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Impacts of Anthropogenic Land Use Changes on Nutrient Concentrations in Surface Waterbodies: A Review

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Increased population leads to land use (LU) changes from natural to urban and agricultural LU. These disturbances not only decrease the natural treatment potential but they also worsen surface water quality (SWQ). The aim of this review is to assess studies about impacts of anthropogenic LU changes on levels of nutrient concentrations in surface waterbodies, highlighting the important parameters needed for an integrated simulation. The results reported in the literature are not always fully consistent. These contradictory results can sometimes be explained by field measurements under different climatic conditions, different features of landscapes, air deposition rates on ground surfaces, and groundwater flow interactions with surface water. Integrated modelling has been suggested to overcome these inconsistencies. Physical-based and empirical models are the most popular approaches for LU-SWQ studies. Generally, anthropogenic LU such as agricultural and urban areas usually enhances nutrient concentrations much more than natural lands such as forest and barren. Developing sustainable metropolitan areas instead of rural areas, establishing high-standard waste-water treatment plants, and practicing efficient fertiliser application would ameliorate the poor nutrient conditions in SWQ. Riparian vegetation, grassed swales, and construction of artificial wetlands as buffer zones are the most promising natural water quality control measures.

1. Introduction, Aim, and Objectives

Water quality challenges have become an increasing global concern due to the adverse impacts of rapid population growth and corresponding anthropogenic activities such as irrigation practices, mining, and urbanization.[1] Man-made disturbances produce different types of pollutants such as nutrients (e.g., nitrogen and phosphorus), which play an important role in plant growth, and are often discharged either untreated or partially treated into surface waterbodies.[2] The excess of nutrient levels in waterbodies accelerate their eutrophication process that has harmful effects on drinking water supplies, recreation, fisheries, and wildlife.[3]

The increased pressure on water sources to meet current and anticipated demands is critically dependent on pollution resulting from various human-induced activities. However, finding a promising relation between land use (LU) and surface water quality (SWQ) is challenging.[4] Search

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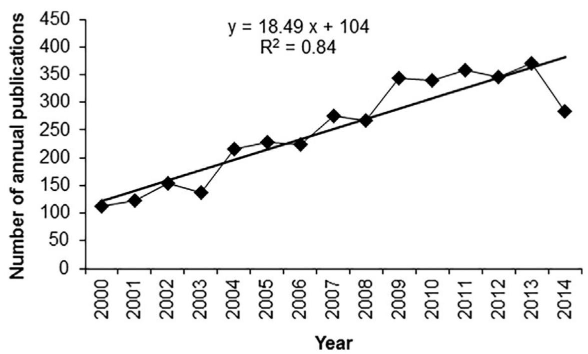

Figure 1. Annual publication rates for the keywords "land use change" and "surface water quality" using scopus.com.

results using the keywords "land use" and "surface water quality" are shown in **Figure 1**. Annual publication rates are ascending and a review of recent findings is therefore useful.

This paper aims to assess the impacts of anthropogenic LU changes on nutrient concentrations in surface waterbodies. The review highlights key points regarding the input dataset parameters such as LU, climatic conditions, and landscape features for LU and SWQ interaction studies. Reported correlations between nutrient concentrations and anthropogenic LU changes are assessed to explain the logical relationships. Finally, some practices that have been recommended to preserve water quality despite negative impacts of LU changes are introduced as well as key conclusions are drawn from this review.

2. LU Changes and SWQ

Alteration of land to provide shelter for humans and agricultural products are the primary anthropogenic LU changes.[5] The LU changes associated with an increase in population growth form complex interrelationships, which require comprehensive spatial and temporal studies.[6,7] Classification of LU changes, for example, in Portugal between 1958 and 2007 are shown in **Figure 2**.[8]

Anthropogenic LU changes release significant nutrient loads into waterbodies, which worsen SWQ conditions.[9] Agricultural LU usually releases nutrients into waterbodies through non-point sources (NPS), leading to diffuse pollution, which has become a major environmental concern.[9] Numerous diffuse nutrient pollution studies focused on the effects of runoff flowing over agricultural land.[3] These studies reported that agricultural land coverage strongly influences nitrogen,[9,10]

