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Utilising Pollution Indices and Spatial Interpolation for the Analysis of Soil Pollution Risk

Heavy metal pollution from industry degrades soils and ecosystems, sometimes damaging them to such an extent that there are subsequent economic and health issues for the local population due to large-scale contamination, reduced yield and nutritional quality of crops, and the loss of arable land. This case study demonstrates how spatial interpolation using Geographic Information System (GIS) and pollution indices can be utilised to analyse pollution extent and risk.

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Abstract

Monitoring soil pollution is essential for safeguarding human health and maintaining ecosystem functioning, particularly in regions impacted by industrial activities. This study emphasises the importance of identifying and assessing soil contamination by heavy metals. These can have serious implications for yields and the nutritional quality of crops and can lead to land degradation. The study looks at two methods of pollution monitoring. First, pollution indices, such as the geo-accumulation index (I_{geo}), contamination factor (C_f) and degree of contamination (C_{deg}) indexes, can be used to determine contamination and risk of this via classification. Second, spatial interpolation using GIS with inverse distance weighting (IDW), offers a comprehensive approach to understanding the spatial distribution of pollutants. These methods are crucial for informing risk assessments, guiding remediation efforts and ensuring that land use practices do not pose a threat to public health or the environment. Continued monitoring and application of advanced analytical techniques are imperative for effective pollution management and sustainable development.

Learning Outcomes

1. Recognise and examine the potential issues caused by heavy metal pollution within a soil environment.
2. Identify the benefits of using GIS for the prediction of soil contamination.
3. Use and compare pollution-specific indices for the determination of risk from potential soil pollution.

Which Sustainable Development Goals (SDGs) Does the Case Support?

- **Goal 3:** Good Health and Well-Being – Providing advanced analysis of the local area allows for the local population to make advised decisions as to where crops can be grown to reduce the risk of health issues.
- **Goal 15:** Life on Land – Information for more targeted management of contaminated land and prevention of further contamination. Management techniques can also be utilised to reverse the land degradation caused by the contamination and subsequent abandonment of farmland in the area.

Introduction

Monitoring soil pollution is crucial for safeguarding both human health and ecosystem integrity. Contaminants such as heavy metals and other toxic chemicals can accumulate in soils, leading to loss in crop health/yield and land degradation. As these pollutants enter the food chain or leach into water sources, they pose significant risks to human health, including cardiovascular issues, neurological problems and significant illnesses including cancer. Additionally, polluted soils can disrupt ecosystems, impair plant growth, reduce soil fertility, and negatively affect local wildlife through direct health implications or loss of food sources. Therefore, consistent and comprehensive soil pollution monitoring is essential for identifying contamination sources. This can be done with the utilisation of pollution indices. Pollution risk indices are a useful tool in order to determine the full extent of contamination at a location. The locations are allocated relative risk levels using a formula and these risk levels can then be used to advise of the risks to local populations.

Spatial interpolation using Geographic Information System (GIS) utilises programmes such as ArcGIS Pro to conduct geographical analysis of data that can then be combined with maps. These visualisations can be helpful in identifying areas that have similar characteristics. Inverse distance weighting (IDW) is one of these interpolation methods, meaning it uses known values to predict values between known points, allowing a site to be analysed where you are unable to sample, or it would be to work intensively to sample an entire site. By integrating data on contaminant levels with spatial analysis, GIS mapping can offer precise predictions of pollution spread and intensity, helping to inform risk assessments and management decisions. This approach enables more effective targeting of remediation efforts and supports the development of strategies to protect human health and maintain ecosystem balance.

Pollution Sources

Industrial activities are a significant contributor to soil pollution, primarily through the deposition of contaminants such as heavy metals, chemicals, and other hazardous substances into soils via chemicals being used or how they are being released from industrial processes. This can occur through both deliberate dumping and accidental deposition through transmission through air and water systems and are often by-products of the manufacturing processes. These pollutants can accumulate in the soil, leading to long-term environmental degradation and can result in toxic effects on plants, animals, and humans. This necessitates effective monitoring and remediation efforts to mitigate the adverse impacts on soil health and ecosystem stability.

