Spatial Vulnerability Assessment of Groundwater Contamination in the Swan Coastal Plain, Perth, Western Australia (6479 words)

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Abstract

Groundwater is an important source of freshwater worldwide. However, industrial activities and agricultural practices have led to groundwater contamination. Nitrate and arsenic have emerged as significant pollutants with negative effects on the human body and ecological impacts. This study focuses on assessing the spatial vulnerability to nitrate and arsenic contamination in the Swan Coastal Plain, Western Australia, by utilizing the DRASTIC and DRASTICL models under three seasonal scenarios. The models were created by assigning rating and weight values to environmental parameters in ArcGIS, and the robustness of the model to each parameter were evaluated by map removal sensitivity analysis. Following the process, we validated the accuracy of the models to each contaminant by Kendall rank coefficient test. Reflecting the results of correlation test, we considered the practical application of the DRASTIC and DRASTICL models using the Cochran-Armitage test and Fisher's exact test with the risk classification and concentration threshold levels. The DRASTIC model was consistent with the vulnerability map by Gozzard (2010). The Kendall correlation test proved statistically significant in the correlation between the models and nitrate concentration. Four risk classification maps showed a linear trend between higher risk levels and the ratio of samples exceeding the threshold of nitrate concentration of 5mg/L. Our findings offer the potential application of DRASTIC to address the area with a nitrate concentration level exceeding 5mg/l. The DRASTIC model could also predict the area vulnerable to the nitrate concentration above 25mg/l or 50mg/l.

Keyword

Groundwater contamination, Nitrate, Arsenic, DRASTIC, DRASTICL

1. Introduction

Groundwater is one of the important sources of freshwater worldwide. Groundwater plays a pivotal role in irrigated agriculture and influences the health of many ecosystems (Gleeson et al., 2012). Recently, industrial activities and modern agriculture practices have been associated with contamination of groundwater quality.

Particularly, nitrates have emerged as significant pollutants, as they have detrimental effects on the human body, especially in infants. For example, infants fed with contaminated water at the nitrate concentration level of 22.9 and 27.4 mg/L developed blue baby syndrome (Knobeloch et al., 2000). Some epidemiological studies indicated the potential effect of nitrate on the human body at 5mg/L (Brender et al., 2013; Jensen et al., 2023). Nitrate contamination can also negatively affect the ecosystem. For example, high concentrations of inorganic nitrate can lead to acidification and eutrophication of aquatic ecosystems, adversely affecting aquatic animals' ability to survive and reproduce (Camargo & Alonso, 2006).

High concentrations of nitrate nitrogen groundwater are strongly associated with well-drained soils dominated by irrigated cropland (Spalding & Exner, 1993). The substance is also reported from non-agricultural sources, such as wastewater and solid waste disposal (Wakida & Lerner, 2005). Naturally, most nitrogen exists as organic nitrogen in the soil since microorganisms fix nitrogen gas and amass it as body tissues. After the microorganisms die, organic nitrogen decomposes into ammonia nitrogen. The ammonia nitrogen is nitrified by soil microorganisms under aerobic conditions and changes to nitrate nitrogen via nitrite nitrogen. However, if plants did not absorb nitrate nitrogen, the chemical leaches into groundwater due to its low adsorption on soil solid phases (Di & Cameron, 2002). Furthermore, nitrate nitrogen undergoes denitrification by microorganisms under anaerobic conditions, and it converts to nitrous oxide or nitrogen, which is released into the atmosphere.

Arsenic also has gained attention as a potential carcinogen, and drinking water contaminated by the element leads to serious sanitation (Smith et al., 2000). The high amount of arsenic is often observed in endorheic basins in a semi-arid environment or aquifers derived from alluvium (Smedley & Kinniburgh, 2002). Also, gold mining can pollute groundwater, as arsenic is also found in gold-containing ores (Muibat et al., 2016).

Geology in Perth is characterized by its sandy soils and shallow aquifers. These conditions make nitrate and arsenic prone to leaching into groundwater systems. Nitrate contamination was observed in Perth's groundwater due to excessive fertilizer use (Appleyard, 2004). High amounts of arsenic were also detected in Perth's groundwater. For example, 7 mg/L of arsenic was measured in the Gwelup groundwater area as the presence of pyrite oxidation products and falling Eh values triggered the release of arsenic (Appleyard et al., 2006). This concentration level is the same as the maximal limit of arsenic for drinking water according to the Australian Drinking water guideline (NHMRC, 2011). Considering that water resources are limited in semi-arid regions like Perth, and 40% of the groundwater is used for drinking water, the protection and conservation of groundwater are essential in the region.

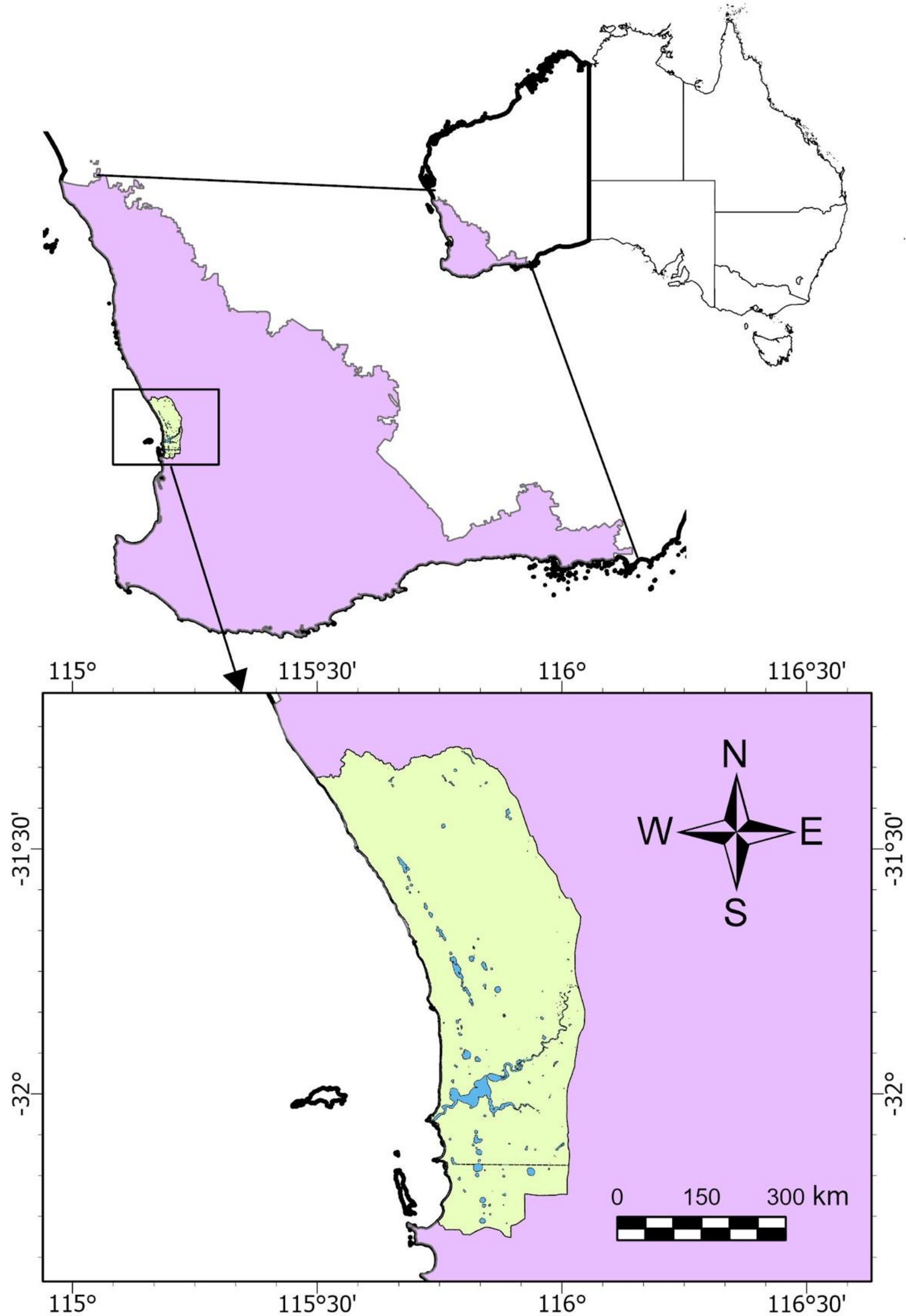
To identify areas with high concentrations of contaminants, it is essential to consider a range of environmental factors that influence the concentration in the groundwater. The DRASTIC model was devised for this purpose by the U.S. Environmental Protection Agency (Aller et al., 1985). Also, some research combines the land use model with the DRASTIC model to consider the source of contamination. For example, Kumar et al. (2020) demonstrated that the vulnerability index had a higher correlation coefficient with the nitrate concentration for the DRASTIC model, including the land-use parameter than for the conventional DRASTIC model. Gozzard (2010) has measured the vulnerability of groundwater contamination in the Swang Coastal Plain by considering the depth of the groundwater table, the nature and characteristics of the materials above and below the groundwater table, climatic factors, and the nature of the contaminants. However, there is no research evaluating the vulnerability of groundwater contamination with standardized models, such as the DRASTIC model. Given the limited research on measuring the vulnerability of groundwater contamination in the region, this research aims to identify areas vulnerable to groundwater pollution through the DRASTIC and DRASTICL models with different scenarios. Then, we conduct sensitivity analysis to estimate the robustness of the model outputs to each environmental factor. Subsequently, we compare the obtained output with the concentration of nitrate and arsenic for its validation. Based on the validation, we finally evaluated how the DRASTIC or DRASTICL model can be used to assist groundwater management for the high concentration of contaminants. In this thesis, the term DRASTIC(L) will be used to refer to both the conventional DRASTIC model and the DRASTICL model, which considers the land-use parameter.

2. Method

As displayed in Figure 1, Swan Coastal Plain is located along the southwestern coast of Australia, with its geographic coordinates ranging from 115°25’-116°05’ E longitude and from31°15' to 32°20' S latitude. The total study area is 28.3 ha, and the majority of the population is concentrated in the region of Western Australia. The Swan River crosses this area, dividing it into two parts, which lie on different superficial aquifers. Gnangara aquifer is placed in the northern part, while the Jandakot aquifer spreads in the southern part.

Figure 1

The Location of the Study Area



2.1 DRASTIC and DRASTICL model

The DRASTIC model is one of the most commonly used methods for analyzing spatial groundwater vulnerability (Machiwal et al., 2018). The model was developed by the U.S. Environmental Protection Agency (Aller et al., 1985), and this method combines expert judgement with a quantitative approach using seven environmental parameters: depth to water (D), net recharge (R), aquifer media (A), soil media (S), topography (T), the impact of vadose zone (I), and hydraulic conductivity (C). In this model, each parameter is assigned weight values according to their relative significance to groundwater vulnerability. Subsequently, Each parameter is assigned a rating score reflecting the relative impact of each parameter, eq. (1).

$$V = DrDw + RrRw + ArAw + SrSw + TrTw + IrIw + CrCw \tag{1}$$

D, R, A, S, T, I and C represent each parameter of the DRASTIC mode. r and w indicate the rating and weight scores of each parameter, respectively. For this study, the weights of each parameter were set as $Dw = 5, Rw = 4, Aw = 3, Sw = 2, Tw = 1, Iw = 5, Cw = 3,$ *and* $Lw = 5$ (Aller et al., 1985).