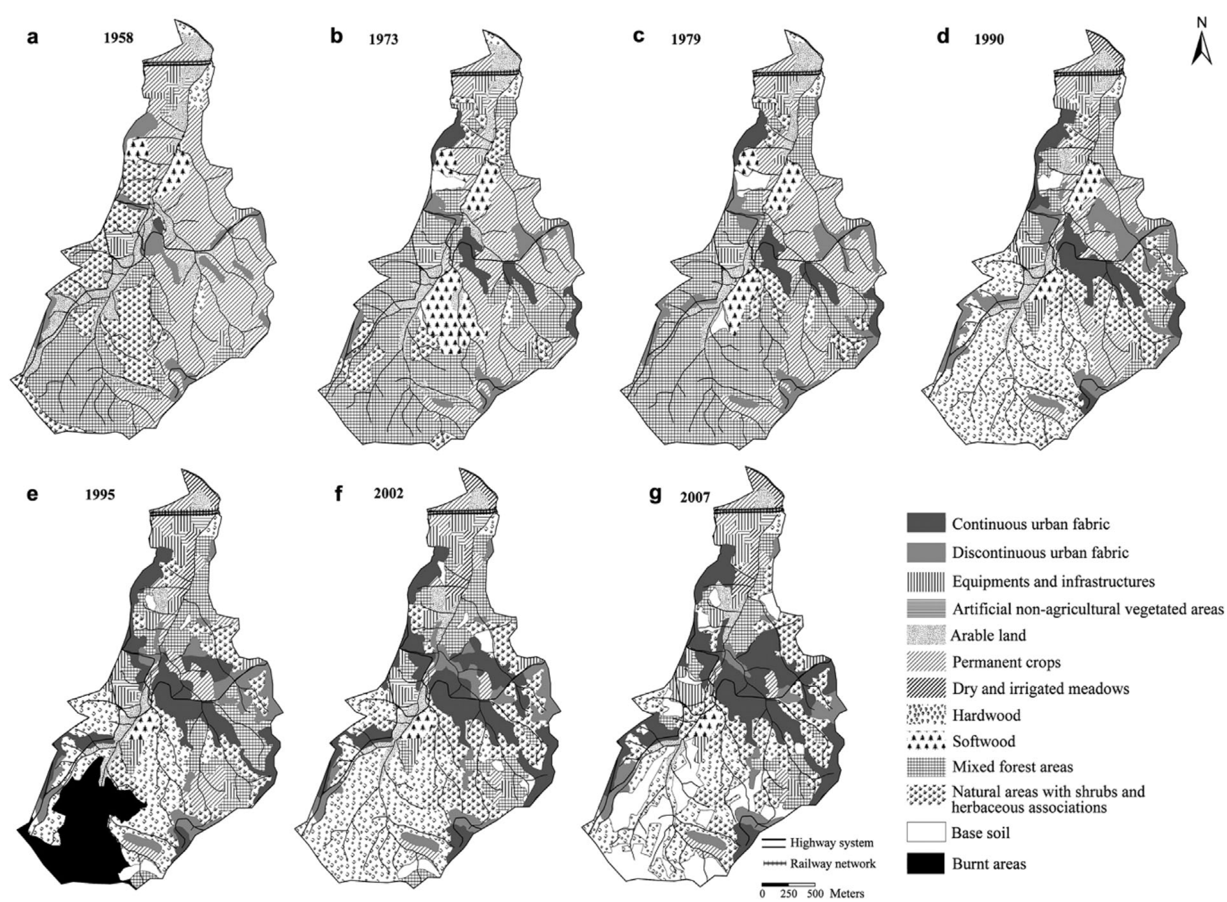

Figure 2. Temporal LU map changes in central Portugal in a) 1958; b) 1973; c) 1979; d) 1990; e) 1995; f) 2002; and g) 2007.[8]

phosphorus,[11] and total suspended solid concentrations[10] as well as sediment loads in watercourses.[12]

Urban LU affects SWQ through two different ways: Point sources (PS) and NPS of nutrients discharging into waterbodies. PSs contribute to surface water pollution by directly discharging domestic and industrial wastewater into the corresponding waterbodies. Nitrate concentration usually has a statistically significantly positive correlation with urban density due to wastewater PS discharges.[13]

Urban LU can contribute to nutrient loads discharged into waterbodies through rainfall conversion to runoff and/or drained water as well as washing-off non-point nutrient pollution sources.[14] An increase in impermeable area due to urbanization may lead to higher runoff volume and lower percolation.[15] Increased runoff washes out nutrients from surfaces, eventually entering a stream. The absence of vegetation often plays a central role in soil erosion and wash-out of nutrients.[16] Ghaffari et al.[17] have highlighted the significant contribution of increases in urban areas to the water quality deterioration and the alteration of flow regimes. They asserted that LU changes from 1967 to 2007 led to a 33% increase in urban runoff volume and a 22% decrease in groundwater recharge. Runoff from urbanised areas carries pollutants such as increased loads of nutrients and solids.[18] Researchers reported that between 66 and 75% of deforestation leads to noticeable signals in nutrient concentrations in surface waterbodies. Washing-out the leaves originating from urban trees by runoff was identified as the main source of total nutrients.[19] They found a statistically significant correlation between urban density and leaf breakdown rate ($R = 0.91$). Increases in urban density from 10 to 30% would increase the leaf breakdown rate by threefold. Walsh et al.[20] pointed out the ecological impacts on SWQ. They underlined that urbanity enhances surface water nutrient and toxicant concentrations as well as changes surface water hydrology. Larger peak flow, shorter lag time and a disturbing frequency of overland flow are the influences of urbanity on SWQ. **Figure 3** exhibits the difference between natural and urban land–water balance.[21] Runoff makes the greatest contribution in water balance in urban LU (55%). However, just 10% of water is attributed to surface runoff in rural LU.

Many soils comprise clay and organic matter. Clay having a negative charge can immobilise compounds with positive charge such as potentially toxic metals.[22] The soil organic fraction adsorbs organic compounds into runoff passing over soil.[23] Thus, natural treatment of diffuse pollutants plays an important role in water quality management of natural lands. Meyer et al.[19] calculated the soluble reactive phosphorous and ammonium cation uptake rates as a function of urban LU density. They found statistically significantly negative correlations between both of them. Their results revealed that a 10% increase in urban density may half soluble reactive phosphorous and ammonium cation uptake rates.