The source-pathway-receptor model is a widely used framework for understanding and managing environmental contamination, including soil contamination. An example of the implementation of this framework can be seen in Fig. 1, with tanneries as an industry example. According to this model, contamination occurs when a pollutant is released from a source, travels through a pathway, and eventually reaches a receptor (Waldschläger *et al*., 2020). In the context of soil contamination, sources can include industrial activities, agricultural practices, waste disposal, or accidental spills. Pathways refer to the mechanisms by which pollutants travel through the environment, such as disposal methods that deposit contaminants, water bodies that facilitate their movement, and rain or wind that disperse them across the air and ground. Additionally, the decay of organisms can serve as a pathway for pollutants to re-enter the soil or groundwater. Receptors are the endpoints where contamination accumulates, including animals (humans included), plants, or any other organisms exposed to contaminated soil, as well as environmental sinks like the soil itself. Understanding the interactions between sources, pathways, and receptors allows for the development of targeted interventions to mitigate the risks posed by contamination. This model is instrumental in conducting risk assessments alongside other environmental hazard indicators, such as the geo-accumulation index of heavy metals in soils and environmental risk factors (Latosińska *et al*., 2021).

Heavy metal effects of plants

The introduction of heavy metals into the food chain through their uptake by organisms presents a significant risk to human health and wildlife. A considerable proportion of heavy metal accumulation within the food chain occurs through uptake and subsequent bioaccumulation in plant root systems. This bioaccumulation of heavy metals can cause several issues for the plants such as loss in the yield of crops, poorer crop nutritional value, stress responses that alter plant physiology and, in some cases, plant death.

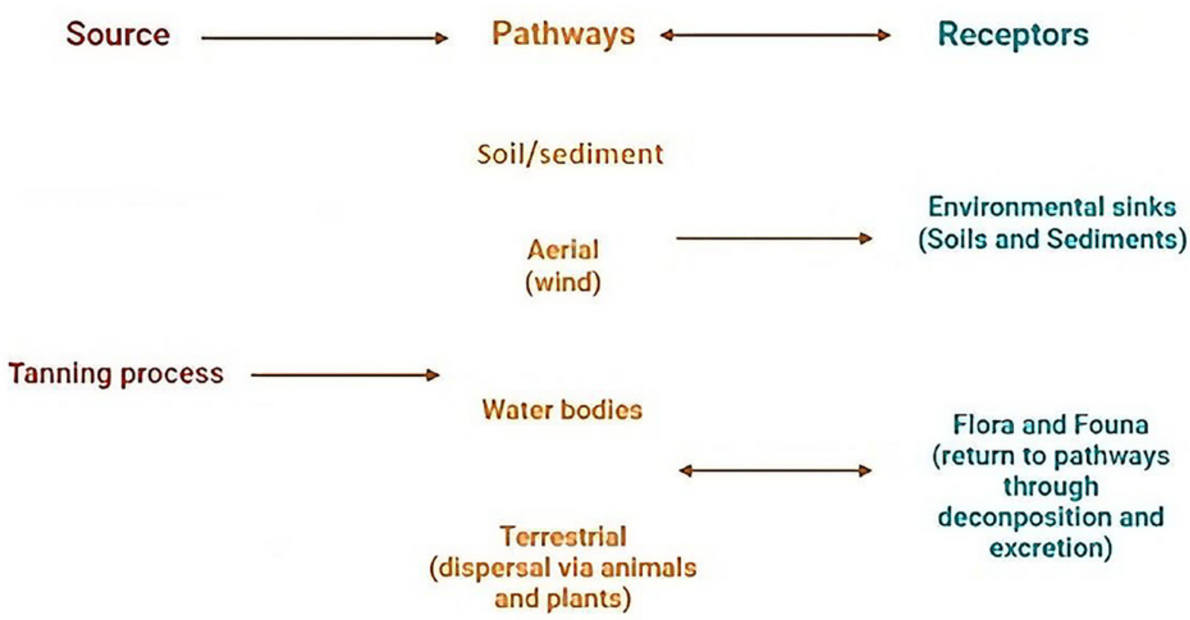

Fig. 1. Source-pathway-receptor model for the leather tanning industry.

Heavy metal effects on human and animal health

The introduction of heavy metals into the food chain through uptake and biomagnification in organisms poses a significant risk to both human health and wildlife. This process presents a serious health risk to humans, primarily through direct consumption of crops contaminated with heavy metals (Chary *et al*., 2008). While ingestion is the main route of exposure, other pathways, such as inhalation and dermal contact, also contribute a risk (Padoan *et al*., 2020). The toxic effects in humans arise when heavy metals accumulate in the body, as they cannot be metabolized effectively (Sobha *et al*., 2010). These effects may manifest as various health issues within people including birth defects, cancers, developmental issues, and death in extreme cases. The severity of these health impacts is influenced by various factors, including the individual's age, overall health, biological sex, and lifestyle (Nriagu *et al*., 2015).

