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Developing a New Matrix Model to Estimate the Urban Run-Off Water Quality

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ABSTRACT: This research aims at developing a new relation to estimate the urban run-off water quality through urban land use. According to the first phase of this research, six urban characteristics and land use indices have been defined concerning all parameters with either direct or indirect impacts on urban water quality: Population, land use type, meteorological factors, local physiographical parameters, urban patterns etc. have been considered when developing the new indices. Three study areas, including different urban land uses, have been selected in Tehran Metropolitan and urban drains maps and structures have gone under study to determine the sampling points. Multi-statistical analysis, discriminate analysis, and multi-linear regression analysis have been applied for all water quality results and urban indices in each site, with the results revealing very strong relations between urban land use and water quality variation. Temporary population especially in downtown site has proved to be an effective temporal factor on how even public transport could not have any significant effects, in case population density has no significant influence on water quality, as all sanitary waste water in selected sites is collected through urban wastewater systems separately. General slop is a significant factor in hydrocarbons and heavy metals, once they are not alongside the streets route. All told, this paper recommends reusing urban drained runoff locally before joining other regions' collectors. Here in urban drainage system, collection and aggregation of water could not be an appropriate factor in water quality management unlike river systems. The model could be employed in urban local water consumption management in irrigation and public recovery.

Keywords: Urban Drainage System, Urban Land Use, Commercial and Administrative, Green Space, Residential Zone.

INTRODUCTION

The urban population of the world is growing. It is expected that by 2007, world's population will be predominantly urban for the first time in human history. UN projections suggest that over the next 30 years, virtually all of the world's population (Adams & Papa, 2000) growth occurs in the urban areas of low- and middle-income countries mainly in the South (Wang et al., 2008). The storm water pollution problem has two main components: the increased volume and

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velocity of surface runoff and the concentration of pollutants in the runoff. Both components are directly related to development in urban and urbanizing areas. Together, they alter hydrology and water quality which in turn result in a variety of problems like habitat loss, increased flooding, decreased aquatic biological diversity, and increased sedimentation and erosion, while affecting our health, economy and social well-being (Demirat et al., 2006). Some impervious covers, such as exposed rock or hardpan soil, are natural land development (Akan & Houghtalen, 2003); however, it greatly increases it. Human-made impervious cover comes in three varieties: rooftop imperviousness from buildings and other structures; transport imperviousness from roadways, parking lots, and other transportation-related facilities; and impaired pervious surfaces, also known as urban soils, which are natural surfaces that become compacted or otherwise altered and less pervious through human action. Examples of hard soil include the base paths on a baseball diamond or a typical suburban lawn (Coffman et al., 2001). The creation of additional impervious covers also reduces vegetation, thus magnifying the effect of the reduced infiltration (Alley & Smith, 1981). Trees, shrubs, meadows, and wetlands, like most soil, intercept and store significant amounts of precipitation. Vegetation is also important in reducing the erosional forces of rain and runoff. In one study, conversion of forest to impervious cover triggered an estimated 29% increase of runoff during a peak storm event (Coffman, 2001). Because of urban sprawl, residential land is now the dominant land use in 64% of the nation's water supply reservoirs (Wilson and Chakraborty, 2013). It has long been recognized that covering land with impervious surfaces, such as roofs and roads, reduces both the volume of water infiltrating into soils and the volume of water lost to the air through evapotranspiration, thus increasing the volume of runoff after a rainfall (Leopold, 1968).

A study concerning the influence of land use and land cover patterns on seasonal water quality (Shi, 2017) showed that urban and agricultural land had negative and forest and grassland had positive effects on water quality (Anandakumar et al., 2007). These results agreed with most previous studies, demonstrating that stream water quality variables displayed highly temporal variations, with electrical conductivity (EC), ammonium nitrogen (NH_4 +-N), nitrate nitrogen (NO_3 −N), and total suspended solids (TSS), all of which generally displayed higher levels in the wet season, while there were higher concentrations of biochemical oxygen demand (BOD_5), chemical oxygen demand (COD), and dissolved oxygen (DO) in the dry season (Collins et al., 2010). Stream water quality showed significant spatial and seasonal variations in the Dan River basin, with land use having a strong relation with water quality during the wet season.

Chen has employed Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) models to identify the impact of land use and population density on surface water quality in the Wen-Rui Tang River watershed of eastern China (2016). He examined the influence of six water quality predictors, such as the type of the land-use and population density on five water quality parameters in the Wen-Rui Tang River watershed during wet and dry seasons. Spatial and seasonal scales affect land use on water quality (Gobel et al., 2007). Also, agricultural land use has been found to be the primary influential factor on Nitrogen (N) and Phosphorous (P) in suburban and rural areas.

Effective factors, with an influence on water quality, have been investigated in some different urban and sub-basins with different urban land use (Giri & Qiu, 2016). It was found out that geographically weighted regression can explain complex relations between land uses and water quality.