2.1. LU-SWQ Investigations

2.1.1. Background

Although SWQ field measurements are the most reliable data, they are sometimes costly and hard to perform.[24] Computer modelling aids field measurements to generate a field-validated model that can predict the fate of nutrients under different conditions after calibration and validation.[25] Developing a computer model needs a comprehensive understanding about on-going processes affecting the nutrients' fate, which might be difficult and complex.[26] First, the researcher needs to identify the active processes and sources of nutrient transport in a watershed as shown in **Figure 4**.[27] Second, someone can predict the impacts of change in the watershed. Third, authorities and watershed managers can assess water quality promotion strategies for watersheds. Finally, using field-validated computer modelling tools reduce the need for field measurements under difficult conditions and at high expense.[28]

The target of LU-SWQ models is to make connections between LU maps and SWQ. These models are considered a strong tool for managers to study the impacts of LU on SWQ and find the best practice to reduce nutrient loads. Several models

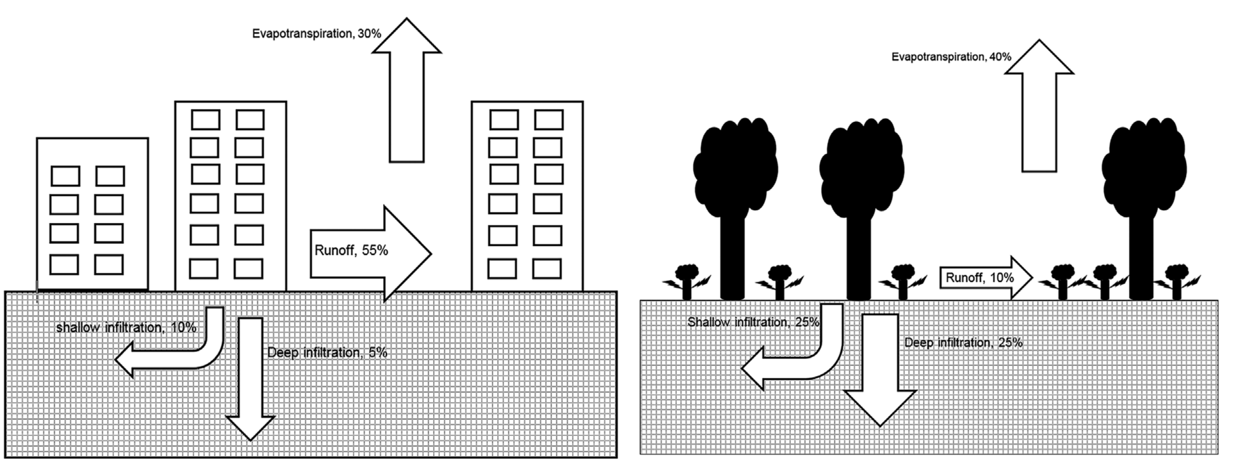

Figure 3. Impacts of LU on the natural drainage cycle.[21]

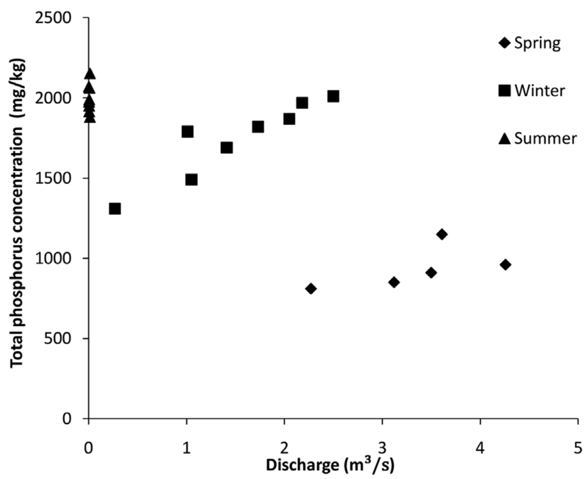

Figure 4. TP content in soil around (less than 20 m) a river in Iran.[27]

have been suggested and refined to achieve this goal.[24] Mathematical models utilise simulated processes (representing natural processes) to model the hydrology of watersheds. Higher speed and larger calculation volumes, clearer chronological sets of relations as well as logical steps between input and output make the mathematical models promising for simulating complicated processes in the future.[29] Mathematical models are divided into two different groups: Physical-based and empirical approaches.[30]

2.1.2. Physical-Based Models

Because of the limited current understanding regarding hydrological processes governing the field, it is hard to develop a fully physical-based mathematical model. Common procedure using physical-based models is initiation by sensitivity analysis to recognise sensitive parameters and understand the dominant processes among several probable processes during model calibration using one independent data set. Then another independent data set is used to validate the calibrated model. A validated model can be utilised to predict the different LU planning impacts on SWQ.[29]

Tu[31] developed a geographical information system-based watershed model simulator to predict the condition of nitrogen loads and water quantity for eastern Massachusetts, USA. The better assessment science integrating (BASIN) function is included in this type of simulator and has been tested to predict nutrient loads in Ohio State.[32] Kling et al.[33] developed a model called LUMINATE to assess impacts of agricultural LU on water quality with decision-making features. Zhang et al.[28] coupled the soil and water assessment tool (SWAT) and the conversion of LU and its effect at small regional extent (CLUE-S) models to predict the future LU impacts on nitrogen and phosphorous loads in China. They reported that agricultural activities increase nitrogen and phosphorous loads by 14 and 10%, respectively. SWAT is a semi-continuous model in space (some parameters fed to the model as distributed parameters while some others have one value for the whole of the watershed) and continuous in time simulating nutrient, pesticide, pathogen and hydrological responses to LU changes according to water mass balance equations.[34]