Additionally, it is essential to consider the potential effect of land use. Kumar et al. (2020) improved the accuracy of the vulnerability index for nitrate by integrating land-use factor. In the Swan coastal plain, groundwater beneath agricultural land was found to be vulnerable to nitrogen loading due to the application of fertilizers. Also, industrial areas were found to have contamination plumes continuing to migrate with the groundwater flow. Thus, integrating land use into the DRASTIC model considers the specific sources of contamination related to land use and shows a detailed pattern of groundwater vulnerability. The DRASTIC model with land-use parameter, DRASTICL model, was calculated as shown in eq. (2)

$$V = DrDw + RrRw + ArAw + SrSw + TrTw + IrIw + CrCw + LrLw \tag{2}$$

The scores for rating and weight values are the same as those in the DRASTIC model. The weight value for land use was set as $Lw = 5$.

In this research, we used ArcGIS to manipulate spatial data related to the environmental parameters (Table 1) and implemented the DRASTIC(L) model by combining the spatial data.

Table 1

The Data of Parameters Used for DRASTIC and the DRASTICL Model

Parameter	Data Name	Data Source	Data Type
Depth to water	Gnangara Jandakot Depth to Groundwater (Contours) 2019 Min (DWER-095), Gnangara Jandakot Depth to Groundwater (Contours) 2019 Max (DWER-096)	*	Raster (10m×10m)
Net Recharge	Deep drainage from 2014 to 2023	The Bureau of Meteorology	Raster (5km×5km)
Aquifer media	Soil Landscape Mapping - Systems (DPIRD-064)	Data WA	Vector
Soil media	Soil-landscape mapping Western Australia – WA Soil Group proportions	Data WA	Vector
Topography	SRTM-derived 1 Second Digital Elevation Models Version 1.0	Geoscience Australia	Raster (30m×30m)
Impact of vadose zone	Soil-landscape mapping Western Australia – WA Soil Group proportions	Data WA	Vector
Hydraulic conductivity	Soil Landscape Mapping - Systems (DPIRD-064)	Data WA	Vector
Land use	WA CLUM August2018 Swan.zip(SHP), WA CLUM August2018 PeelHarvey.zip(SHP), WA CLUM August2018 NorthernAgriculture.zip(SHP)	Data.gov.au	Vector

*Spatial data for "Depth to water" was requested from the Department of Water and Environmental Regulation

Depth to water was directly converted to rating scores without additional manipulation (Appendix A). As for the parameter of net recharge, the monthly amount of net recharge into groundwater from 2013 to 2023 was obtained as NetCDF from the Bureau of Meteorology (Table 1). Then, the amount of net recharge was read as a raster layer in ArcGIS and calculated through the process described in the 3.1.1 Scenario section. The rating process for aquifer media and hydraulic conductivity used the same original vector layer gained from Data WA (Table 1). The vector data included a summary description of each polygon feature, explaining the soil texture, which was based on the rating system for aquifer media in Table 2. In contrast, Figures 6 and 12 from DWGWA (2008, pp. 78, 85) were consulted for information on secondary aquifer media to estimate hydraulic conductivity in Table 3.

Table 2

Rating for Aquifer Media

Feature name	Primary Aquifer Media	Rating Score (Appendix A)
Bassendean System	Sand and Gravel	8
Coonambidgee System	Sand and Gravel	8
Dandaragan System	Sand and Gravel	8
Forrestfield System	Sand and Gravel & Massive shale	5
Moore River System	Sand and Gravel	8
Pinjarra System	Massive shale	2
Quindalup South System	Sand and Gravel	8
Reagan System	Sand and Gravel	8
Spearwood System	Massive limestone	6
Vasse System	Sand and Gravel	8
Yanga System	Massive shale	2

Table 3

Rating for Hydraulic Conductivity

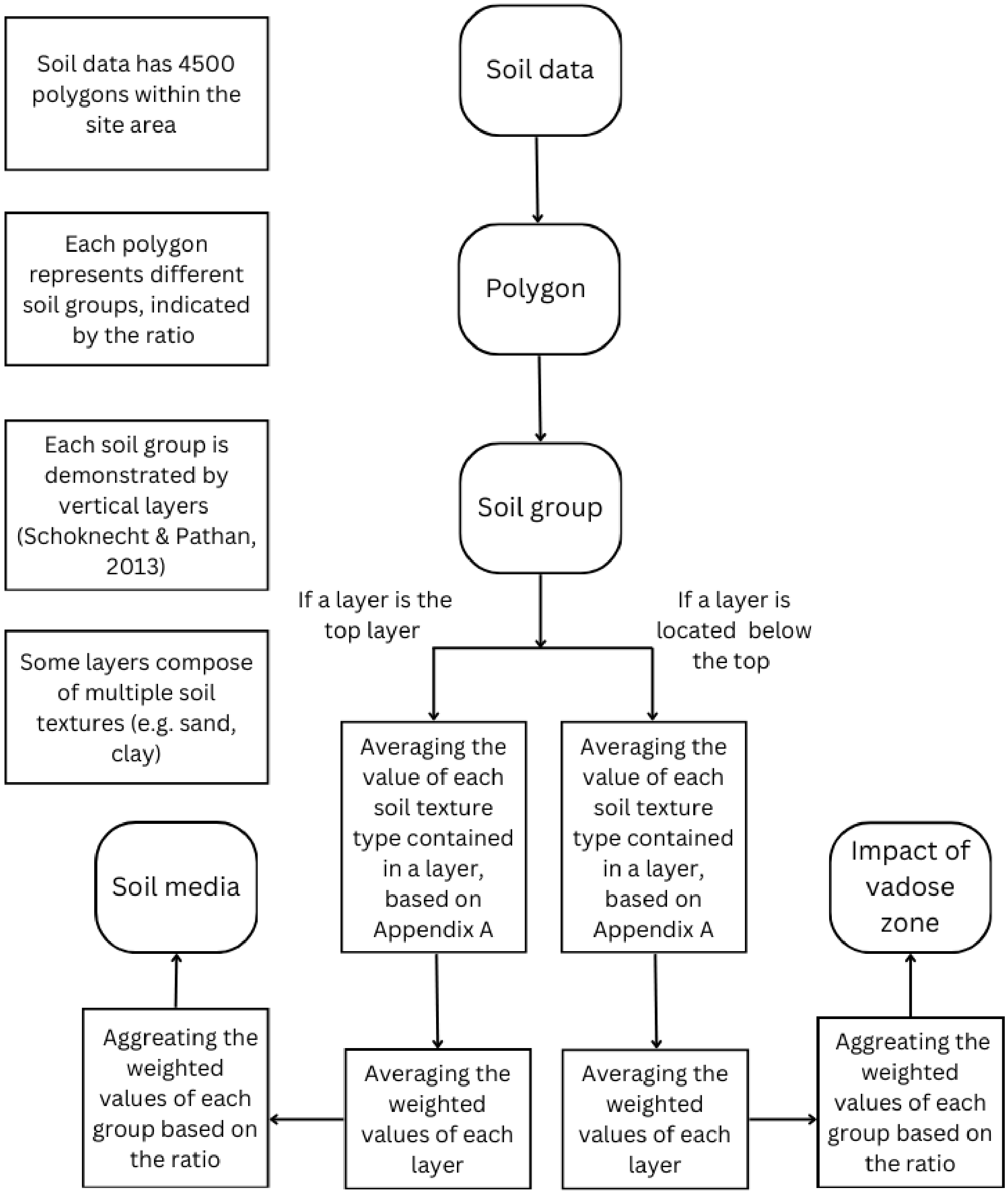
Feature name	Secondary Aquifer Media	Hydraulic Conductivity (m/day)	Rating Score (Appendix A)
Bassendean System	Bassendean	9.2*	2
Coonambidgee System	Colluvium	2*	1
Dandaragan System	Colluvium	2*	1
Forrestfield System	Yognup	6.5*	2
Moore River System	Alluvium	20-300**	10
Pinjarra System	Guildford Clay	1*	1
Quindalup South System	Safety bay sand	15*	4
Reagan System	Colluvium	2*	1
Spearwood System	Tamala limestone	120*	10
Vasse System	Alluvium	20-300**	10
Yanga System	Guildford Clay	1*	1

*Values were taken from Table 7-1 (Section 7.2, p51) DWGWA, (2010)
** Values were taken from (Walker et al., 2018)

The parameters of soil media and impact of vadose zone also used the same original data. The rating process for the parameters was made by classifying the soil types and their respective rating scores based on permeability in Figure 2

Figure 2

The Rating Process for Soil Media and Impact of Vadose Zone



Topography in Table 1 indicates the slope, as the degree of slope affects the infiltration rate. Steep slopes tend to increase runoff speed, and it reduces the amount of water seeping into the soil. The geoprocessing tool of slope function was used to calculate the degree of slope from

DEM data in ArcGIS. The difference in altitude between adjacent cells of the raster is detected as the slope gradient and assigned rating scores based on Appendix A.

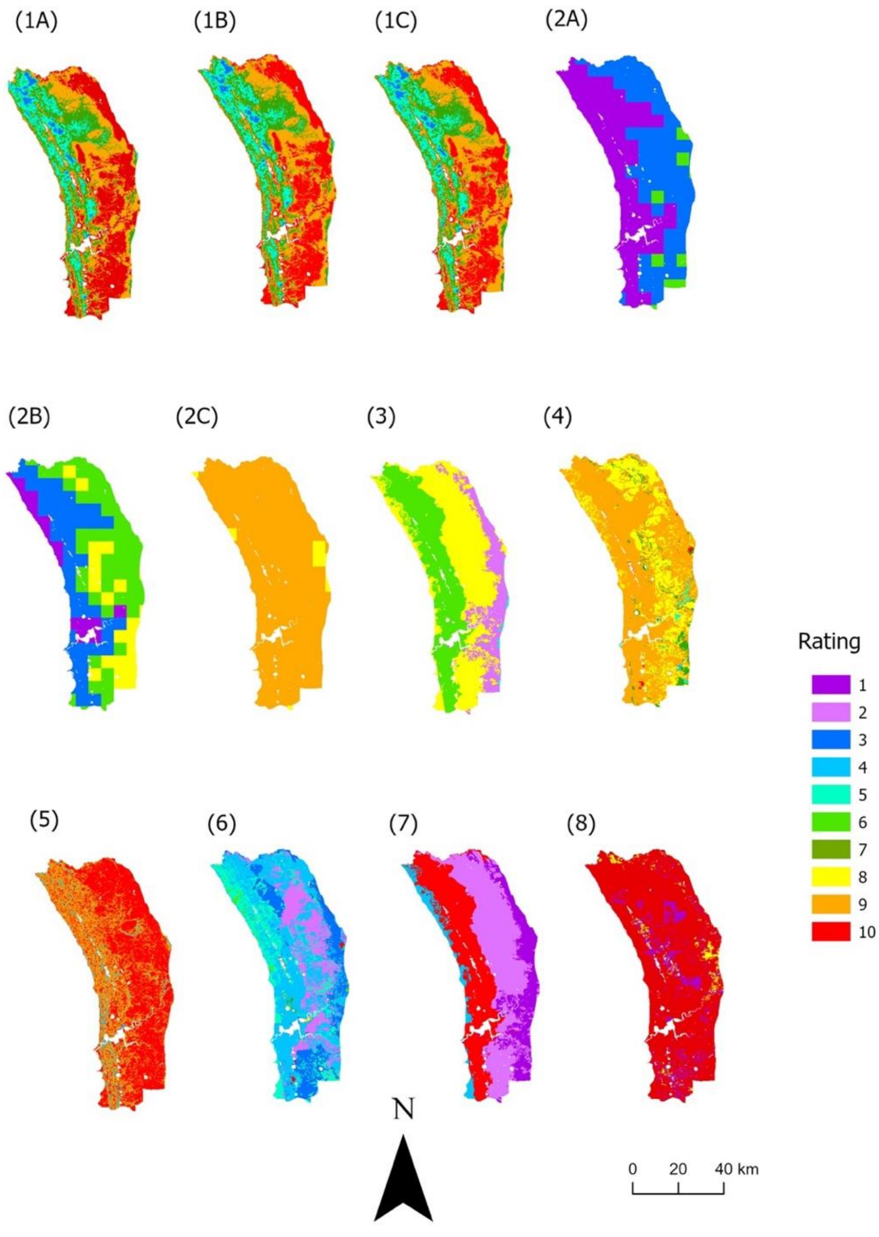
2. 1.1 Scenario

In arid regions, the concentration of nitrate in groundwater tends to be higher in wet seasons than in dry ones (Aghapour et al., 2021). The seasonal variation in the nitrate concentration can be attributed to several factors. During wet seasons, the higher amount of precipitation increases the loading of contaminants into groundwater. Additionally, the shorter depth to groundwater from the surface also facilitates their transport. Thus, this study reflects the seasonality by considering three scenarios based on the seasonal variability in the depth to groundwater and net recharge: (1) minimal scenario, (2) mean scenario and (3) maximal scenario. The depth to groundwater from the surface reaches the shortest from March to May and the longest from August to November. The depth to groundwater for (2) mean scenario was calculated by averaging the value of depth to groundwater of (1) minimal and (3) maximal scenarios.

