to ascertain whether their distribution is Gaussian. The histogram of residual values for the Larson index (Figure 5a) demonstrates a high concentration of residuals around zero, while the raw residuals are distributed over a range from -0.20 to 0.14, which is characteristic of a normal distribution. This indicates

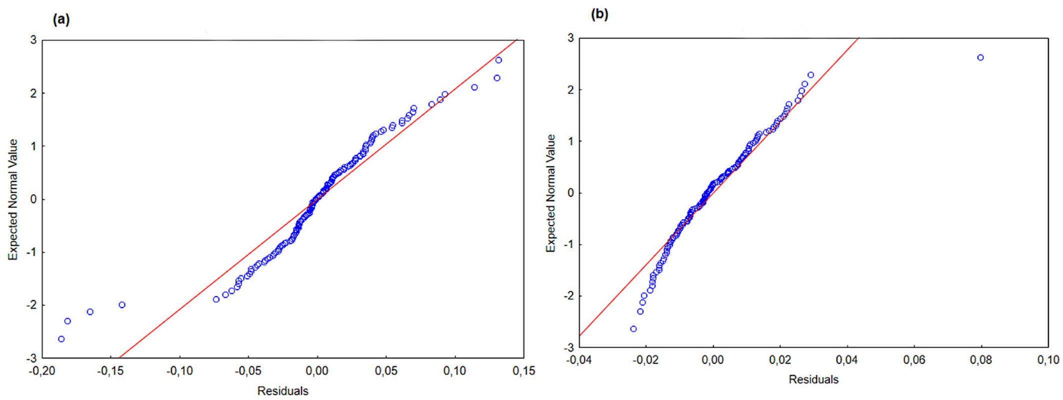

Figure 4. Result of the normality test for (a) the Larson index (b) Leroy index

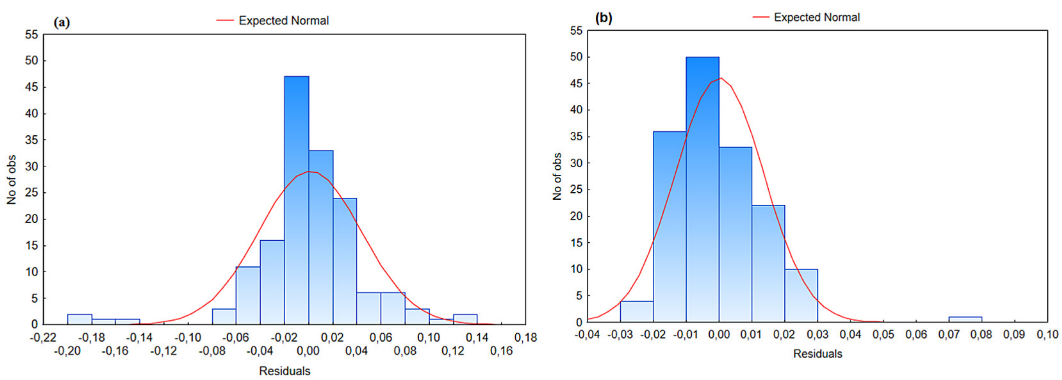

Figure 5. Result of the histogram of residual values for (a) Larson index and (b) Leroy index

that the majority of model predictions are close to observed values, suggesting that the model performs well. However, the presence of residuals at negative and positive extremes indicates the potential for significant outliers or prediction errors in some observations. These extreme values should be investigated to ascertain the underlying causes and, if necessary, adjust the model to address them.

The Figure 5b depicts a histogram of residual values for the Leroy index. The raw residuals are distributed on a scale from -0.03 to 0.08. The histogram illustrates the frequency of residuals in different value ranges. The concentration of residuals is close to zero, indicating a normal distribution of residuals (Tranmer et al., 2020). However, the presence of a few residuals at the extremes indicates the potential for deviations from normality.

Analysis of the relationship between residues and predicted values

Figures 6a and 6b illustrate the distribution of residuals as a function of the values predicted by the multiple linear regression model. The predicted values for the Larson index (Figure 6a) range from -0.1 to 0.6, covering a broad spectrum. Residuals are close to zero with a standard deviation of -0.19 to 0.14, indicating minimal prediction errors and no systematic bias (Chesneau, 2017). Most residuals fall within the 95% confidence intervals, confirming model reliability (Cordero-Ahiman et al., 2021). No heteroscedasticity is observed, as residuals show a constant variance across predicted values (Delacroix et al., 2021).

For the Leroy index (Figure 6b), predicted values range from 0.6 to 1.1. Residuals are slightly more dispersed (-0.03 to 0.08), indicating slightly lower accuracy than for the Larson index. However, most residuals remain within the 95% confidence intervals, ensuring prediction reliability (Chesneau, 2017). No heteroscedasticity is detected, confirming consistent prediction errors (Tranmer et al., 2020).