Flash floods have been investigated as effective factors on urban drainage system. Hur et al. employed model FFC-QUAL for dry and wet periods (2018), showing that the model should be useful in urban watersheds due to its simplicity capacity to model common pollutants such as biological oxygen demand (BOD), chemical oxygen demand (COD), Escherichia coli (Ecoli), suspended solids (TSS), and total nitrogen and phosphorous in runoff (Grum & Hans Aalderink, 1997). They also used this in design studies to determine how changes in infrastructure affect the runoff and pollution loads, and compared the three models, finding that there was some variations between FFC-QUAL and other models (ILLUDAS, SWMM, and MOUSE).

This study aims at figuring out the impacts of urban land use on urban runoff based on urban dynamics and event interval. It investigates effective factors through three sampling programs due to three rainfall events, in three urban sub-basins in Tehran metropolitan.

MATERIAL AND METHODS

For this research, three study areas with different dominated urban land uses types were selected. The investigated land uses are as follows:

1. Commercial and administrative districts
2. Green space and urban spaces districts
3. Residential districts

Other kinds of land uses, like streets and pedestrians, were not considered since the average percent of their area in all three zones fell below two. Characteristics of each study site got extracted from Tehran metropolitan municipality database, released in 2017. Afterwards, experimental steps were taken in field sampling from the main collectors of urban drainage system in 10 minutes after the start of precipitation and continued until the drainage flow descended to the base flow. The average of water quality parameters were used here in this research. Some water quality variables (DO, Temperature, TDS, EC, pH) were measured through in-situ measurements. Also, laboratory measurements were carried out for water quality variations and a statistical analysis was applied on data.

Tehran, the capital of Iran, like many metropolitan cities around the globe faces an increasing freshwater demand and water resources limitation due to rapid population growth. This paper considers urban runoff water quality and local recycling potential as a sustainable solution for water supply of Tehran. Three districts in different land uses were selected as main case study in Region 6 (Fig. 2), Tehran (Fig. 1). Table 1 presents the average characteristics of different land uses of Tehran and Region 6. All three study districts got categorized by their dominant urban land use. Table 2 shows the ratios of urban land use in each sub basin, based on the dominant urban land use type.

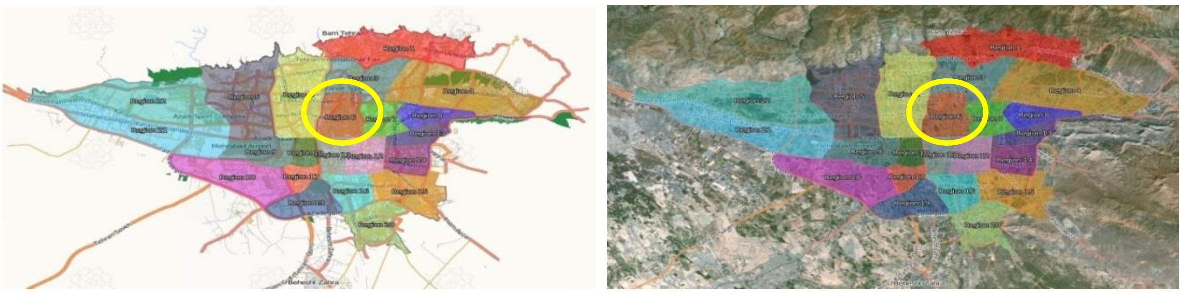

Fig. 1. Tehran metropolitan and its municipality regions in general and satellite views

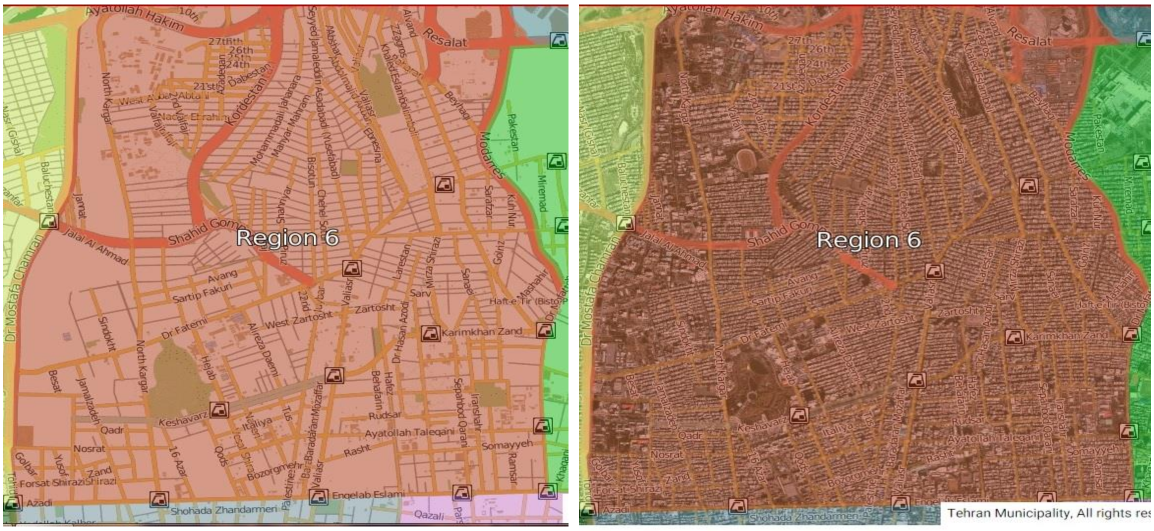

Fig. 2. Region 6 of Tehran metropolitan and its municipality regions in general and satellite views