The monthly mean amount of net recharge into groundwater was then matched to each of the periods set for (1) minimal scenario and (3) maximal scenario. The net recharge for (2) mean scenario was calculated by averaging the recharge amount of every month from 2013 to 2023. The maps in Figure 3 represent the output of each DRASTIC(L) parameter in the study area.

Figure 3

Rating Scores of DRASTIC(L) Parameters - (1A-C) Depth to Groundwater (Minimal, Mean, Maximal Scenario), (2A-C) Net Recharge (Minimal, Mean, Maximal Scenario), (3) Aquifer Media, (4) Soil Media, (5) Topography, (6) Vadose Zone Impact, (7) Hydraulic Conductivity, (8) Land Use



2.2 Sensitivity analysis

Sensitivity analysis evaluates how changes in each of the parameters affect the overall vulnerability index of the DRASTIC(L) models. This analysis is useful in understanding which parameters have the most or least impact on the output of the models. Map removal sensitivity analysis (Lodwick al et al., 1990) was conducted for this study. Compared with single-sensitivity analysis (Napolitano et al., 1996), the Map removal sensitivity analysis considers both the number of parameters used and the parameters themselves. Thus, it helps to compare the sensitivity of each parameter to each model between the DRASTIC model and the DRASTICL model. The map removal sensitivity analysis was carried out by removing the effect of one parameter from the overall vulnerability index using the following Eq. (3).

$$S = (|V/N - V'/n|/V) \times 100 \tag{3}$$

In Eq. (2), V represent unperturbed vulnerability index, while V' indicates the vulnerability index with a targeted parameter removed. N and n are the number of parameters, corresponding to V and V'. Finally, S was calculated to express sensitivity measures.

2.3 Model validation

We analysed the statistical relationship between the DRASTIC(L) model and the concentration of nitrate and arnice in order to evaluate the accuracy of the DRASTIC(L) model. Datsbase for samples measuring the concentration of the contaminant is available in Australian Groundwater Exploer (Bureau of Meteorology http://www.bom.gov.au/water/groundwater/explorer/map.shtml). Samples of arsenic, nitrate within the study area were processed through two steps. First, samples with negative values were converted to zero values. The negative values likely indicate that the concentration of a contaminant is below the minimal concentration level detected by the device.

Second, we averaged the values of the samples located at the same geographic coordinates. Although these samples were presumably taken in different periods, we generalized the concentration of the contaminants due to the lack of temporal information.

2. 3.1 Kendall rank correlation coefficient

The concentration of each contaminant did not follow a normal distribution and contained samples with zero values (see the Result section). The unique data distribution poses a challenge to correlation analysis for Pearson correlation analysis, which assumes that variables follow a normal distribution. Spearman and Kendall rank correlation coefficients do not consider the normality of data and are common methods to test correlation for non-parametric data. Given that the Kendall rank test is more resilient to tied values, including many zero value, this study applied Kendall rank correlation coefficient between the vulnerability index of the DRASTIC(L) models and the actual concentration of contaminants.

2.3.2 Fisher exact test and Cochran-Armitage test

We further reviewed the applicability of the models in a more practical context by risk categorization and setting environmental threadholds. Cochran-armitates and Fisher's exact test were applied to nitrate concentraions since arsenic did not show statistical significance in the Kendall ran correlation test.

Table 3

Categorization of Risk Levels for DRASTIC Index and DRASTICL Index

Risk Level	Criteria	DRASTIC index	DRASTICL index
Very low	$x_1 \leq \mu - \sigma$	$x_1 \leq 124.9$	$x_1 \leq 165.7$
Low	$\mu - \sigma < x_2 \leq \mu$	$124.9 < x_2 \leq 138.6$	$165.7 < x_2 \leq 184.1$
High	$\mu < x_3 \leq \mu + \sigma$	$138.6 < x_3 \leq 152.2$	$184.1 < x_3 \leq 202.4$
Very high	$\sigma < x_4$	$152.2 < x_4$	$202.4 < x_4$

We divided the total study area into risk zones based on the mean and standard deviation of the DRASTIC(L) model in the mean scenario(Table 3). Using risk categories is useful in makeing straightforward decisions compared with continuous index, and helps to effectively communicate groundwater vulnerability with the stakeholders involved.

Subsequently, we set three levels of thresholds for the concentration data. The first threshold is 50 mg/L, the maximal limit of nitrate for drinking water, as described in the

Australian Drinking Water guideline (NHMRC, 2011). Some epidemiological studies indicated the potential effect of nitrate on the human body at 5mg/L (Brender et al., 2013; Jensen et al., 2023), so 5 mg/L was also selected as the lower limit. Additionally, we set 25mg as a threshold, half of the maximal limit, to comprehensively understand how different levels of nitrate affect the result. Then, we transformed the concentration data into binary values based on whether each exceeds the given threshold.

Given the non-normal distribution of the contaminant's data and a large number of zero values, parametric tests and log-transformation are not suitable. Instead, Johnson et al. (2015) demonstrated that it is more informative to compare groups with zero-inflated distributions by chi-square test at different ranges than a median test.

Cochran-Armitage test was conducted to analyze whether a higher risk level corresponds to the higher concentration. The Cochran-Armitage test is extended from the chi-squared test by considering the ordinality of the categorical data, and the statistical test detects a linear trend in proportions across the ordinal data. In this study, risk level zones are ordinal data, while the concentration data Risk zones in this study are ordinal data as they are derived from the DRASTIC index, while the concentration data categorized by thresholds were treated as binary data for this test.

Additionally, Fisher's exact test was conducted to complement the result of the Cochran-Armitage test, violating Cochran's rule that 20% of the expected counts should be less than 5. Violating the rule can lead to Type I or II errors and can produce incorrect p-values (Kroonenberg & Verbeek, 2018). Kroonenberg & Verbeek (2018) also mention that the 2×4 contingency table behaves according to Cochran's rule better than the 2×3 contingency and recommend the exact tests in that case. Although Fisher's exact test does not detect the linear trend like the Cochran-Armitage test, it still helps to analyze the association between two categories.

3. Result

Figure 3

Outputs of The DRASTIC Model within the Swan Coastal Plain under (a) Minimal, (b) Mean (c), Maximal Scenario

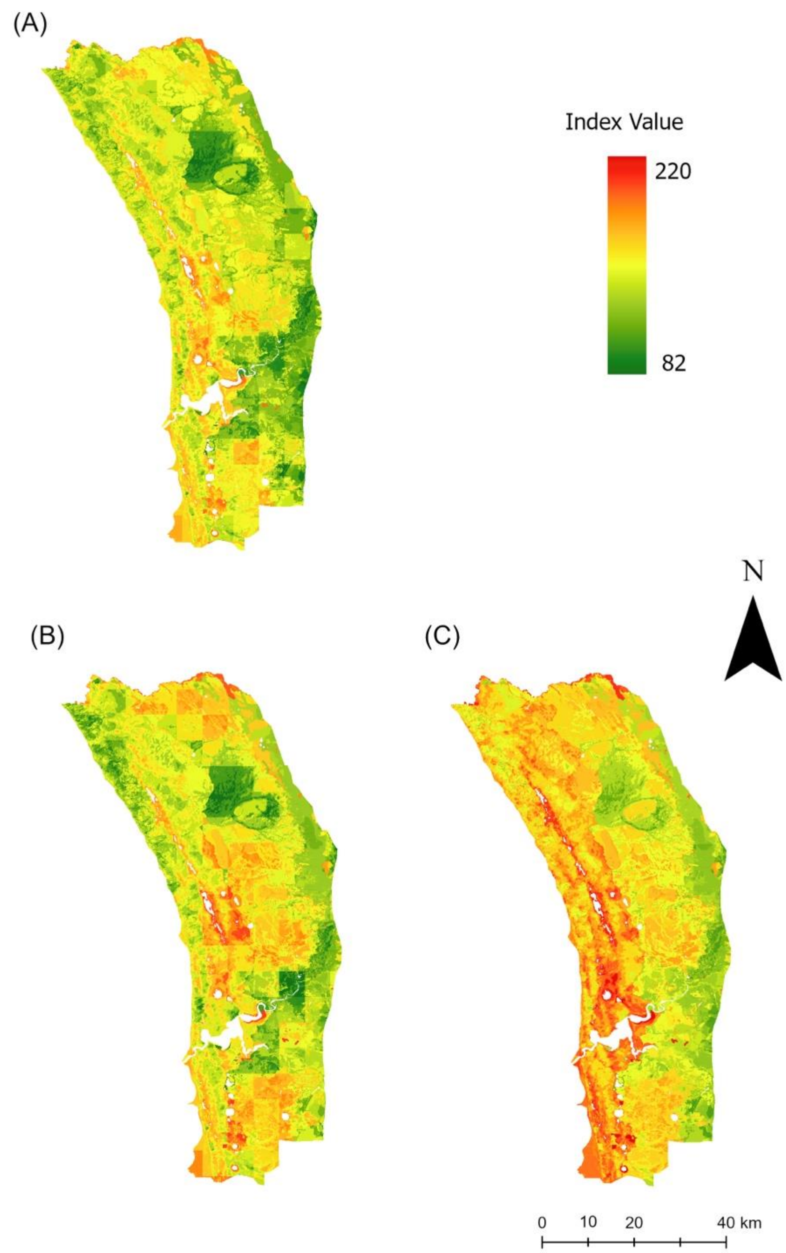


Figure 4

Outputs of the DRASTICL Model within the Swan Coastal Plain under (a) Minimal, (b) Mean, (c) Maximal Scenario