2.1.3. Empirical Models

Despite being physical-based models, empirical models usually require less input data to establish empirical relationships between LU and SWQ. The export coefficient (E_k) approach is considered to be a popular approach in this model category.[35] E_k are derived by monitoring station measurements of discharge and nutrient loads to represent the effluent mass under specific climatic and LU conditions. In addition to LU, meteorological parameters, soil type and topography may affect the results in this approach. Steady and uniform distributions of parameters are among major assumptions. Generally, this method tries to find the load of pollutants based on Eq. (1).

$$L = \int_0^T QC\mathrm{d}t \tag{1}$$

where L is the pollution load, Q is the river discharge, C is the concentration of pollutant and T is the time of interval.

But in general, the discharge and concentration data are not continuous functions in time. Therefore, the integral in Eq. (1) should be converted to summation. Equation (2) can be used to determine the role of each LU item in the pollution of a watershed,[36] and is usually solved by applying a multiple linear regression method.

$$L = PS + \sum_{i=1}^{n}\sum_{k=1}^{m} A_i E_k \tag{2}$$

where L is the expected output load, A_i is the area of each LU category, E_k is the export coefficient, m is the total number of area and n is the number of LU classes.

This method was utilized to study the nutrient loads discharged into Fuji River in Japan. It was reported that forest LU with 62% and agricultural LU with 20% of the TP loads have the most significant contributions in phosphorous pollution of the watershed.[37] In another investigation, the phosphorous pollution in the south plain of England was studied by E_k. It was noted that domestic wastewater has the greatest share in this area and 80% of the treatment would lead to a 52% reduction in TP load.[38] Some results of phosphorous E_k reported in the literature are given in **Table 1**.[39–41]

Multiple[42] and bivariate[43] linear regression models can be used to achieve good correlations between water quality parameters and LU with high level of accuracies. Stepwise multiple linear regression models, which select the most effective LU parameters, were also developed to achieve this goal.[44] Pearson correlation and analysis of variance were applied to assess the variation of water quality with different LUs.[16,45] The exploratory spatial data analysis and the geographically weighted regression methods were used to express changes of pollutants in any LU spatially.[46]

Generally, physical-based models have better accuracies than empirical models. However, they need larger input datasets.[29] A

Table 1. Phosphorous export coefficients values for several LUs reported in the literature.

Land cover classification	Phosphorous export coefficient	Reference
Agriculture	0.42	[37]
Irrigated pasture	5.8	[39]
Land with coniferous cover	0.02	[40]
Market garden	7	[39]
Native vegetation	0.015	[39]
Orchard	0.02	[40]
Urban	1.4	[39]
Urban	0.83	[41]
Urban	1.73	[37]

comparison of SWAT (physical-based model) and E_k approaches revealed that the application of SWAT for hydrological models seems more promising due to lower errors. It has been reported that SWAT and E_k methods predict phosphorus loads with about 7 and between 9 and 33% error, respectively, in a watershed in Iran.[27]

2.2. Key Variables in LU-SWQ Studies

2.1.1. Background

LU, meteorological parameters, landscape features and pollutant sources play a central role in determining nutrient concentrations levels in waterbodies. LU changes affect water balances, paths, and flow rates in watersheds.[47] Because evapotranspiration and infiltration rates vary with LU changes,[48] LU maps help in understanding flow paths and infiltration rates. Neglecting a nutrient source may lead to lack of knowledge of the full cycle of the nutrients in the examined watershed.[38] Heavy rainfall may transfer the nutrients over a long distance. Furthermore, landscape features such as slope, soil texture as well as shape and size of a watershed influence the impacts of LU on SWQ.

2.2.2. LU and Land Cover Maps

LU maps are necessary to study the impacts of LU changes on water quality.[49] These maps may offer detailed information (layers) for each type of land cover and each water quality parameter measured in appropriate time steps. Updating of LU maps showing the intra- and inter-LU temporal and spatial variations is essential for promising predictions of water quality.[46] There are several methods to incorporate remote images with water quality results such as satellite images (Moderate-resolution Imaging Spectroradiometer, Landsat and Satellite for Observation of Earth) and aerial photographs.[49]

LU-SWQ has been successfully modelled using satellite imagery based on LU and land cover data on various spatial scales.[50] There are two main approaches: The first one is referred to as "one image" (i.e., one time step), which is the most commonly used method to assign the impacts of different LUs to water quality.[51] The second approach is based on successfully identifying a relationship between differences of two images and the changes in concentrations to assess the effect of LU variations on water quality.[52] Obtaining raster images from satellites is the first step of this type of study, followed by characterising LU, which can be done using several parameters such as the normalized difference vegetation index,[12] forest disturbance[53] and arranging LU.[54]

2.2.3. Climatic Parameters

Heavy rainfall can lead to the washing-out of nutrients from the ground. Therefore, the time during which water samples are collected may significantly affect the correlation between LU and water quality parameters. The effect of LU on water quality changes according to season.[55] Some researchers suggest that measurements should be undertaken during storm periods when different runoff paths join.[56] Runoff scrubbing nitrate originating from manure and fertilisers is dominant during the wet season, while PS pollution from urban LU is dominant during the dry season.[57] Measuring the phosphorous content in the soil near Kan River, Iran, seasonal variations were observed as shown in **Figure 5**.[27] Positive correlations between soil phosphorous content and river discharge are the highest in autumn and winter, when the corresponding river discharge is relatively high. The authors associated this positive correlation with soil erosion occurring by runoff and accumulation of phosphorous around the river.