Table 1. Ratios of main urban land use types for Tehran and Region 6, wherein the study sites are located

No.	type of land use	Tehran province (percent)	Region 6 (percent)
1	Residential	8.28	35
2	commercial-administrative	2.4	
3	industrial-manufactory	4.4	
4	urban services	1.8	30
5	Military	2.7	
6	no built	7.6	
7	transportation and warehousing	9.4	29
8	pass way and access network	6.18	
9	green space	4.11	6
10	Agriculture	7.5	
	Total	100	100

Table 2. The ratio of each sub basin, based on dominant urban land use type

Administrative land use	Green space land use	Residential land use	Case Study Sub basin
25%	0%	81%	Residential area\land use
8%	82%	16%	Green space area\land use
67%	18%	3%	Administrative area\land use
100%	**100%**	**100%**	**Sum**

Field survey, inspection, and sampling took place 10 minutes after the rainfall when the concentration time had passed (Regier et al., 2020; Martin, 1988) at the main collector of urban drainage system in each districts as sampling stations. The sampling stations were selected in sub-basin outlet, where the upper sub-basin flow enters the downstream one. Sampling points were on the main collector sub-basin's runoff and though samples could represent the runoff of sub-basin with studied urban land use.

Figures 3 to 5 illustrate both satellite and general outlooks. The administrative study district includes a university campus, some national offices, and commercial complexes (Fig. 3). Green space study district includes a big park and some public urban spaces and urban squares (Fig. 4). The residential land use includes some residential blocks and local apartments (Fig. 5). Some water quality variables were measured in-situ (Walsh & Wheeler, 1989) by means of portable spectrophotometry instruments (Combo Water Tester3551 AZ

Instrument Co.). These were dissolved oxygen (DO), total suspended solids (TSS), total dissolved solids (TDS), electrical conductivity (EC), Temperature (T), and pH. Samples for laboratory measurements were taken and stored in standard containers (USEPA, 2007) and kept in a cool box under standard conditions as they got transferred to the laboratory (USEPA, 2007). Samples were stored in cool boxes at 4 °C to avoid any ongoing chemical processes of organic compounds during transportation (Fisher et al., 2015).

The precipitation that made the run-off was investigated after the event by Tehran Meteorological Institute and was considered with a six-month return period. The event with same run-off and different precipitation duration was popular in both Spring and Autumn in Tehran (Razeghi Khamsei, 1999).

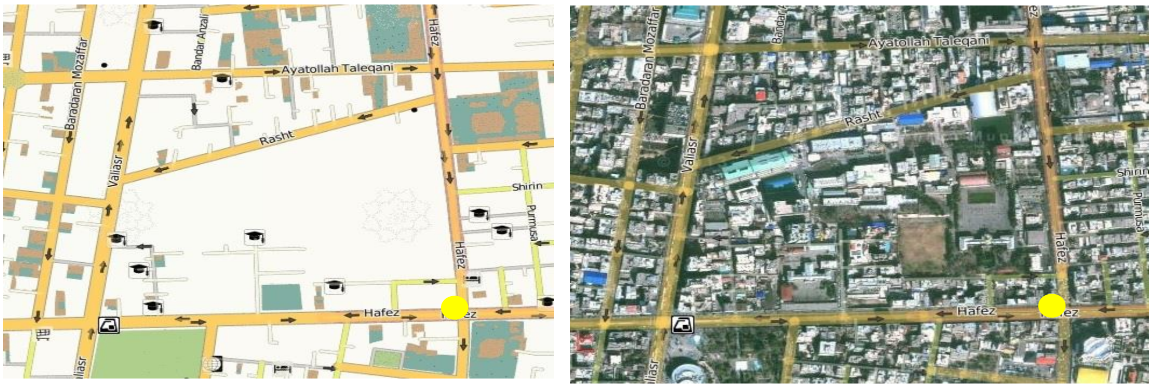

Fig. 3. Administrative and commercial urban land use district in general and satellite view and sampling stations