Mapping Pollution

Assessing pollution levels and risk

Achieving fine spatial resolution directly from soil samples is challenging. Collecting samples from a target area takes time and money to achieve. Thus, issues arising from having large distances between sample locations (particularly for locations that are difficult or dangerous to reach due to the geography or ecology of the area) can hinder high-resolution analysis. Consequently, geostatistical spatial interpolation is employed to extrapolate data from sampled locations and use this information to predict values in unsampled areas (Kim and Choi, 2019). This method enhances spatial resolution, with larger datasets leading to more accurate predictions.

Spatial interpolation is a widely used tool in pollution assessment (e.g., Ferguson, 2017; Cui *et al*., 2018). The collected data is placed within a GIS programme such as ArcGIS Pro. In ArcGIS Pro, spatial interpolation techniques like Inverse Distance Weighting (IDW), Kriging, and Splining are essential for estimating values at unsampled locations. IDW estimates cell values by averaging sample data points, with closer points having more influence. Kriging involves exploratory statistical analysis, variogram modelling, and surface creation, considering spatial autocorrelation to provide linear unbiased predictions and an estimation error measure. Splining uses a mathematical function to fit a smooth surface through known data points, minimizing overall surface curvature, which is useful for creating continuous surfaces and handling complex topographies. The resulting spatial distribution maps offer a visual approach to identifying areas of high pollution and potential hotspots, which may not be apparent from the initial sampling locations. These maps play a critical role in informing policy makers and landowners about areas likely to exceed permissible soil contaminant limits.

Mapping pollution – case study – landfill leaching in Kent, UK

Spatial distribution is a crucial measure for assessing heavy metal contamination across a site. It is essential for identifying areas of high levels of contamination that are above permissible limits and helps in pinpointing safe and unsafe locations (where immediate action may be required) (Adimalla, 2019). Spatial analysis using IDW enables the prediction of contaminant concentrations in unsampled areas by generating a 'heat map' based on sampled site data. This method is valuable for estimating ecological and human health risks across an entire area and for identifying locations that potentially exceed established safety limits, such as the EU safe limits for heavy metals in soil. Accurate contamination predictions require high spatial resolution; otherwise, the predictions may be misleading.

Spatial distribution was utilised to map heavy metal at Milton Creek Country Park, a regenerated landfill site situated in Kent, United Kingdom. This site was tested to determine the extent of heavy metal leaching that had occurred from a capped landfill site and from other historical industrial sites nearby including brickworks, barge works, and a paper mill. In Fig. 2, the distributions of chromium as calculated by IDW can be seen. This visual representation easily identifies areas of higher pollution that may pose a risk to populations if used for recreational or agricultural processes.