DISCUSSION

The findings of this study provide a comprehensive understanding of the relationship between water corrosivity and calco-carbonic balance in Fez, Morocco. The findings indicated an inverse proportional relationship between corrosivity and calcocarbonic balance. The development of multiple linear regression (MLR) models to predict the Larson and Leroy indices has yielded significant results, with R^2 values of 92.02% and 98.76%, respectively. This high level of accuracy serves to substantiate the reliability of the MLR approach in explaining and predicting water quality parameters. Furthermore, the results presented in Figure 2 suggest that seven factors are associated with the Larson index. The parameters that influenced the corrosivity of water included CAT, TH, DO, chloride, LSI, conductivity, and sulfate. As illustrated in Figure 3, seven factors have been identified as influential elements in the corrosion of water: CAT, TH, oxidability, chlorine residual, LSI, conductivity, and sulfate. Collectively, these nine parameters contribute to the overall corrosivity of the drinking water.

The study's findings are consistent with those of prior research conducted in analogous contexts, wherein physicochemical parameters such as CAT, chloride, sulfate, and LSI have been demonstrated to exert a substantial influence on water corrosivity. For example, studies conducted in Iran (Sadat-Noori et al., 2013), India (Kumar et

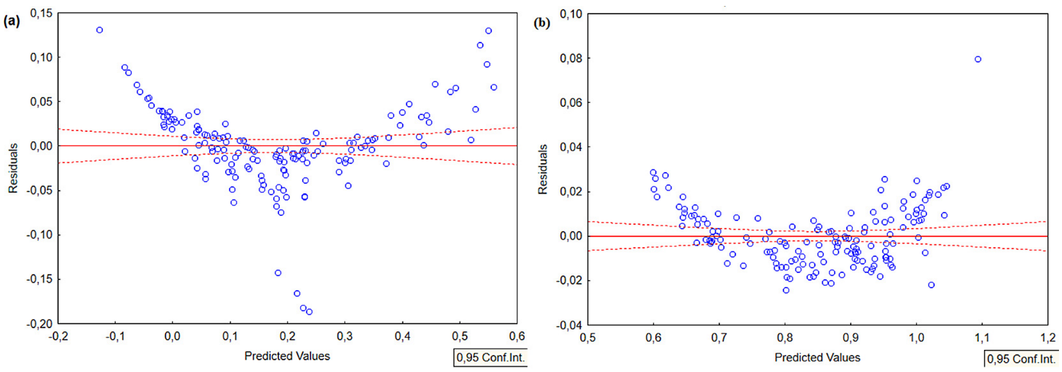

Figure 6. Analysis of predicted scores versus residuals for the Larson (a) and Leroy (b) indexes variables

al., 2023) (Alam and Kumar, 2023) and Algeria (Bensoltane et al., 2018) also indicated that scaling and corrosion tendencies are closely related to these parameters, confirmed the results findings in Fez. Furthermore, the use of the Langelier and Larson indices as indicators of water corrosivity has been validated by other studies (Yousefi et al., 2017) (Yousefi et al., 2016), emphasizing their effectiveness in predicting water behavior within distribution networks.

The report offers vital information for Fez's water management. To protect the integrity of the water distribution system and lower the possibility of metal leaking into drinking water, an ideal balance between corrosivity and scaling must be maintained. This is especially crucial for Fez, where the distribution infrastructure is mostly made up of corrosion-prone galvanized steel and ductile iron pipes. Operational teams can benefit greatly from the predictive models created in this work, which allow for proactive risk monitoring and intervention by identifying the factors responsible in the corrosivity and scaling of water. The findings of this study contribute to the enhancement of water quality monitoring throughout the water distribution system in Morocco. This enhanced monitoring facilitates the maintenance of water quality and stability, leading to a reduction in corrosion and scaling. Consequently, this guarantees the distribution of potable water to the population, thereby reducing the occurrence of health risks related to heavy metal release. Furthermore, it reduces economic losses incurred due to the impact of water corrosion and scaling on drinking water distribution systems and household appliances.

CONCLUSIONS

This study successfully demonstrates how mathematical modelling, specifically multiple linear regression, can be used to analyze and forecast the carbonate-carbonic balance and water corrosivity in the drinking water distribution network in Fez, Morocco. Examining key physicochemical parameters such as LSI, conductivity, chloride, sulfate, total hardness, CAT, dissolved oxygen, oxidability and residual chlorine enabled the models to achieve high predictive accuracy, with R^2 values of 92.02% and 98.76%, and small standard errors of 0.04 and 0.01 for the Larson and Leroy indices, respectively. The findings show that safeguarding water distribution infrastructure requires striking a compromise between corrosivity and scaling, especially in networks made up of corrosion-prone galvanized steel or ductile iron pipes. To ensure the longevity of water supply systems and provide safe drinking water, avoiding potential health risks, this study emphasizes the importance of ongoing water quality monitoring and applying predictive techniques to foresee problems such as corrosion and scaling. Distributed water in the Fez region conforms to the Moroccan government's standards, namely NM 03.7.001 (NM 03.7.001, 2006) and NM 03.7.002 (NM 03.7.002, 2011). Moreover, the water is not corrosive, as it is not aggressive. In other words, it is well-balanced in terms of corrosivity and calco-carbonic balance, indicating that the water quality is maintained within acceptable standards. While the models demonstrate significant explanatory power in the Fez region, their applicability in regions with comparable environmental conditions could be explored. This study helps us to manage the distribution of drinking water and minimize health risks to the population of Fez.

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