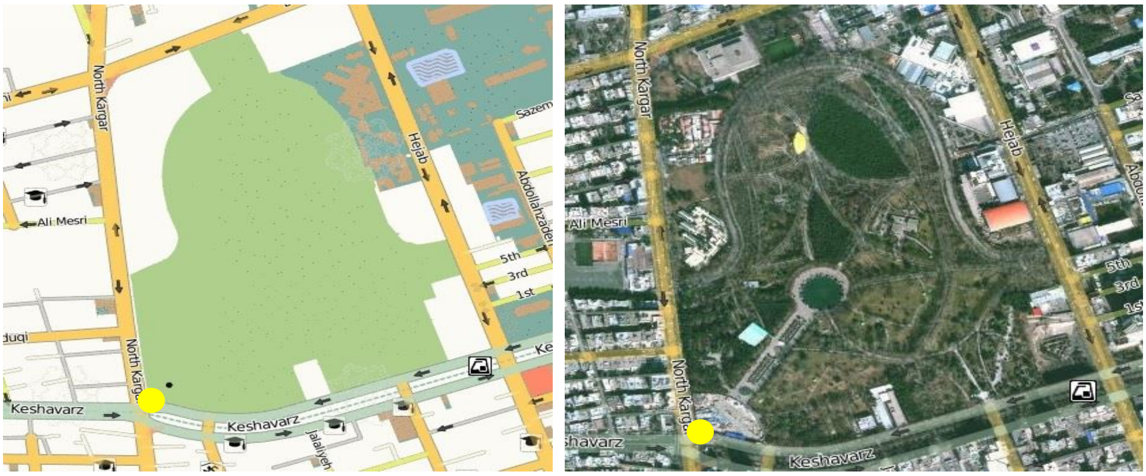

Fig. 4. Green space urban land use district in general and satellite view

Fig. 5. Residential urban land use district in general and satellite view

There were also some laboratory issues such as weekend availability, laboratory locations in relation with remote sites, sample's holding time, and lack of a specific time frame for laboratories to report the results. The chemical variables underwent direct testing under laboratory conditions. The samples got collected in 125ml bottles and were filtered through Whatman 0.45μm filter (Pall Corporation, Ann arbor, MI), thence to be collected in two 25 ml vials for analysis of NO_3, colour, BOD, and COD. The remaining unfiltered part of each sample was used to analyse Lead, Asbestos, coliform, etc. After filtering, all the filtered and unfiltered water samples were acidified to a pH of 2 with one drop of ultra-pure concentrated sulfuric acid (H_2SO_4) for every 20-25 ml of sample. The filtered and unfiltered portions of samples were stored in a cool box in 4^{o}C temperature until getting transferred to the laboratory for analysis. Samples were analysed for their respective nutrients within 28 days of sampling as recommended by the USEPA. All the analyses were performed according to Quality Assurance/Quality Control requirements (a spike, repeat, continuing calibration standard, blank, Practical Quantitation Limit (PQL).

Turbidity was measured in accordance with Standard Method 2130B (APHA et al., 1998) with a Hach Turbidimeter 2100N (Hach Company, Loveland, CO). The turbidity cell was placed in the turbidimeter, and an average reading was taken from the first 30 seconds after the sample cell was placed in the turbidimeter. The measurement was recorded in units of NTU. Fecal coliforms were enumerated using the membrane filtration technique, Standard Method 9222D (APHA et al., 1998).

Water quality variables, measured in this research, were selected based on the probable sources in the case study. They can be seen in Table 3.

Table 3. Water quality variables and possible resources in urban area

Water quality parameter	Units	Possible resources	Description
Suspended solids	ppm-mg/L	The urban wastewater containing suspended organic solids. Sometimes Industrial usage cause minerals enter water like immiscible liquid such as oils and greases	According to EPA, maximum is 30 mg for output stream of purified wastewater
Turbidity	NTU	Industrial and domestic wastewater like soups, detergents and emulsifier	According to standard of water affair of us , FTU=0.1 for drinking water
Color	TCU	In reaction with tiny organic components such as leaf and industrial sewage from textile industry, refineries, and slaughterhouse	
Taste and smell	TON	Organic materials like materials manufactured in oil industry Biological decomposition of organic material and creation of liquids and gases	According to health organization, TON=3 for drinking water
Total dissolved solids	ppm-mg/L	Minerals, metals, gases and organic materials of plants decomposition	Depending on the type of use for TDS component, various testing are carried out on TDS
Alkaline	mg/L caco3	Detergents in wastewater or chemical fertilizers	
Asbestos	mg/m3	Remains of brake pads and clutch plates that exist in waste water	Silica minerals like iron and manganese silica
Biochemical oxygen demand	mg/L		
Chemical oxygen demand	mg/L		
Coliform	Number of microorganism per 100 Ml	The feces of warm-blooded animals or organic materials in soil and remains of plants	
Nitrate	mg/L	Mainly founded from non-nitrogen sources in the atmosphere, such as fertilizer and animal droppings	
Lead	mg/L	Basically, lead enters the air via 2 ways: soot from heavy machinery and industrial coal burning	
Soot		incomplete combustion of heavy hydrocarbons	

Statistical approaches are usually proposed to predict water quality variables based on enormous recorded database in relation with distance and travel time, with the first predictive models being auto regressive, auto regressive moving average (ARMA), and auto regressive integrated (ARIMA) models (Ding et al., 2016). This paper employed a kind of matrix factorisation, called MF hereinafter (Yu et al., 2016), or matrix regressive model (MRM). This approach allows researchers to decompose a given matrix into two matrices (Kim & Giannakis, 2013), one of which is the prediction factors matrix.