The amount of nitrogen in waterbodies is directly related to the volume of urban stream flow.[31] Rainfall may lead to runoff that washes out nutrients from soil that subsequently enters waterbodies.[58] In a large Belgian catchment (114 km^2), nitrate concentrations had two annual peaks; one during winter storms (51% total nitrate load) and the other when groundwater flow join surface waters, which represents 28% of the total load.[59] Comparing urban and forest LU revealed that nutrient measurements have a peak in urban LU that is related to high water flows.[27] However, nutrient loads can follow an almost constant trend in both urban and forest LUs[60];for example, **Figure 6** shows the nitrate responses of three different catchments to a storm in 2003.

Most of the nutrient loads are usually discharged to waterbodies from agricultural LU during the initial part of a storm event.[60] This initial but significant load is called the first (foul) flush.[3] As shown in Figure 5, Poor and McDonnell[60] revealed that forest LU has the lowest nitrate export during storm periods. In contrast, urban LU has the highest export during all storms; it can be referred to as a PS load due to anthropogenic activities. Agricultural LU has higher exports during storms after long dry periods (first flushes) and the load decreases during wet periods progressively.

2.2.4. Landscape Features

Details such as type and size of agricultural activity, crop intensity and pattern, soil type, meteorological data such as rainfall and temperature, irrigation, and drainage system are

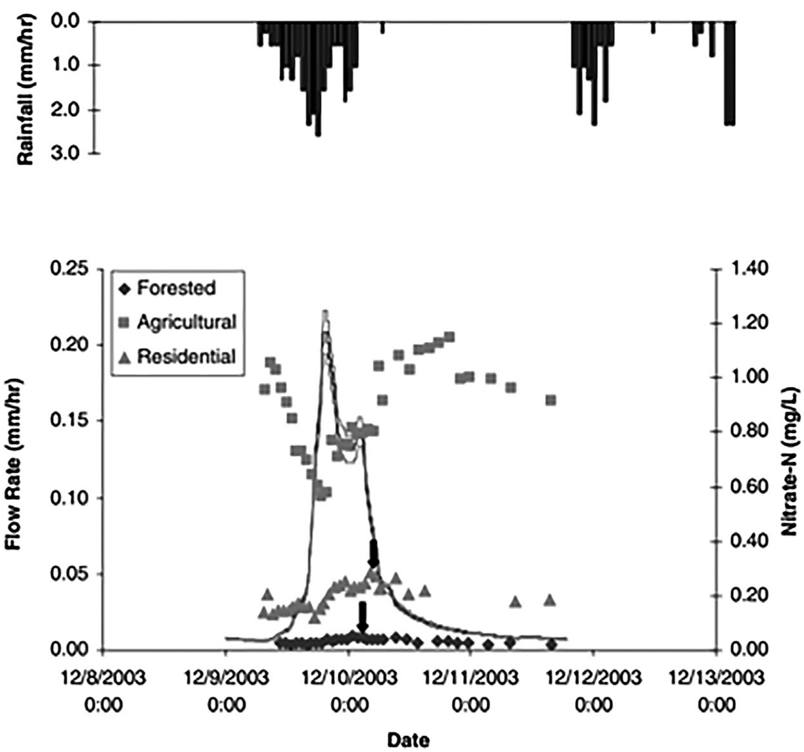

Figure 5. Nitrate-nitrogen (nitrate-N) responses of three different catchments to a storm in 2003. Only the agricultural hydrograph is displayed.[60]

required to predict water quality accurately.[61] Akhavan et al.[62] reported that higher nitrate leachate occurred during potato rotation compared to wheat. This nitrate leachate for potato cultivation was about 30–42% of the total nitrogen (TN) applied to the soil. Upstream LU, width of catchment, fertilizer application and number of stocks play a pivotal role in concentrations of higher order streams, while lower order streams (i.e., local ones) are affected by other factors such as location of stock crossing, point of access to stream and level of riparian damage.[1]

Each landscape has its own features such as slope, size, shape, human-induced activities as well as number and order of rivers, which distinguish it from other landscapes. Considering basin characteristics can improve model results, making them more reliable. Lee et al.[14] reported that the responses of TN and total phosphorus (TP) are in accord with the topographical properties of LU. Impacts of LU on water quantity (surface runoff) have been studied for a range of watersheds between 1 and 73 km^2 in size located in the Loess Plateau of China.[63] They found that LU changes have similar impacts in conversion of precipitation to runoff in large watersheds, regardless of precipitation variations. While LU changes in smaller watersheds have fewer impacts on runoff generations during higher precipitations. Impacts of landscape slope in NPS discharging loads into waterbodies have been given in **Table 2**.[64–66] which indicates that the slope of a watershed plays an important role in nutrient release rates in a watershed.