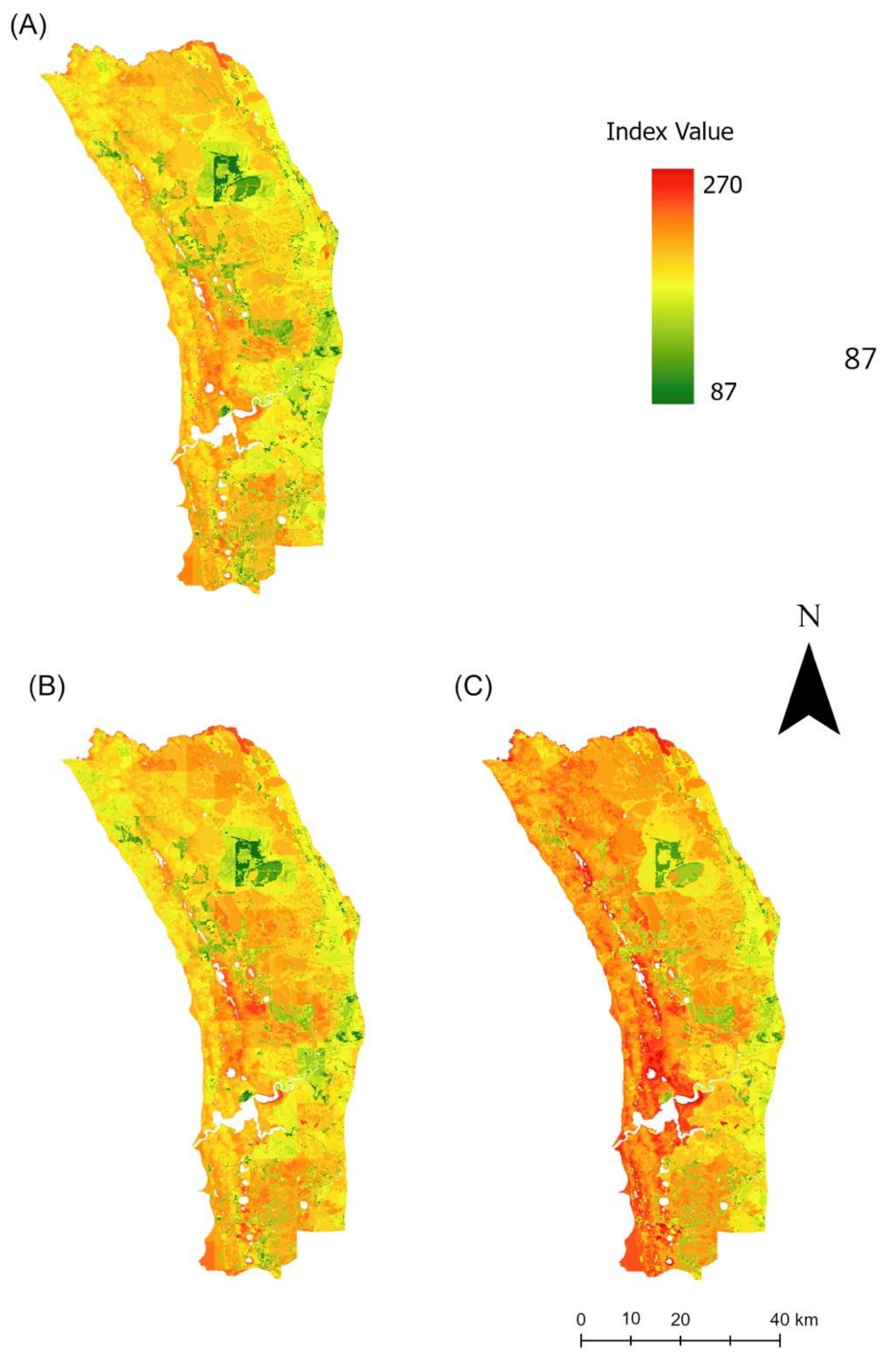


Table 4

Summary of the DRASTIC and DRASTICL Model under Three Scenarios

Model	Scenario	Description			
		Minimal	Maximal	Mean	SD
DRASTIC	Minimal	82	190	128.3	12.6
	Mean	85	202	138.6	13.7
	Maximal	106	220	155.0	13.4
DRASTICL	Minimal	87	240	173.8	17.8
	Mean	90	252	184.1	18.4
	Maximal	112	270	200.5	18.6

Table 4 shows the statistical sumary of the DRASTIC and DRASTICL models under three scenarios. The minimal value of the DRASTICL model was higher than those of the DRASTIC model by the percentage increase, ranging from 5.4% for the Maximal scenario to 5.7% for the Minimal. In contrast, The maximal value of the DRASTICL model weas higher than those of DRASTIC model by the percentage increase, ranging from 18.5% for the Maximal scenario to 20.8 % for the Minimal. Indeed, Figure 3 illustrates that the vulnerability index of the DRASTIC model in the minimal and mean scenarios are relatively low, while the index of the DRASTICL model in all models showed relatively high values in Figure 4.

3.1 Sensitivity Analysis

Table 5

Statistics of map removal sensitivity analysis for DRASTIC index with three scenarios

Parameter Removed	Minimal Scenario		Mean Scenario		Maximal Scenario	
	Mean	SD	Mean	SD	Mean	SD
Depth to goundwater (%)	2.99	1.23	2.57	1.07	2.07	1.03
Net recharge (%)	1.28	0.55	0.89	0.46	1.51	0.34
Aquifer media (%)	0.68	0.51	0.61	0.51	0.59	0.52
Soil media (%)	0.23	0.19	0.32	0.22	0.51	0.20
Topography (%)	1.14	0.18	1.24	0.17	1.36	0.15
Impact of vadose zone (%)	0.53	0.42	0.52	0.43	0.54	0.42
Hydraulic conductivity (%)	1.52	0.33	1.49	0.40	1.36	0.57

Depth to groundwater showed the highest mean and Standard Deviation (SD) for the sensitivity rate, and the mean value was approximately closed to 3% in the minimal scenario

(Table 5). It indicates that this parameter has the strongest impact on the overall the vulnerability indes of theDRASTIC model and its variation compared with other parameters. While hydraulic conductivity was the second biggest sensitive factor to the DRASTIC index in the minimal and mean scenarios, net recharge was more sensitive to the index for maximal scenario than the hydraulic conductivity. Conversely, Soil media showed the lowest mean sensitivity rate.

Table 6

Statistics of Map Removal Sensitivity Analysis for DRASTICL Index with Three Scenarios

Parameter Removed	Minimal Scenario		Mean Scenario		Maximal Scenario	
	Mean	SD	Mean	SD	Mean	SD
Depth to groundwater (%)	1.65	0.82	1.44	0.73	1.20	0.68
Net recharge (%)	1.06	0.40	0.59	0.44	0.80	0.27
Aquifer media (%)	0.45	0.41	0.44	0.43	0.49	0.43
Soil media (%)	0.37	0.15	0.44	0.16	0.55	0.15
Topography (%)	1.00	0.13	1.05	0.12	1.11	0.11
Impact of vadose zone (%)	0.42	0.32	0.45	0.33	0.51	0.33
Hydraulic conductivity (%)	1.06	0.40	1.04	0.45	0.97	0.56
Land use (%)	2.13	0.40	1.94	0.35	1.66	0.25

Land use showed the highest mean sensitive rate in all the scenarios, especially its sensitivity rate exceeding 2% in the minimal scenario. Depth to groundwater was the second most sensitive to the Index in all the scenarios. However, compared with the mean sensitive rate of the parameter in Table 6, the rate was smaller due to the number of parameters of the DRASTICL index.

Aquifer media, soil media and impact of vadose zone showed low sensitivity rates as their mean rates were less than 1% in all scenarios.

Table 7

The Number of Nitrate Samples at Ranges of Concentration Levels

Concentration (mg/L)	The Number of Samples	Proportion (%)
0	814	46%
0.001 - 0.01	11	1%
0.01 - 0.1	162	9%
0.1 - 1	321	18%
1- 10	353	20%
10 - 100	94	5%
Total	1755	100%

Figure 5

Spatial Distribution of Nitrate Samples in the Northern Part of the Swan Coastal Plain

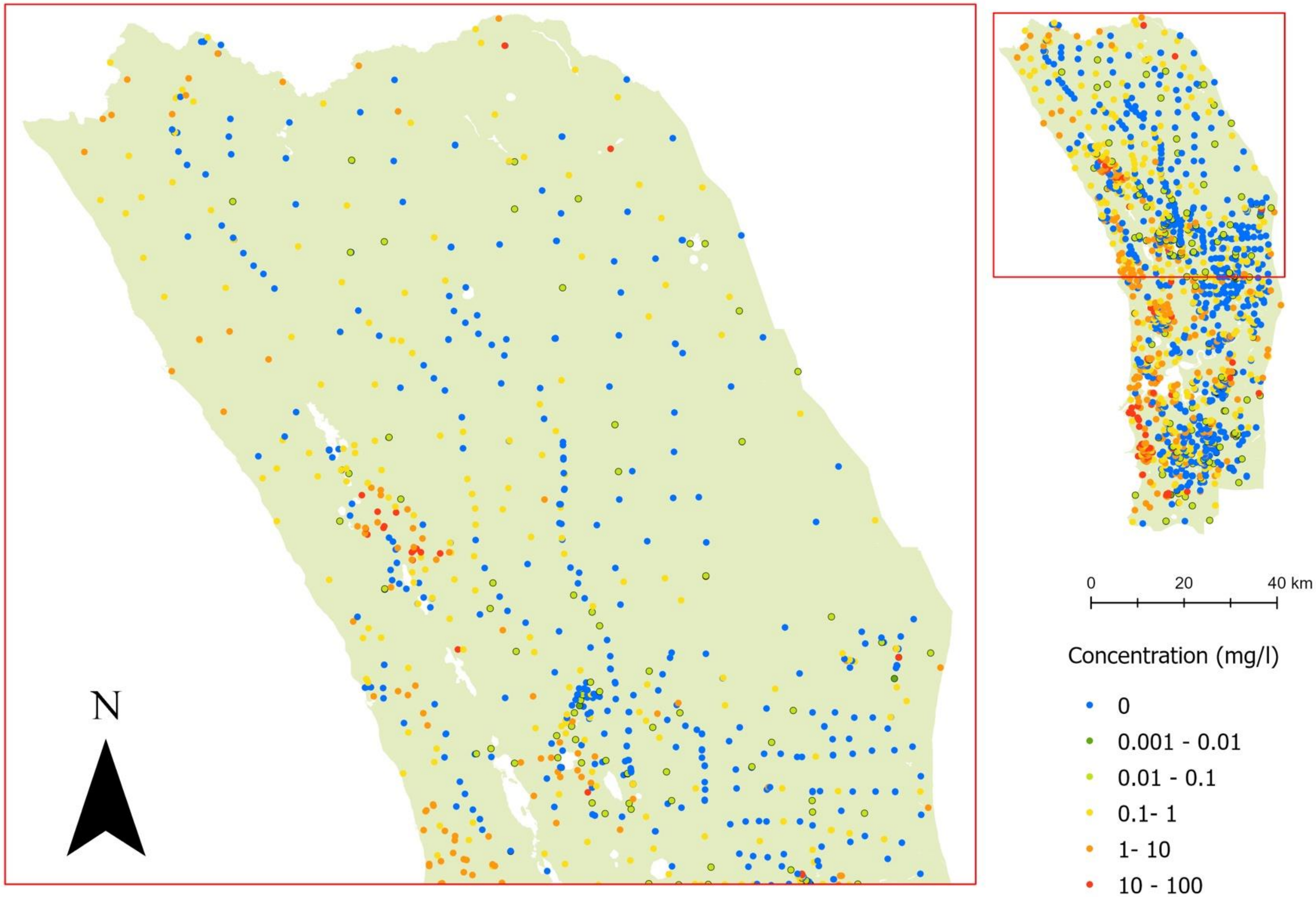


Figure 6

Spatial Distribution of Nitrate Samples in the Southern Part of the Swan Coastal Plain