RESULTS AND DISCUSSION

The statistical analysis found first the effective factors, then the effect coefficient. In matrix solution, the following equation has been solved through multi variable matrix regression approach.

$$\mathrm{L}_{ij\times}\phi_{jk} = \mathrm{C}_{ij} \rightarrow [L]\{\phi\} = \{C\} \overset{\textit{to calculate impact coeficient matrx}}{\Rightarrow} \{\phi\} = [L]^{-1}\{C\} \tag{1}$$

Where L is urban land use matrix including three urban districts, described before as study districts. Moreover, i stands for the counter of any district and j, the counter for the column on matrix L which includes urban effective factors such as general slope, percentage of the area of any urban land uses such as green space, roofs, commercial, residential, and administrative zones, and the ratio of the district's streets and passages against its entire area. Furthermore, ϕ is the impacts coefficient matrix with C being the concentration matrix, representative of water quality variables in drainage systems. Here, k is the counter of water quality variables including TDS, TSS, NO3, COD BOD_5, Pb, pH, temperature, DO (%), DO (ppm), EC, and salinity. Thus, the counters could be shown here as the following. Therefore any array in matrix C is the concentration of a water quality variable in each district with dominated individual land use type.

i=n ; n=1-3
j=m; m=1-6
K=p; p=1-12

By solving the above matrix equation through field study data, matrix ϕ could be generated to estimate matrix C. So it could be possible to estimate water quality variables in any study districts (i) through matrix C.

There are various ways to obtain solution. One convenient way, appropriate for a few land use types, is Cramer's rule which states each unknown variable in a system (here matrix ϕ) via linear algebraic analysis. In the matrix analysis, l, c, and ϕ are shorthand notation of the entire matrix L, C and ϕ. So l_{12} will be the percentage of administrative area in residential district according to Table 4. Then ϕ is the main object of this matrix analysis. Therefore multiplying inverse format of matrix L by the matrix C (which we have through field study), is the solution for unknown matrix ϕ.

The reliability of using physio-chemical variables as evaluation measure depends directly on the level of sampling and testing performed. Errors in monitoring and variability in the concentration can result in incorrect conclusions regarding concentration and dynamic situation of sampling time. Furthermore, concentration measurement based on laboratory tests is subject to error due to the variability between the experiments or laboratory test results, leading to inconsistent control management (Balch and Evans, 1999).

The quality was controlled consistently to reduce the possible errors during field study and analytical procedure and to increase results reliability, with quality assurance procedures being performed and necessary precautions being taken. Reagent free deionized water acted as blank samples (Gries, 2007 & USEPA, 1995) and both duplicates/replicates sampling and analysis of the standard reference were carried out. The duplicate sample analysis was done for 15% (USEPA, 1995) of the total samples. It provided a good measure for processing and analytical precision.

Field blank samples, collected during the sampling procedure, were processed in parallel two samples and followed the same analytical scheme. The present study witnessed five different concentrations of standard mixtures injected with every batch of samples.

Table 5 gives the results of laboratory measurements. Initially, it seemed that in green space zone organic maters and related pollutions were significantly higher than other areas in aggregation; however, in terms of individual water quality variables, there was some differences.

$$\begin{bmatrix} l_{ij} & \cdots & \\ \vdots & \ddots & \vdots \\ & \cdots & l_{3,6} \end{bmatrix} \times \begin{bmatrix} \phi_{jk} & \cdots & \\ \vdots & \ddots & \vdots \\ & \cdots & \phi_{6,12} \end{bmatrix} = \begin{bmatrix} c_{ik} & \cdots & \\ \vdots & \ddots & \vdots \\ & \cdots & c_{3,12} \end{bmatrix}$$

Table 4. Description of elements of matrices based on each counter index for each matrix

Counter index number (n,m,p)	i (urban study district)	J (areal percentage urban land use and effective parameters)	k(water quality variables)
1	Commercial and administrative districts	Residential land use	TDS (ppm)
2	Green space and urban spaces districts	Administrative land use	TSS(ppm)
3	Residential districts	Green space land use	NO_3(ppm)
4		Roof area	COD(ppm)
5		General slope	BOD_5(ppm)
6		ratio of streets and passages of district with entire area of district	Pb(ppm)
7			pH
8			Temperature (centigrade)
9			DO(%)
10			DO(ppm)
11			Salinity (ppm)

Table 5. Water quality variables of urban runoff in three studying districts

No.	Test	Test location	Method/ Device	administrative land use	green space land	residential land use	Measurement unit
1	TDS	in lab	Multimeter AZ2500	361	640	325	mg/I
2	TSS	in lab	Photometer	573	167	211	mg/I
3	NO_3	in lab	Photometer	141.7	124.1	101.9	mg/I
4	BOD_5	in lab	BOD meter	380	230	170	mg/Io2
5	COD	in lab	Photometer	568	498	243	mg/Io3
6	Pb	in lab	Atomic absorption	0.077	0.01	0.01	mg/I
7	PH	in situ	Combo Water Tester	8.96	8.43	9.45	
8	Temperature	in situ	Combo Water Tester	18.4	19.6	19.6	C
9	DO	in situ	Combo Water Tester	3.4	4.1	2.9	Ppm
10	EC	in situ	Combo Water Tester	475	889	735	Us
11	SALT	in situ	Combo Water Tester	0.26	0.51	0.42	Ppt

Statistical analysis of the data was performed, using SPSS 14. The dependent variables were subjected to analysis of variance (ANOVA), via the GLM procedure along with Schiffer for all pair-wise comparisons. This indicated whether there was any difference among the means and, om case there was, which one differed from the others. Test of statistical significance was done at α = 0.05. The physiochemical parameters of water temperature and dissolved oxygen were correlated with denitrification potential, using CORR procedure to determine Pearson's correlation coefficient. The concentration of NO_3-N was also correlated with denitrification potential via the same procedure. Figure 6 illustrates the comparative graphs for each water quality variation in each and every district of the specific urban land use.