The LU impacts on SWQ with landscape scale vary spatially and chronically in a watershed located in Japan.[1] It was noted that two first-order stream zones with some similar features such as vegetation, topography and size had significant differences in nutrient levels; nitrate, ammonia and TP were 20, 10, and 2 times larger in one of them, respectively. The authors related this difference to the number of stocks that were grazing during the measurements. Lee et al.[14] pointed out that spatial pattern metrics support better the prediction of water quality as a function of surrounding LU. They figured out that edge and patch densities and the nearest-neighbour are the most effective metrics in TP and TN predictions in a watershed located in South Korea.

2.2.5. *Surface Water Pollutant Sinks and Sources*

A mass balance equation is concerned with the conservation of mass considering accumulation, influent, effluent, sink and source of a pollutant in a controlled volume.[67] Any LU leaves its own impacts on a watershed, which comprises inflow, outflow, several characteristic reaches and potentially several tributaries. Measured values of any contaminant at a certain site are not necessarily indicators of the role of the associated LU. However, these measurements show the total nutrient concentrations of target pollutants at this site. Ignoring potential sources of contamination might lead to a significant deviation from reality.[63–67]

A nutrient load may originate from the upstream watershed of a basin, entering the basin as part of the inflow. It was reported in Indiana, USA, that 19% of the non-urban LU conversion to urban area caused 17 and 13% reductions in nitrogen and phosphorous loads, respectively.[68] This result was mainly related to a sparse presence of agricultural LU (just 2.7%) in urban LU neighbourhoods. Studying LU-SWQ in the USA with a weighted regression technique, it was found that recreation LU in low-density urban areas has a positive relationship with dissolved nutrient runoff loads, while this LU somehow dilutes nutrients when it is adjacent to dense urban LU.[46] These studies highlighted the importance of adjacent LU and mass balance. Different pathways such as atmospheric deposition[69] and groundwater interactions with surface water have been assessed.[70]

Neglecting wastewater treatment plant effluents often decreases the goodness of correlation between the LU category urban area and water quality parameters.[71] For instance, 36% of TP load is associated with domestic wastewater released into a river in Iran.[27] Therefore, SWQ investigations should always consider pollutant mass balances in watersheds or control volumes.[72]

2.3. LU-SWQ Modelling Outcomes

Natural LU such as a forest functions often as a pollution sink. Zhang et al.[28] reported that LU conversion from forest to

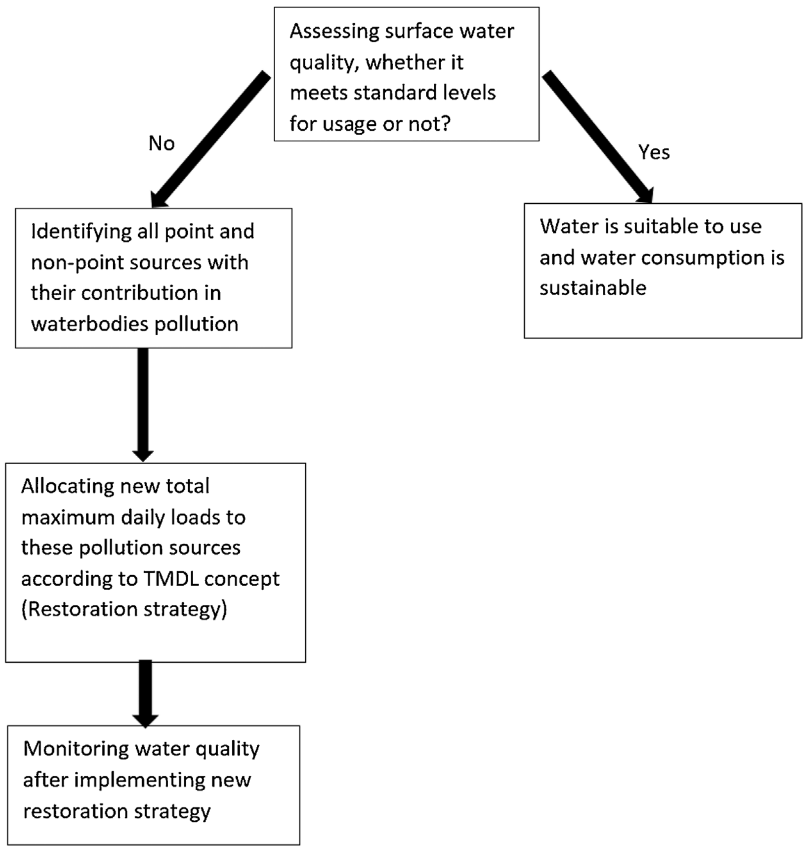

Figure 6. Schematic procedure for the total maximum daily load.

orchards caused 5 and 4% reductions in nitrogen and phosphorous loads, respectively. Statistically significant negative correlations found in Georgia (USA) between forest LU and TN (–0.43; $p < 0.007$), organic nitrogen (–0.45; $p < 0.005$), nitrate (–0.4; $p < 0.018$) and phosphorous (–0.47; $p < 0.002$) support this observation.[73] Nutrients in natural LU such as forest are usually part of suspended solids.[74]