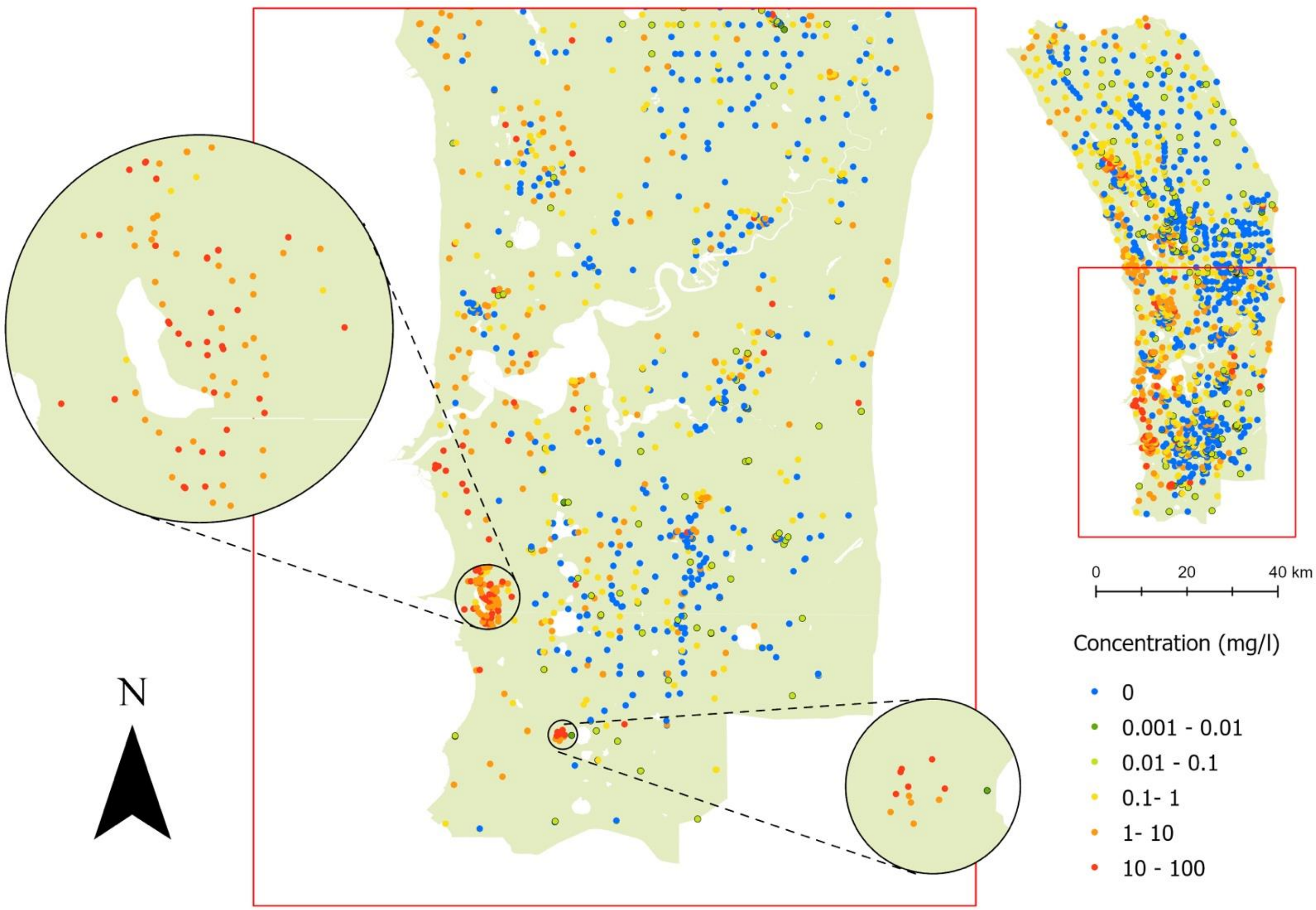


Table 7 shows the overall distribution of samples for nitrate concentration across the study area. The majority of the samples have zero values, and these samples were distributed in the western part of the study area. Excluding the samples with zero values, the concentration levels ranging from 0.1 to 1 mg/L and 1 to 10 mg/L contain the largest proportion of samples, with 18% and 20%, respectively. While samples with the concentration level from 0.1 to 1mg/L distribute evenly in the study area, samples with the concentration level from 1 to 10 mg/L concentrate on the western part in Figure 5 and Figure 6. Although the concentration level from 10 to 100 mg accounted for 5% of the total, these samples concentrate cluster on specific areas close to the coast or lakes

Table 9

The Number of Arsenic Samples at Ranges of Concentration Levels

Concentration (mg/L)	The Number of Samples	Proportion (%)
0	634	75%
0.00001 - 0.0001	2	<1%
0.0001 - 0.001	35	4%
0.001 - 0.01	130	15%
0.01 - 0.1	41	5%
0.1 - 1	3	<1%
Total	845	100%

Figure 7

Spatial Distribution of Arsenic Samples in the Swan Coastal Plain

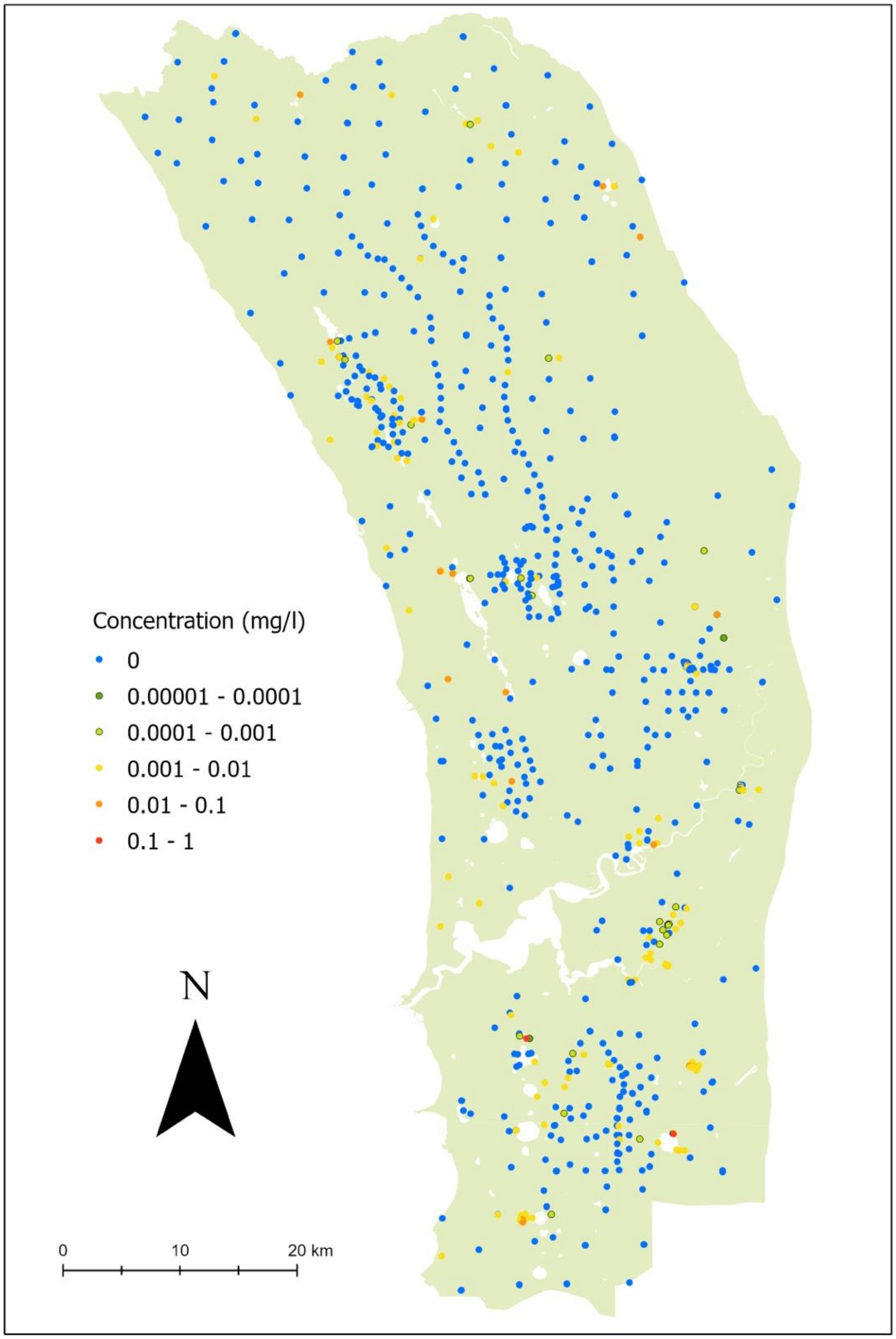


Table 9 shows the overall distribution of samples for arsenic concentration across the study area. Over half of the samples have zero values. Excluding the samples with zero values, the concentration levels ranging from 0.001 to 0.01 mg/L contains the largest proportion of samples, accounting for 15% of the total. Samples with high arsenic concentration level were observed in the area surrounding lakes.

Figure 8

Scatter Plots illustrating the Relationship between of Nitrate Concentration and DRASTI(L) Models: (A) DRASTIC (Minimal), (B) DRASTIC (Mean), (C) DRASTIC (Maximal), (D) DRASTICL (Minimal), (E) DRASTICL (Mean), (F) DRASTICL (Maximal)