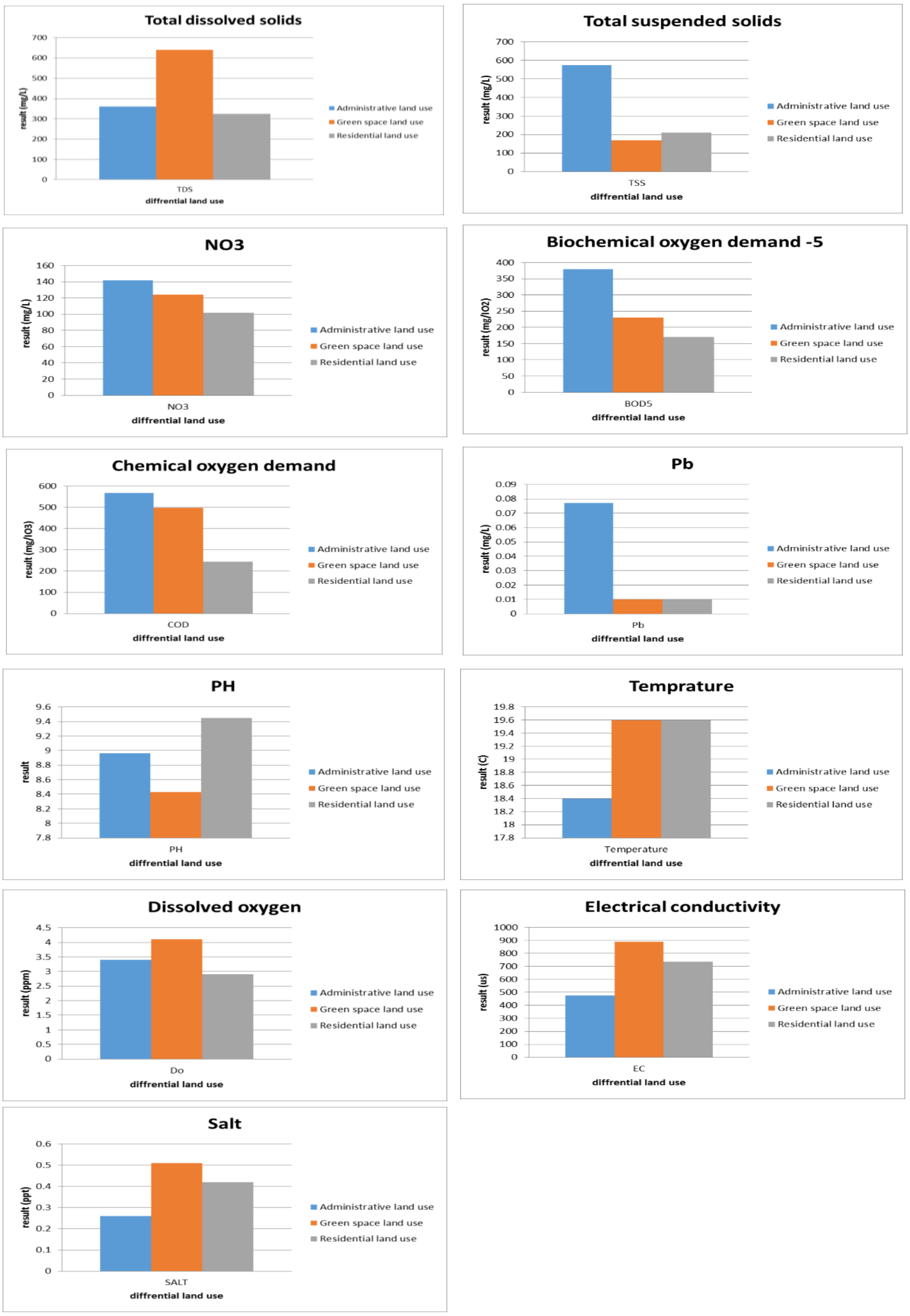

Fig. 6. Comparative graphs for each water quality variations according to urban land uses in different districts

TDS, DO, Salinity, and EC in green space land uses district were significantly higher than the rest. The possible reason might be soil wash phenomenon, which got discharged into the collectors via runoff. TSS, BOD_5, NO_3, COD, and Pb in administrative urban land use districts were detected to stand higher than other land uses. According to Figure 7, Region 6 includes the maximum administrative land use ratio in Tehran and based on the author's knowledge on study urban districts of Tehran, administrative urban land use districts feature more public transportation.

In residential districts, both pH and temperature rose compared to other land uses. It seems domestic activities such as home care, cooking, air condition discharge plum effluents, etc. may cause this difference with other districts as well as air temperature variations with other districts (Göbel et al., 2007). Urban infrastructures, streets' width, and population are the main factors to cause significant dissimilarities among different land uses. This difference is followed by water quality differences.