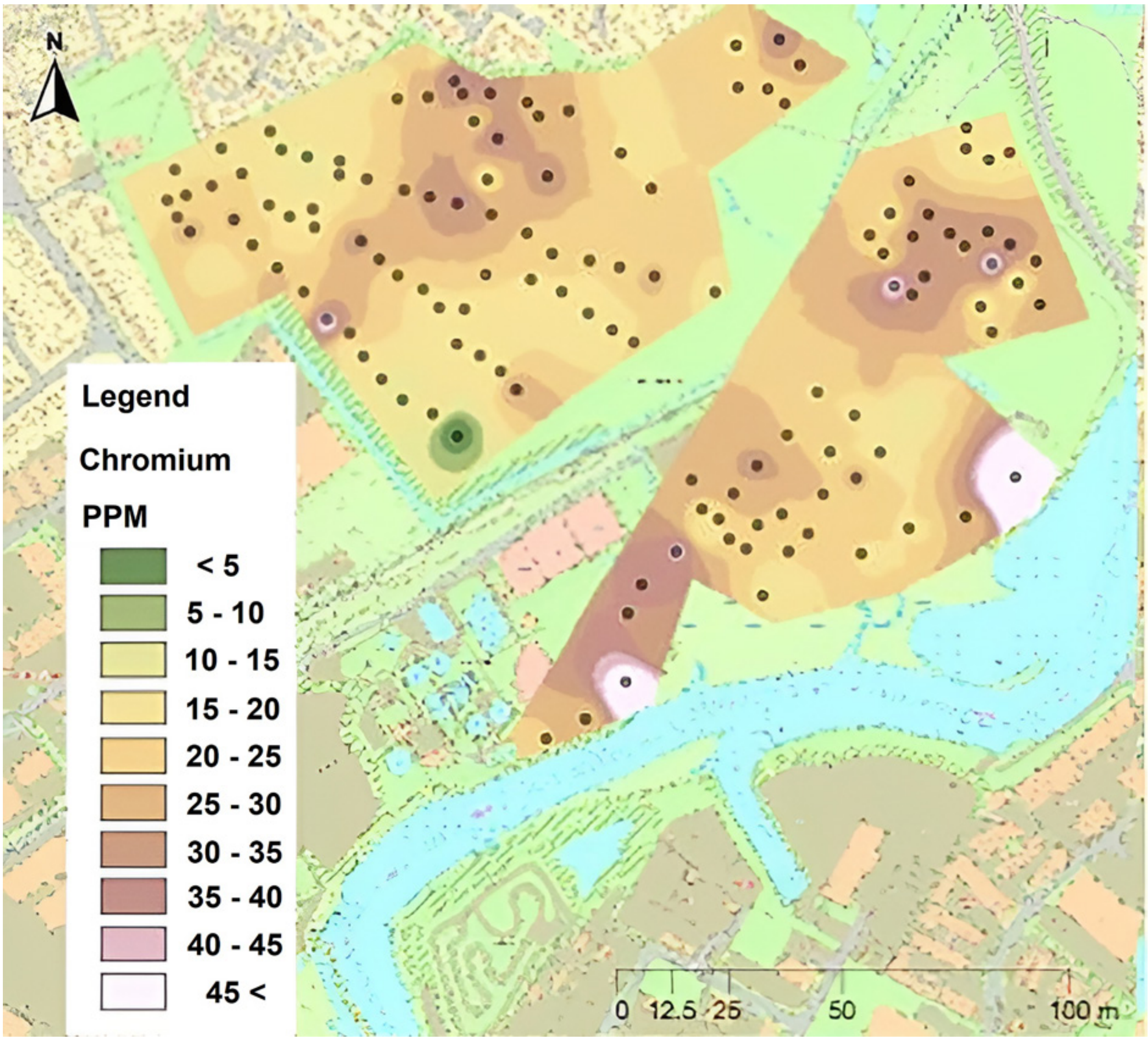

Fig. 2. Chromium distributions across Milton Creek Country Park (adapted from Ferguson, 2017).

Indices for pollution

Geo-accumulation index

The geo-accumulation index (I_{geo}) for each individual heavy metal is calculated using Equation 1, where C_n represents the measured heavy metal concentration from the sample, and B_n denotes the ambient background levels (levels from outside the analysis area) of heavy metals in the area (Zafarzadeh *et al*., 2021) (Equation 1: Geo-accumulation index).

$$I_{geo} = \log_2(C_n / 1.5B_n) \tag{1}$$

I_{geo} is classified into seven categories originally defined by Muller (1969), each indicating increasing pollution severity (Zafarzadeh *et al*., 2021). These categories are shown in Table 1.

Table 1. Description of each I_{geo} classification.

0	Igeo < 0	Practically uncontaminated
1	0 < Igeo < 1	Uncontaminated to moderately contaminated
2	1 < Igeo < 2	Moderately contaminated
3	2 < Igeo < 3	Moderately to heavily contaminated
4	3 < Igeo < 4	Heavily contaminated
5	4 < Igeo < 5	Heavily to extremely contaminated
6	5 < Igeo	Extremely contaminated

Contamination factor and degree of contamination

The contamination factor (C_f) quantifies the extent of heavy metal contamination in soil due to anthropogenic activities (Bali and Sidhu, 2021). Unlike pollution load, which requires pre-industrial background levels, C_f is based on current concentrations in the Earth's crust. C_f is calculated by dividing the concentration of each heavy metal by its ambient background concentration as outlined by Hakanson (1980). The degree of contamination (C_{deg}) is then derived from C_f, providing an overall assessment of heavy metal pollution at a site, considering all measured metals collectively (Hakanson, 1980) (Equation 2: Degree of contamination).

$$C_d = \sum C_f \tag{2}$$

Geo-accumulation indexing – case study – tanneries in Tamil Nadu, India

Tanning involves the use of various chemicals at different stages in the process, generating large volumes of wastewater at each step. As leather production increases, so does the volume of wastewater produced. This wastewater contains heavy metals, including chromium, copper, cadmium and lead, making tanneries a significant source of pollution for the surrounding environment.