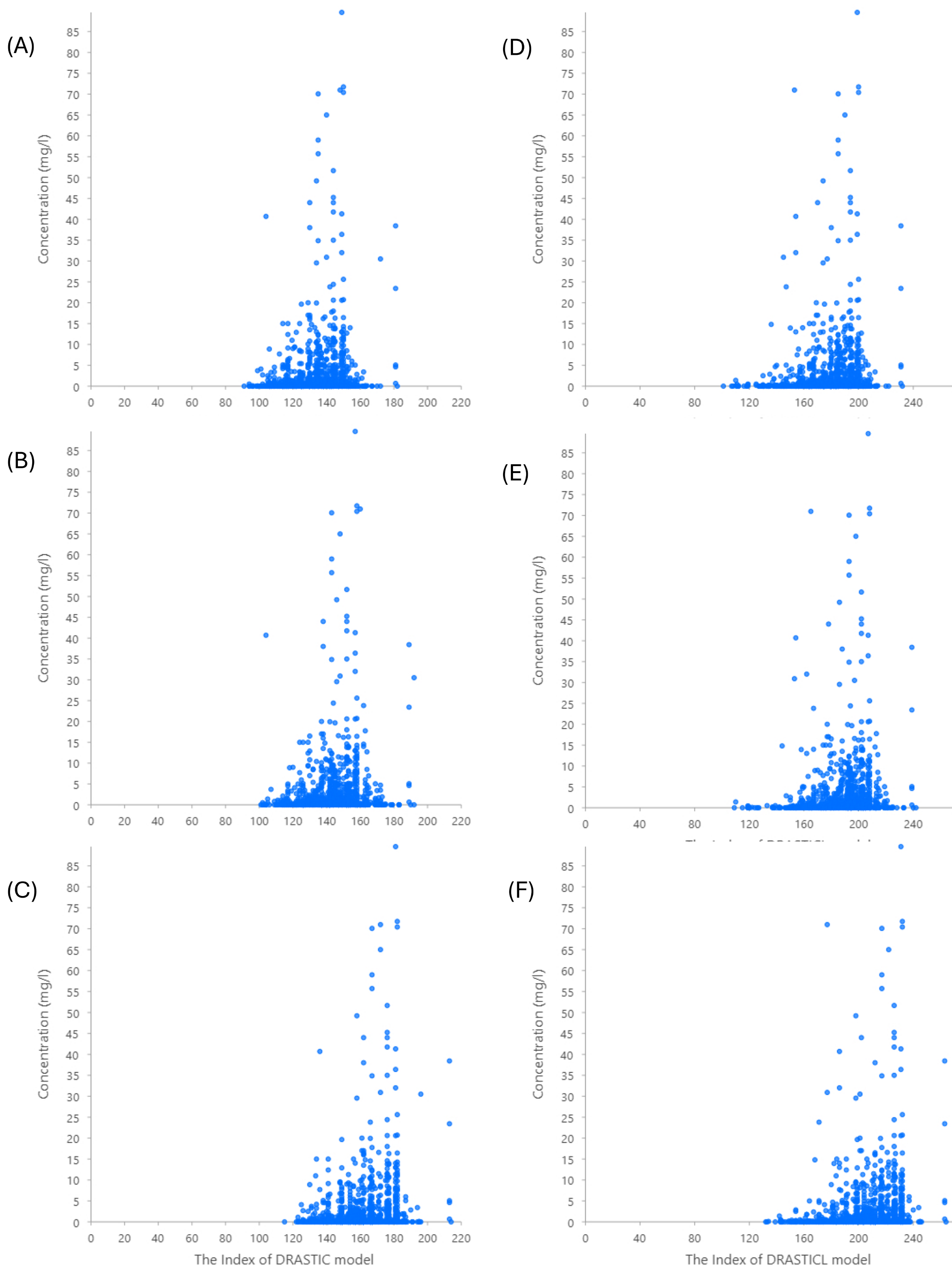


Figure 9

Scatter Plots illustrating the Relationship between Arsenic Concentration and DRASTI(L): models (A) DRASTIC (Minimal), (B) DRASTIC (Mean), (C) DRASTIC (Maximal), (D) DRASTICL (Minimal), (E) DRASTICL (Mean), (F) DRASTICL (Maximal)

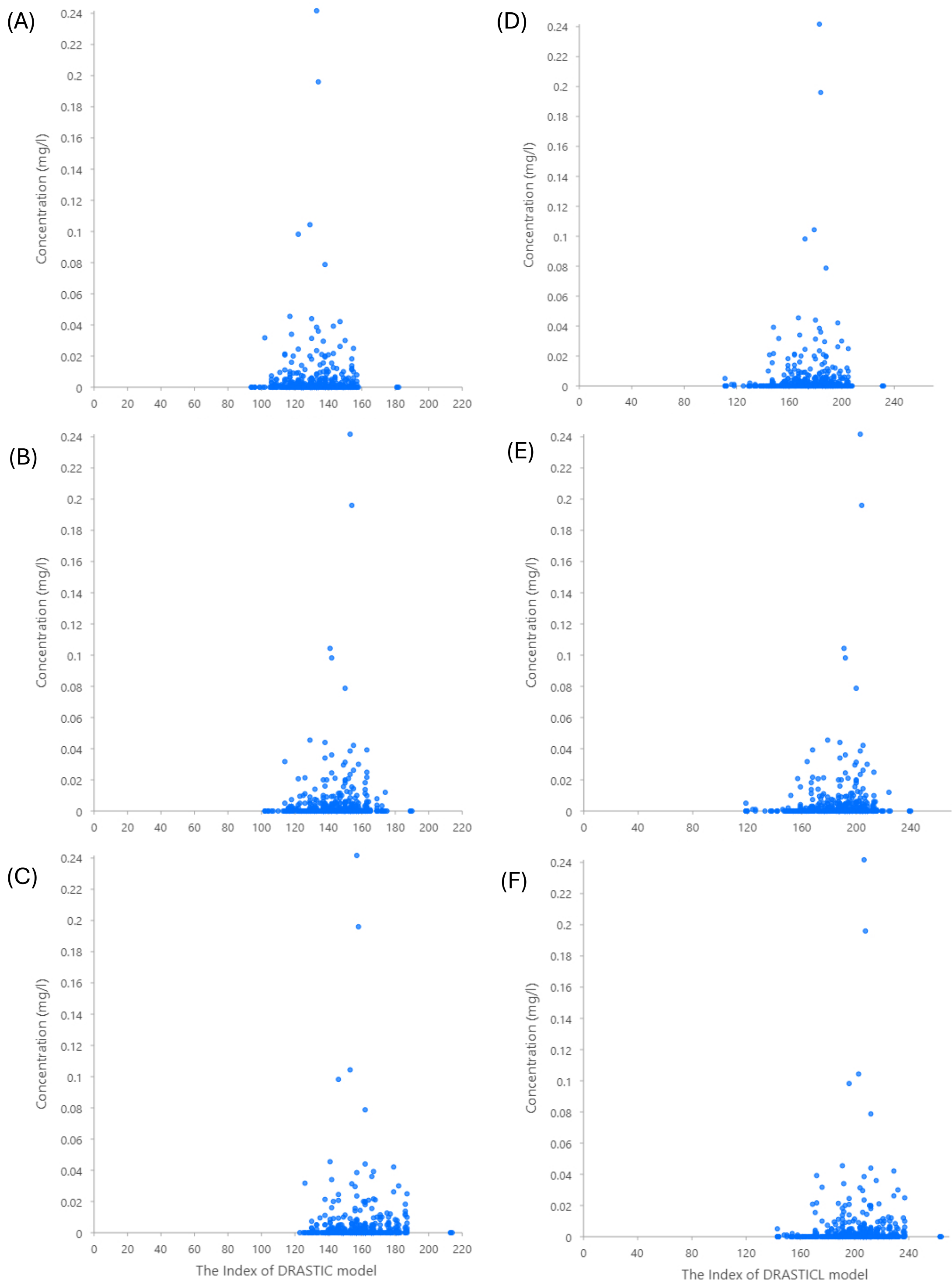


Table 10

The Result of Kendall's τ Correlation Test

Contaminant	Model	Scenario	Coefficient	p-value
Nitrate	DRASTIC	Minimal	0.12	< 0.001***
		Mean	0.06	0.002**
		Maximal	0.15	< 0.001***
	DRASTICL	Minimal	0.12	< 0.001***
		Mean	0.05	0.010*
		Maximal	0.13	< 0.001***
Arsenic	DRASTIC	Minimal	0.01	0.811
		Mean	0.06	0.035*
		Maximal	0.01	0.629
	DRASTICL	Minimal	0.04	0.234
		Mean	0.05	0.115
		Maximal	0.01	0.651

The DRASTIC and DRASTICL models displayed weak but statistically significant positive correlations with nitrate concentrations in Table 10. Minimal and maximal scenarios showed the highest τ coefficient for these correlations. Figure 8 demonstrates the scatter plot between the DRASTIC(L) model and the nitrate concentration. In contrast, the arsenic correlations between the models and arsenic concentrations are not statistically significant except for a very weak significant correlation with the DRASTIC model in the mean scenario. Given the low tau coefficient, even the significant correlation between the models in the mean scenario and nitrate concentration can be considered negligible. Figure 9 illustrates the scatter plot between the DRASTIC(L) model and the arsenic concetnration.

Figure 10

Spatial Distribution of Nitrate in the Northern Part of the Swan Coastal Plain, with Samples Exceeding the Environmental Standard (Dark Red), Half of the Standard (Orange), One-Tenth of the Standard (Yellow), and Other Samples Below One-Tenth of the Standard (Blue)

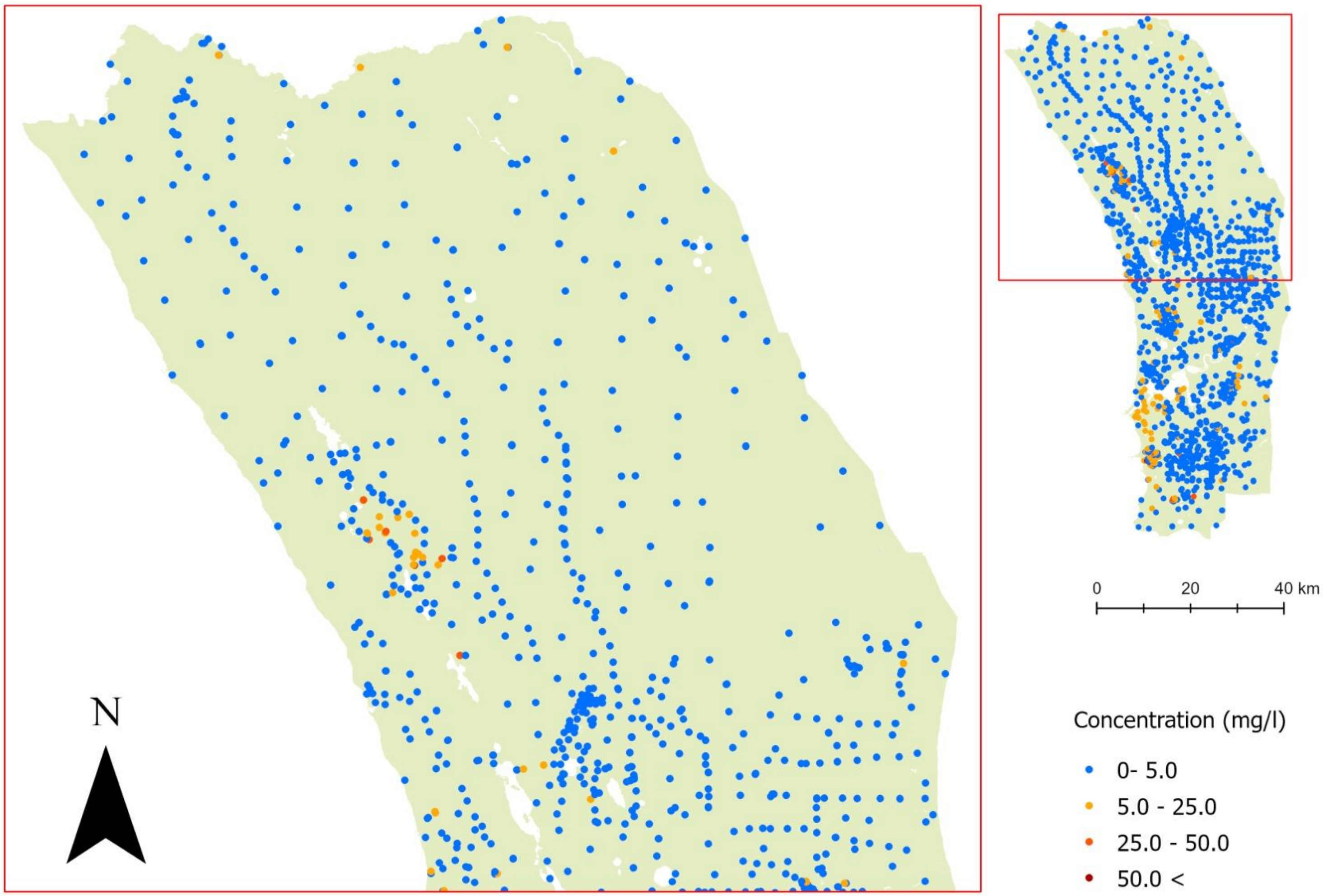


Figure 11

Spatial Distribution of Nitrate in the Southern Part of the Swan Coastal Plain, with Samples Exceeding the Environmental Standard (Dark Red), Half of the Standard (Orange), One-Tenth of the Standard (Yellow), and Other Samples Below One-Tenth of the Standard (Blue)