Based on the results, the researchers found a relation between air temperature and weather conditions, on the one hand, and urban runoff water quality, on the other. Population may be one of the main important effective factors for water quality. Investigating administrative districts showed that daily and temporary inter-city immigration would lead to day population, heavy traffic, and, consequently, particle materials emission. Then water quality might differ between nightly and daily precipitation runoff. Table 6 presents urban indices, investigated in this research. In comparison to urban indices and effective factors, green space ranked first rank among effective factors for salinity, TDS, and EC. Results showed that administrative urban land use districts, though in need of less public water demand, might be associated with more pollution. The majority of water consumption and public water demand in the research study area belonged to green space land uses, residential, and administrative districts from the highest to the lowest, respectively.

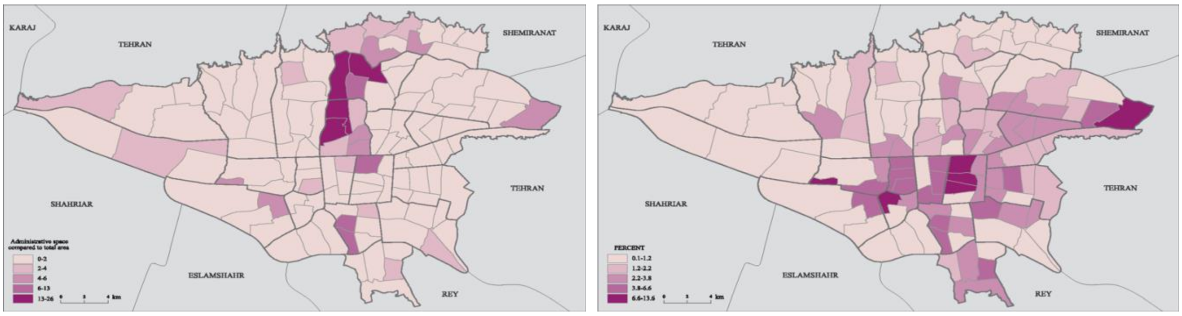

Fig. 7. Administrative and commercial urban land uses' ratio in all Tehran regions and districts

Table 6. Urban indices, investigated in this research

Urban texture	**Percentage of aligned street slope with basin dominant slope**	**Land use (residential, administrative, green space and)**	**Percentage of street gutter with vegetation**
Population	Green space per capita	Changes of level height	Ratio of covered canal
The average of Street width	Form of area	Traffic	Percentage of used space by roof
Daily fixed and immigrated population	Percentage of used space by yard		

During extraction of multiple matrices, the dynamic matrix of the impacts' coefficients during Cramer's rule could be calculated as the matrix below and Table 7:

$$\begin{bmatrix} \phi_{jk} & \cdots & \\ \vdots & \ddots & \vdots \\ & \cdots & \phi_{6,12} \end{bmatrix} = \begin{bmatrix} 302.1 & \ldots & 0.46 \\ \vdots & \ddots & \vdots \\ 2959.8 & \ldots & 5.6266 \end{bmatrix}$$

Table 7. Amounts of elements of matrix ϕ

Water Quality Varables / Effective factors	TDS	TSS	NO_3	BOD_5	COD	Pb	pH	T	DO (%)	DO(ppm)	EC	Salinity
Residential land use	302.1	28103	116.3	196.9	239.2	0.016	11.32	22.93	35.42	3.123	806.7	0.46
Administrative land use	447.7	752.2	176.2	496.7	754	0.106	10.31	21.24	45.66	4.158	503.2	0.272
Green space land use	1007	-109.1	133.6	171.4	586.3	-0.036	8.785	22.83	61.07	5.448	1333	0.774
Roof area	-1002	1624.1	57.082	645.27	483.64	0.2869	-2.936	-13.721	-35.792	-2.9609	-1946.5	-1.1684
General slope	17135	7150.7	2473.6	8356.8	20293	1.5359	-4.8401	83.406	886.89	82.612	5476.7	2.9693
Ratio of streets and passages of district with entire area of district	2959.8	-3554.6	284.28	-1426.7	-1825.6	-0.8476	73.801	162.54	222.35	18.663	9559.8	5.6266

Therefore, for a similar urban land use, ϕ_{jk}could be used to predict the water quality variables in urban run-off. This research's accuracy to predict the analysis of same water quality measurements in other regions of Tehran has been investigated for other rainfalls (two events in the same season) with the same return period but differing duration. It caused different run off volume and similar flow rate in drainage systems (±15% variation). Therefore the behaviour of the prediction through impacts coefficient matrix was evaluated, based on MRM regarding two criteria:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|r_t - r_r\right| \qquad (2)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left|r_t - r_r\right|^2} \qquad (3)$$

In both formulae, (1: Mean Absolute Error and 2: Root Mean Square Error), n is the number of data in the test set; $\hat{r}_t$, a predicted value; and r_r, the real value corresponding to $\hat{r}_t$. Two methods were applied to all data including the study area as well as other regions with same return period events, based on the recorded database to compare our approach. Table 8 shows that MRM model and impacts coefficient matrix (ϕ_{jk}) for the three study areas with more than 45 data could have good accuracy, with the exception of DO and Pb, neither for temperature which is affected by many other ambient parameters. Table 9 shows the evaluation of prediction, regardless of water quality variables in three urban regions, dominated by urban land use types.