Agricultural activities may lead to the discharge of nutrients into surface waterbodies and subsequently stimulate eutrophication of waterbodies such as lakes and rivers.[60] These nutrient sources include but are not limited to the following sources: Applying fertilisers, insecticides and herbicides on farmlands and residential areas; sediment from improperly managed construction sites, crop and forest lands and eroding stream banks; salt from irrigation practices; deposition of pollutants in atmosphere; and hydro-modifications. Nitrate is the major element in agricultural runoff.[47] The application of fertiliser to agricultural land has a statistically significantly positive correlation with the corresponding nitrogen export load.[62] In the Han River basin, China, weak Pearson correlation coefficients were found between agricultural LU and ammonia (0.21) and nitrate (0.22).[16] The authors reported a moderately positive correlation between agricultural LU and dissolved phosphorous (0.45). Phosphorous is usually related to NPS pollution due to agricultural activities.

Table 2. NPS contribution at different slopes for various references.

Zhang et al.[64]		Zhang et al.[65]		Huang et al.[66]	
Slope (%)	NPS load (kg)	Slope (%)	NPS load (kg)	Slope (%)	NPS load (kg)
5	0.43	6	0.51	5	0.47
10	0.84	12	0.99	10	0.78
13.67	1	13.67	1	13.67	1
20	1.09	18	1.02	–	–
25	1.6	24	1.06	–	–

During a study in Australia, a principle component analysis showed that TN and TP had weak correlations with suspended solids, which renders that nitrogen and phosphorous are present in dissolved forms in urban and rural areas.[74] However, an increase in the proportion of urban area improves this correlation. A significant correlation ($p < 0.05$) was found between dissolved nutrients and urbanised area.[73] In a study in China, low Pearson correlations figures were found between both nitrate and ammonia with urban LU, which were 0.25 and 0.14, respectively, inferring that there is no correlation between urban LU and these nutrients.[16] On the other hand, the authors reported a statistically significantly correlation between dissolved phosphorous and urban LU (0.80). TP has a linear relationship with the level of urbanisation.[75] It was noted that urban LU in 1973 contributed about 9 and 18% in TN and TP loads, respectively, while these contributions in 1991 enhanced to 20 and 36% for TN and TP in this order. The results of urban LU correlation with different nutrient forms reveal that urban LU increases nutrient loads.[73] In this study, it was reported that urban LU has a positive correlation with TN (0.49), organic nitrogen (0.52), nitrate (0.53) and phosphorous (0.56). Some of the results of LU-SWQ are shown in **Table 3**,[76] which displays some empirical equations derived between LU and nutrients as well as correlations between different LU changes and nutrient loads. Table 3 indicates the debilitating impacts of anthropogenic LU changes on SWQ.

Despite of some common relationships between LU and SWQ, there are some contradictory findings in terms of correlations between LU and nutrient loads released into surface waterbodies in the literature. These controversial results given in **Table 4** might be due to neglecting the key variables discussed in Section 2.2.

3. Practical Proposals for Water Quality Conservation

Water quality treatment and conservation measures including wastewater treatment,[58] development of urban instead of rural and barren areas,[46] applying pollutant adsorbents such as zeolite to field,[80] fertilizer management,[25] crop rotation in

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Table 3. Summary of investigations about impacts of LU changes on nutrient concentrations in soil water.

LU	Study period	Area (km^2)	Pollutant	Result	Reference
VEG[a)], AGR[b)] and URB[c)]	2005–2006	95 200	Dissolved phosphorus	Higher dissolved phosphorus during the dry season $= 0.001 + 0.047 \times$ URB[c)] (km^2); $R^2 = 0.6$	[16]
			Nitrate	Higher nitrate loading during the rainy season $= 1 + 0.15 \times$ Bareland (km^2); $R^2 = 0.75$	
FRS[d)], AGR[b)]	1995–2004	63.4–104.9	Nitrogen	Significant correlation between nitrogen load and stream flow for seven watersheds ($R^2 > 0.85$)	[31]
URB[c)], FRS[d)] and AGR[b)]	1990–1998	5840	TN	Spearman correlations for URB[c)] $= 0.23$ and AGR[b)] $= 0.19$	[32]
			TP	Spearman correlations for URB[c)] $= 0.34$ and AGR[b)] $= 0.16$	
URB[c)] and AGR[b)]	1997–2007	156 141	TN	Monthly loads based on monthly runoff depth $= 0.205 \times e^{0.0054 * MRD}$; $R^2 = 0.95$	[58]
			TP	Monthly loads based on monthly runoff depth $= 0.185 \times e^{0.0067 * MRD}$; $R^2 = 0.96$	
URB[c)]	1995	6400	TN	Concentration based on buffer size ($B = 2000$ m) $= 2.321 \times e^{2.173 * B}$	[76]
			TP	Concentration based on buffer size ($B = 2000$ m) and river rank (R) $= -2.69 + 1.43 \times B + 0.211 \times R$	
FRS[d)], URB[c)] and AGR[b)]	2001–2002	1010-1309	Nitrate	Correlation with URB[c)] for the Shibetsu area in Japan = 0.51, and correlation with URB[c)] for the Akkeshi area, Japan = 0.50	[77]
URB[c)], GRS[e)], WTL[f)], FRS[d)] and AGR[b)]	2002	~27	TN	Pearson correlations in autumn: URB[c)] $= 0.19$ and AGR[b)] $= -0.03$	[14]
			TP	Pearson correlations in autumn: AGR[b)] $= 0.28$ and AGR[b)] $= 0.10$	

[a)]Vegetation; [b)]Agriculture; [c)]Urban; [d)]Forest; [e)]Grassland; [f)]Wetland.

agricultural LU,[70] optimisation of the fertilizing time,[77] and construction of artificial wetlands[74] have been proposed.