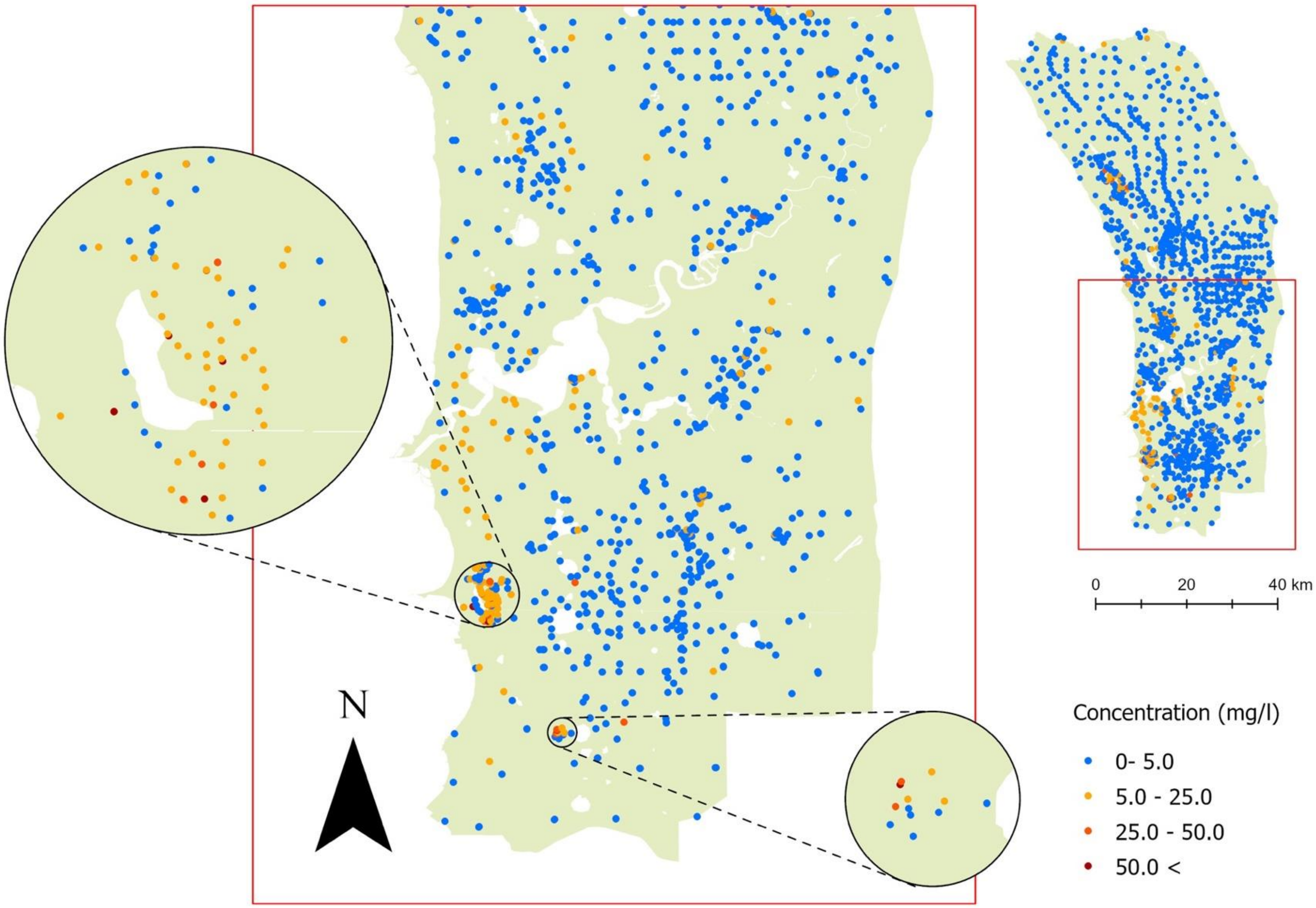


Figure 10 and Figure 11 illustrate the spatial distribution of samples with nitrate concentrations, classified by three thresholds: 5 mg/L, 25 mg/L, and 50 mg/L, respectively. Similarly to Figure 5 and Figure 6, the samples over the concentration level of 5mg/L clustered in the western part, and the samples over the concentration level of 25mg/L and 50mg/L were seen in specific regions closed lakes.

Figure 12

4 Risk Level Classification of the DRASTIC and DRASTICL models (A) DRASTIC model with Minimal Scenario (B) DRASTIC model with Mean Scenario (C) DRASTIC model with Maximal Scenario (D) DRASTICL model with Minimal Scenario (E) DRASTICL model with Mean Scenario (F) DRASTICL model with Maximal Scenario

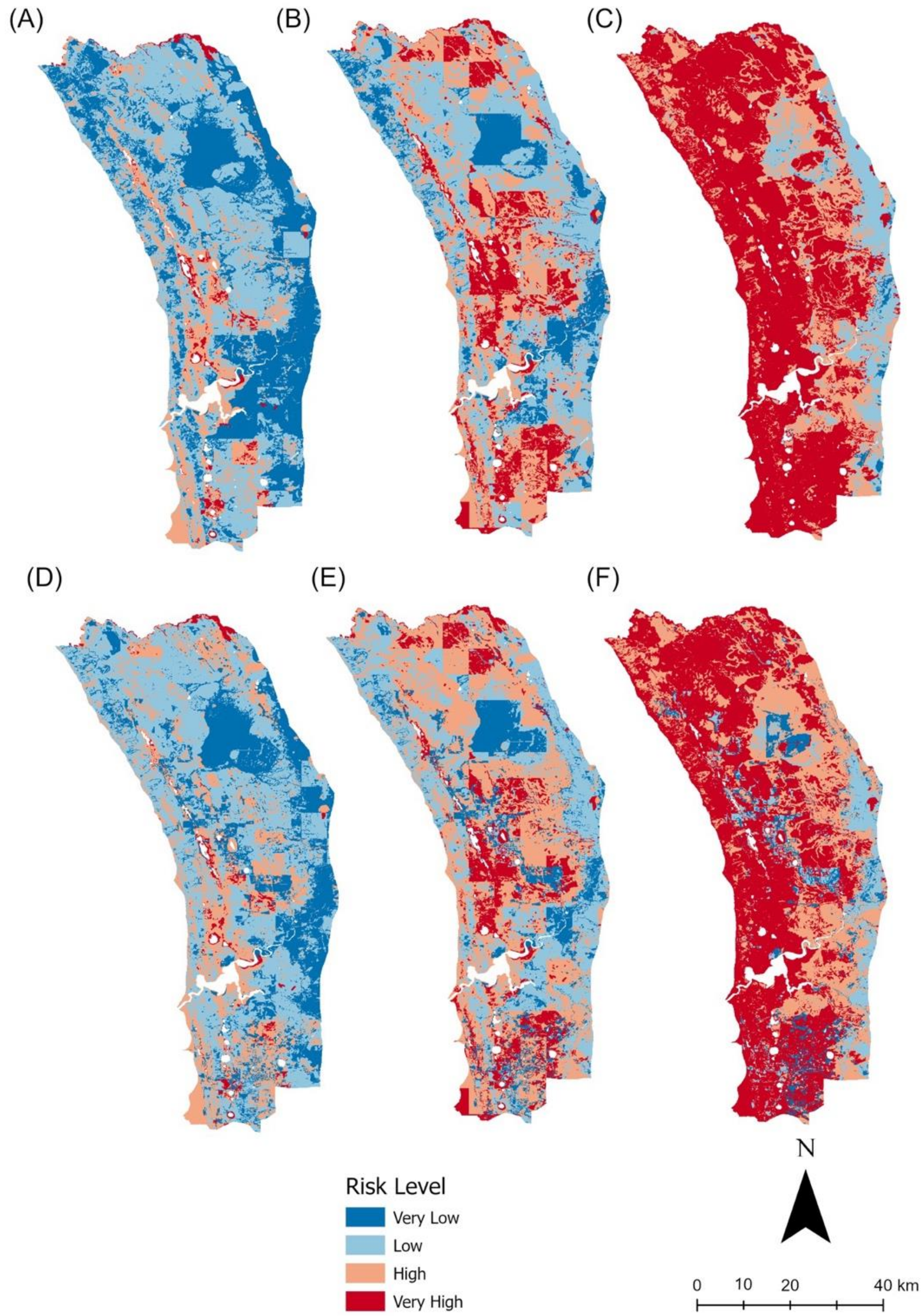


Table11

The Area and Proportion of Risk Levels for DRASTIC and DRASTICL models with three scenarios.

Model	Area (m^2)			Area (%)			Risk Level
	Minimal	Mean	Maximal	Minimal	Mean	Maximal	
DRASTIC	10.06	3.86	0.23	35.5%	13.6%	0.8%	Very Low
	13.00	10.88	3.73	45.9%	38.4%	13.2%	Low
	4.59	9.05	7.13	16.2%	31.9%	25.2%	High
	0.69	4.54	17.24	2.4%	16.0%	60.9%	Very High
DRASTICL	7.30	4.00	1.64	25.8%	14.1%	5.8%	Very Low
	13.76	8.80	2.82	48.6%	31.1%	10.0%	Low
	6.69	11.74	8.60	23.6%	41.4%	30.4%	High
	0.59	3.80	15.26	2.1%	13.4%	53.9%	Very High

Figure 12 ilusterates the spatial distribution of risk levels for both models with the three scenarios. High and Very high risk zones were consistently obeserved around the lake in the central part of the study area regardless of the model and scenario. In the DRASTIC model, zones with Very low risk level occupied 35.5% of the study area, and the occupancy reduces to 13.6% in the mean scenario and 0.8% in the maximal scenario (Table 7). In Contrast, the occupation of Very high risk level increases from 2.4% in the minimal scenario to 60.9% in the maximal scenario. The DRASTICL model shows a similar trend, and zones with the Very Low risk level decrease from 25.8% in the minimal scenario to 5.8% in the maximal scenario. Conversely, an area with Very High risk level increased from 2.1% to 53.9%. While the occupancy of most risk levels monotonically decreases or increases between minimal and maximal scenarios, the occupancy of High risk level was the highest in the mean scenario at 31.9% for the DRASTIC model and 41.4% for the DRASTICL model.