Table 8. MAE and RMSE values for water quality variables

Water Quality Variable	TDS	TSS	NO_3	BOD_5	COD	Pb	pH	T	DO (%)	DO(ppm)	EC	Salinity
MAE	0.09812	1.0962	1.3593	1.4603	1.8452	2.8907	0. 256	3.8450	3.1374	2.9908	1.008	1.3207
RMSE	1.2115	0.9856	1.0114	1.2011	0.8196	2.4052	1.1518	2.8333	2.8988	2.0149	0.5407	1.2319

Table 9. MAE and RMSE values for urban regions with dominated urban land use type

Dominated urban land use in study area	Green space	Residential land use	Adminstrative land use
MAE	0.7908	1.2911	2.1432
RMSE	0.8475	1.09773	1.9833

In another point of view, investigation of MRM model and impacts coefficient matrix (ϕ_{jk}) for matrix L (n=i; i=1-3) through MAE and RMSE, revealed that MRM was more in line with green space urban land use than administrative urban land use area. Also MRM for residential urban land use area was more effective with fewer errors than green space area and administrative urban land use area.

CONCLUSION

The present approach is inspired by the literature, based on enormous recorded data with lots of expensive measurements. But here in this paper a good estimation has been released through an impact coefficient new matrix, employed in prediction MRM.

Regardless of the method used to determine the amount of water quality variables, the availability and mandatory impact of a chemical in the receiving water depends on its chemical form, individual sources and land uses, recycling, and toxicity. In addition, exposure to dangerous compounds such as Asbestos through sedimentation and biological uptake (Jackson and Davis, 1994) depends on the interactions of organisms at various levels of the food chain. Monitoring and testing toxicity generally tends to be chemical-specific, not accounting for the chemical form and the interaction among sediment which leads to inaccurate representation of toxicity conditions in the receiving waters.

The measurements also confirmed the findings by other authors (Dierkes and Geiger, 1999; Reinosdotter et al., 2005) that pollution decreases rapidly with distance from the main streets. High salinity and suspended solid concentrations were found at the urban traffic sites and even higher salinity concentrations at the highways. This corresponds with the findings that during the sampling period the concentrations of suspended solids are significantly higher than storm waters (Westerlund and Viklander, 2006; Westerlund et al., 2003). Concentrations of heavy metals (Pb), measured in the case study in Tehran, are similar to what has been found by other authors (Reinosdotter, 2003; Viklander, 1998); only Glenn and Sansalone (2002) reported significantly higher concentrations for highways.

Testing the matrix model with historical data of the same sub-basin allows analysing the system’s behaviour (Butler and Davies, 2004). Several models for urban drainage (Hosseiny et al., 2020) and rivers have been developed in simulation of urban drainage systems, starting from simple oxygen consumption (Harremoës, 1982) to complex models that can additionally represent such processes as nitrification or photosynthesis (Rauch and Harremoës, 1998) in relation with land use. These models represent important processes which convert pollutants, though not in different urban land uses. Previous studies modelled some individual new elements like sewers (Dittmer et al., 2020), hazard assessment (Gaafar et al., 2020), retrofitting (Saher et al., 2020) etc. The present one, however, facilitated water quality estimation through the new coefficients matrix.

In aggregation administrative areas and commercial districts are subject to more pollution potentiality, especially in terms of chemical and toxic (Liu et al., 2005) contamination. Current indices of urban runoff water quality could not satisfy the immediate in-district water reuse/recycle and all needs for any upgrade due to local condition, water demands, water quality, population, public transportation, traffic, and urban land uses. The nature of the runoff was not clearly linked to traffic with its related pollutants, even though higher concentrations of almost all tested variables displayed greater polluted water in drainages close to the highways.

In order to keep the correlation among air temperature, weather condition, water temperature, and water quality variations, one useful recommendation of this research is to consider urban heat islands in urban runoff water quality simultaneously. The temperature may also evaporate and reduce the runoff water flow discharge (Rice, 1971), which will in turn increases water pollution, definitely.

Impacts coefficient matrix, extracted from this study, is one of the novel application of matrix algebra together with regressive analysis for water quality prediction in urban land use, since urban land use types are specified all over the world in every city and rainfall is regarded a main source of urban runoff as semi distilled water. Afterwards, the most important effective impact on water quality is urban land use, itself, which could be considered a fixed factor at least in every five years according to urban planning system in metropolitans. As a result, the research proposed this matrix algorithm for urban areas to be used with new elements of differing impact coefficient matrix for each city. The proposed MRM is a dynamic one, i.e., the rates of n, m, and p could alter in accordance of any urban management and water quality monitoring infrastructures.

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CONFLICT OF INTEREST
The authors declare that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

LIFE SCIENCE REPORTING
No life science threat was practiced in this research.

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