Analysis was conducted at tannery sites in the region of Dindigul, Tamil Nadu, India. The extent of contamination of land surrounding the tanneries was conducted using pollution indices. This was done in an attempt to advise on reducing the uptake of heavy metal into crops and causing negative health effects if eaten; and to enable targeted remediation of the most contaminated areas. Using the classifications for I_{geo} (Table 1), the geo-accumulation index was calculated for several sites. Different methods for the calculation of B_n exist, either using ambient background or EU permissible limits (European Union, 2006). Therefore, this study calculated two I_{geo} scores using either the ambient background levels at sites or EU permissible limits. The results of these are both displayed in Table 2. In Table 2, there is evidence of contamination for

Table 2. I_{geo} classification per site for both measured ambient background levels and EU permissible limits.

	vs ambient background levels			vs EU permissible limits		
	Chromium	**Cadmium**	**Zinc**	**Chromium**	**Cadmium**	**Zinc**
Site 1	6	0	0	5	1	0
Site 2	3	0	0	3	0	1
Site 3	0	2	0	0	4	1

all metals in at least one experimental site when compared to ambient background levels or EU permissible limits. These results can be used to help demonstrate the risk of each area for the use of agricultural and recreational use, with the soil ranging from practically uncontaminated to extremely contaminated. This analysis can then be taken a step further with contamination factor and degree.

Contamination factor index and contamination degree of heavy metals

The classifications used to categorise the level of contamination are displayed in Table 3, and the results for the contamination factor index (C_f) and degree of contamination index (C_{deg}) are both shown in Table 4. Sites exhibited contamination levels for one or more heavy metals. Chromium was the only metal with a contamination factor classified as very high, but the extent signifies significant risk. Both I_{geo} and C_f showed similar patterns in predicted contamination across the sites; however, contamination factor registered more moderate levels than I_{geo}. The degree of contamination of each site assesses the overall contamination by considering all heavy metals collectively, helping to identify high-risk sites.

Table 3. Contamination factor index (top) and degree of contamination index (bottom) classifications.

$C_f < 1$	Low contamination factor
$1 < C_f < 3$	Moderate contamination factor
$3 < C_f < 6$	High contamination factor
$6 < C_f$	Very High contamination factor
$C_{deg} < 8$	Low contamination degree
$8 < C_{deg} < 16$	Moderate contamination degree
$16 < C_{deg} < 32$	High contamination degree
$32 < C_{deg}$	Very high contamination degree

Table 4. Contamination factor and degree of contamination for sites studied south of Dindigul.

	Contamination factor – C_f			
	Chromium	Cadmium	Zinc	Contamination degree – C_{deg}
Site 1	$6 < C_f$	$C_f < 1$	$C_f < 1$	$32 < C_{deg}$ = Very high
Site 2	$6 < C_f$	$C_f < 1$	$C_f < 1$	$8 < C_{deg} < 16$ = Moderate
Site 3	$1 < C_f < 3$	$3 < C_f < 6$	$C_f < 1$	$8 < C_{deg} < 16$ = Moderate

Conclusions

Two methods of monitoring contamination of industrial contaminated soils were examined within this case study, spatial interpolation using GIS and pollution risk indices. Spatial interpolation using GIS is invaluable for visualising the spatial distribution of contaminants, allowing for the identification of pollution hotspots and areas at risk. This approach not only improves understanding of contamination patterns but also aids the development of effective management strategies. Pollution risk indices provide a simple numerical value for how contaminated a site is (based on an individual or several pollutants) and can identify if local populations and ecosystems are at risk. Different indices can provide different insights regarding the extent of the contamination, depending on how they are calculated. These methods can be used for ongoing monitoring and remediation to mitigate the risks posed by soil pollution, protect human health, and restore ecosystem balance in affected areas. It demonstrates the importance of understanding how a risk score has been calculated to make an informed decision on pollution risk. The two methods could be combined for further analysis but this is complex and beyond the scope of this case study. It would, however, be a good possible future direction of study.

Exercises/Group Discussion Questions

1. Exercise 1 – Discuss what other factors might influence pollution spread and availability within soils of the sites of Milton Creek and Dindigul.

2. Exercise 2 – IDW is one type of interpolation that can be utilised for a study on soil contamination. Research and present at least one other method of interpolation, and critically compare it to IDW.
3. Exercise 3 – Compare and contrast the indices used within this case study. Why do the results differ between indices that are all meant to identify pollution risk?

Conflict of Interest

The authors have no conflicts of interest to declare.

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