Table 12

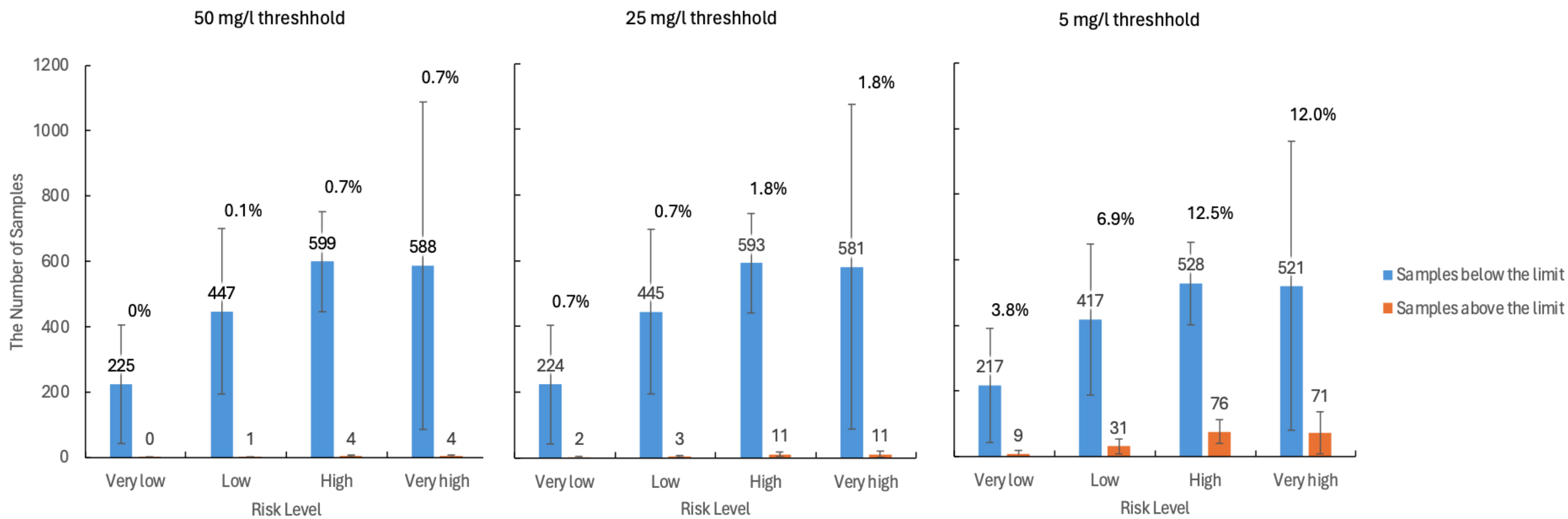
The Result of Fisher's Extract Test and the Cochran-Armitage test

Statistical test	Model	Scenario	Threashold		
			50 mg/L	25 mg/L	5 mg/L
Fisher's Exact Test	DRASTIC	Minimal	0.048*	0.001**	<0.001***
		Mean	0.155	0.047*	<0.001***
		Maximal	0.190	0.006**	<0.001***
	DRASTICL	Minimal	0.023*	0.120	<0.001***
		Mean	0.351	0.070	<0.001***
		Maximal	0.228	0.832	<0.001***
Cochran-Armitage Test	DRASTIC	Minimal	0.028*	<0.001***	<0.001***
		Mean	0.022*	0.011*	<0.001***
		Maximal	0.030*	0.004**	<0.001***
	DRASTICL	Minimal	0.037*	0.056	<0.001***
		Mean	0.153	0.245	<0.001***
		Maximal	0.105	0.129	<0.001***

Overall, Both models showed more freqeunt and higher statistical significance for Fisher's exact test and the Chochran-armitage test at lower thresholds across all scenarios. Particularly, both statistical tests show the p-values of less than 0.001 across all models and scenarios. While DRASTIC models with three scenarios show statistical significance for both statistical tests with their p-values below 0.05 at the threshold of 25mg/L, this trend was not observed for DRASTICL model. At the 50mg/L threshold, the Cochran-Armitage Test indicatedd a significant trend for the DRASTIC models in the mean and maximal scenarios, whereas Fisher's exact Test did not show statistical significance for the categories. The discrepancy in the tests can be related to the overestimation of the tests due to the unbalanced sample ratio.

Figure 13

The mean number and ratio of samples below and above the nitrate concentration threshold of 50 mg/L, 25mg/L and 5mg/L at each risk level across DRASTIC(L) models with three scenarios



Note: % Indicates the Ratio of Samples below and above the Limit. Error Bar Indicates the Standard Deviation of the Values across DRASTIC and DRASTICL Models with Three Scenarios

Figure 13 shows the mean number and ratio of samples in each risk zone at different nitrate threshold levels. The ratio of samples exceeding the 50 mg/L displayed increased a marginal increase of less than 1%, from 0% to 0.7%. Similarly, the ratio for the 25mg/L threshold increased by approximately 1%. In contrast, the ratio of samples exceeding the 10mg/L threshold. The smaple ratio showed a more substantial increase, rising by 8% from 3.8% to 12%. The large error bars for each risk level indicate significant variability in the number of samples falling into each risk zone across models and scenarios demonstrated in Figure 12.

4. Discussion

Primerily, this study aimed to evaluate the groundwater vulnerability in the Swan Coastal Plain using the DRASTIC and DRASTICL models under different scenarios. The Very high and High level risk zones of the vulnerability map by the DRASTIC model in the mean model were mostly consistent with the groundwater vulnerability map by Gozzard (2010), except the surrounding area around a few lakes in the southern part was categorized as Very low or Low risk level. Conversely, the vulnerability map by the DRASTICL model in the mean model showed that the passages between the lakes in the northwestern part were also categorized as Low and Very low levels. DRASTICL. There are two reasons for the classification. First, depth to groundwater was the most sensitive parameter to the index for DRASTIC models in Table 5, while land use was the most sensitive to DRASTICL models in Table 6. Second, since the passage connecting the lakes was categorized as Production from Relatively Natural Environments (Appendix A), a low rating score was assigned to the DRASTICL model in Figure 3.

Subsequently, we hypothesized that both the DRASTIC(L) models could be effective in predicting nitrate contamination and the DRASTICL model has higher accuracy. Consistent statistical significance was proven for the correlation between the models and nitrate concentrations in Table 10. Particularly, the minimal and maximal scenarios of both models showed weak but the highest coefficient in Table 6. However, the coefficient test showed a significant correlation only between the concentration of arsenic and DRASTIC in the mean scenario. Appleyard et al., (2006) mention that pyrite sediments containing arsenic have been observed in peaty layers of wetlands on the Swan Coastal Plain. The dewatering process for construction has exposed pyrite to oxygen, and the oxidation decomposes the pyrite and releases arsenic into groundwater. In this study, a high concentration of arsenic was observed around Swan River and lakes of the study area (Figure 7). Although depth to groundwater is likely related to the distribution of the high arsenic concentration, the complexity of the DRASTIC(L) model and the high number of zero values in Table 9 could underestimate the spatial distribution of arsenic.

Finally, based on the result gained from the correlation test between the DRASTIC(L) model and the nitrate concentration, we aimed to assess whether the DRASTICL model can effectively support groundwater management in a practical setting through the application of risk classification and contamination thresholds. Cochran-Armitage tests proved that there are linear trends between the level of risk zones and the ratio of samples exceeding the nitrate concentration level of 5 mg/L, regardless of the types of models and scenarios in Table 12. This trend supports the high coefficient between nitrate and DRAITC(L) models described by the Kendall rank correlation test.

At the threshold of 25mg/L, while the linear trends were not observed for DRASTICL models, these trends were found between DRASTIC in Table 12. Particulary, the minimal and maximal scenarios showed lower statistical significance at the p-values of less than 0.01, whereas the mean scenario showed the p-value of 0.04.

In Figure 13, the total number of samples and the ratio of samples exceeding the nitrate concentration threshold of 25 mg/L are similar in both High and Very high risk zones. The Very high risk zone has a larger standard deviation compared to the High risk zone, as represented by the larger error bars. Additionally, the High risk zone covers areas identified as both High and Very high risk zones in the DRASTIC model's maximal scenario shown in Figure 12, resulting in a larger number of samples in the High risk zone, resulting in a larger number of samples in the High risk zone. The ratio for the Very high risk zone in the maximal scenario is close to the ratio displayed for the Very High and High risk levels at 1.8 in Figure 13. This is because most samples from the High and Very high risk zones in the mean scenario fall into the Very High risk zone in the maximal scenario in Figure 8. Thus, the Very high risk zone has a higher number of samples but the same ratio, increasing the statistical power for the Very high risk zone of the DRASTIC mode in the Maximal scenario. Finally, this leads to a stronger linear trend in the DRASTIC model's maximal scenario compared to the mean scenario.

In contrast with the DRASTIC model in the maximal scenario, the number of samples in the Very high risk zone was reduced in the minimal scenario as the area of Very high risk zone is only 2.4% and cannot cover the larger number of samples in Table 11. Nevertheless, most areas around the lake were classified as the High and Very High risk zone, but not other areas containing larger samples of a concentration level of less than 25mg/L. As displayed in Figure 10 and 11, the samples exceeding the nitrate concentration of 25mg/L tended to be observed around the lakes. Therefore, although the total number of samples in the Very high risk zone is limited in the mean scenario, the higher ratio increase led to a higher linear trend than the mean scenario.

These significant linear trends proven by the DRASTIC model in the minimal and maximal scenario might be attributed to overestimation. For example, a Very high risk zone accounts for over half the size of the study area in the maximal scenario in Table 11. Additionally, samples with high nitrate concentrations clustered in specific regions that were also covered by marginal Very High and High risk zones in the minimal scenario. Therefore, despite the higher significance of the linear trend in these scenarios compared to the mean scenario, the reliability of these more significant linear trends is uncertain.

Masetti et al. (2009) made a vulnerability index using the likelihood ratio model, combining three different thresholds of the nitrate concentration (4.5, 22 and 50 mg/L) with environmental factors. They found that the smaller threshold value does not affect the quality of the vulnerability index on a broader scale. This indicates that the limited number of samples with a concentration of 50m/l was one factor explaining the lack of significance in the linear trend in the swan coastal region. If more samples were collected, there could be a linear trend between the vulnerability index and the samples exceeding the threshold of 50mg/L.

Our findings offer the pontetial application of DRASTIC to address the area with the nitrate concentration level exceeding 5mg/l. The DRASTIC model could also predict the area vulnerable to the nitrate concentraion above 25mg/l or 50mg/l.

In this research, the correlation between DRASTIC(L) models and the arsenic concentration was not significant despite the unique geological character of the Swan coastal region. In order to address the issue, it might be necessary to create tailored rating score systems for the parameters of (A) aquifer media, (S) soil media and (I) impact of vadose zone. These parameters are directly related to geological materials that can act as the source of pollution. This tailored approach would provide a more comprehensive spatial assessment of groundwater vulnerability.

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Appendix A

No.	Parameter	Weight	Property	Rate
1	Depth to Water (m)	5	0–1.5	10
			1.5–4.6	9
			4.6–9.1	7
			9.1–15.2	5
			15.2–22.8	3
			22.8–30.4	2
			30.4+	1
2	Net Recharge (mm/year)	4	0–50.8	1
			50.8–101.6	3
			101.6–177.8	6
			177.8–254	8
			254+	9
3	Aquifer Media	3	Massive shale	2
			Metamorphic/igneous	3
			Weathered metamorphic/igneous	4
			Glacial till	5
			Bedded sandstone, limestone, shale	6
			Massive sandstone	6
			Massive limestone	6
			Sand and gravel	8
			Basalt	9
			Karst limestone	10
4	Soil Media	2	Thin or absent	10
			Gravel	10
			Sand	9
			Peat	8
			Shrinking and/or aggregated clay	7
			Sandy loam	6
			Loam	5
			Silty loam	4
			Clay loam	3
			Muck	2
			Non-shrinking and non-aggregated clay	1

No.	Parameter	Weight	Property	Rate
5	Topography (slope %)	1	0–2	10
			2–6	9
			6–12	5
			12–18	3
			18+	1
6	Impact of the Vadose Zone	5	Confining layer	1
			Silt/clay	3
			Shale	3
			Limestone	6
			Sandstone	6
			Bedded limestone, sandstone, shale	6
			Sand and gravel with significant silt and clay	6
			Metamorphic/igneous	4
			Sand and gravel	8
			Basalt	9
			Karst limestone	10
7	Hydraulic Conductivity of the Aquifer (m/day)	3	0.04–4.1	1
			4.1–12.3	2
			12.3–28.7	4
			28.7–41	6
			41–82	8
			82+	10
8	Land use	5	Conservation and Natural Environments	10
			Production from Dryland Agriculture and Plantations	10
			Production from Irrigated Agriculture and Plantations	8
			Intensive Uses	10
			Production from Relatively Natural Environments	1