LU changes close to a stream can have major effects on water quality.[78–81] Riparian vegetation and buffer zones can reduce the nutrient loads, sorption, and denitrification as well as control sediment transport.[82] Riparian vegetation is important for stream water quality.[83] However, there is no agreement about the optimum wetland dimensions and distances to the stream.[84] A buffer zone to control diffuse pollution is defined as a permanent green zone close to a waterbody and maintained separately from other land. Buffer zones are promising for keeping nutrients such as phosphorus and nitrogen in the soil and can capture pollutants travelling through air.[85] Vegetation buffer zones can reduce nitrate loads by 30%.[86]

Low impact development practices are utilised to mitigate reverse impacts of developing urbanisation and its consequences on water quality. They include constructed wetlands,[87] permeable pavements,[88] and grassed swales.[89]

The total maximum daily load (TMDL) allocates the acceptable value of discharge for all sources to meet the essential requirement of water quality.[90] Generally, 5–10% of TMDL is assigned to the "margin of safety (MOS)" covering some uncertainties in this method. The TMDL procedure is outlined in Figure 3.[21] Firstly, someone compares the current nutrient concentrations to standards to assess SWQ. In case of pollution (higher concentrations than standard criteria), new loads are allocated to both PSs and NPSs, and the new nutrient concentrations are compared to standard criteria. If they meet

Table 4. Summary of contradictory results about LU and SWQ relations.

Water contamination/LU	Model	Statement	Reference
Nutrients/agricultural LU	BASIN	Positive correlation	[32]
	Statistical analysis	No correlation	[78]
Phosphorus/agricultural LU	Geographical weighted Regression	No correlation	[46]
	SWAT, export coefficient Model	Positive correlation	[27]
Nitrogen/agricultural LU	Pearson correlation	No correlation	[14]
	SWAT, CLUE-S	Positive correlation	[28]
Nitrate/urban LU	Geographical weighted Regression	Negative correlation	[46]
	Regression analysis	Positive correlation	[77]
TP/residential LU	Linear regression	No correlation	[79]
	Bivariate regression	Positive correlation	[75]

the criteria, this maximum daily load is allocated to each source as maximum allowable load.

$$\mathrm{TMDL} = \sum\nolimits_{i} \mathrm{NPS_i} \sum\nolimits_{i} \mathrm{PS_j} + \mathrm{MOS} \tag{3}$$

where TMDL is the total maximum daily load, and MOS is the margin of safety.

4. Conclusions and Outlook

LU changes may alter surface runoff, evapotranspiration and infiltration, affecting the fate of nutrients. The authors understand that beside anthropogenic nutrient loads, which are released into the waterbodies, developing these types of lands leads to decreasing natural self-purification, which occurs for natural LU. For instance, phosphorous compounds can be attached to clay soils. This natural self-purification process is restricted as the LU changes.

There is general agreement that anthropogenic LU change demotes SWQ by discharging nutrient loads. For instance, agricultural LU releases a significant amount of nutrient loads into waterbodies. Impermeable surfaces are increased during urban LU development which causes increases in surface runoff volume and washing-out of nutrients. However, assessments revealed that there is some disagreement among reports regarding impacts of LU on SWQ. These contradictions might be due to different parameters and processes that can affect the results of LU impacts on SWQ. Considering mass balances, meteorological parameters such as precipitation and landscape features including size, shape and slope of watersheds usually play central roles in identifying LU impacts.

Reported statistically significant correlations between nutrient concentrations and anthropogenic LU changes were assessed. There is considerable evidence for positive correlations between urban and agricultural LU on one hand and elevated nitrogen and phosphorus concentrations in corresponding receiving watercourses on the other hand.

Practices that have been recommended to preserve water quality despite negative impacts of LU changes have been reviewed. Water quality treatment and conservation measures including promotion of riparian vegetation, grassed swales and construction of artificial wetlands as buffer zones are most promising.

Sustainable wastewater treatment with integrated constructed wetlands and the sustainable use of fertilisers are the most promising low-cost methods to conserve the water quality of receiving watercourses that are subject to runoff from intensively used agricultural areas. The TMDL program can lead to better watershed management in terms of controlling nutrient loads that are released to waterbodies. In addition, vegetated wet buffer zones around the most sensitive waterbodies are promising passive measures to be tested in the future.

Abbreviations

BASIN, better assessment science integrating; CLUE-S, conversion of land use and its effect at small regional extent; L, expected output load; LU, land use; MOS, margin of safety; NPS, non-point source; PS, point source; SWAT, soil water assessment tool; SWQ, surface water quality; TMDL, total maximum daily load; TN, total nitrogen; TP, total phosphorous.

Conflict of Interest

The authors have declared no conflict of interest.

Keywords

anthropogenic land use planning, best management practices, fertilizer, nitrogen, surface water modelling

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