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Assessing the risk of soil loss using geographical information system (GIS) and the revised universal soil loss equation (RUSLE)

Ekundayo Adesina*[1], Oluibukun Ajayi, [2], Joseph Odumosu[3], Abel Illah[1]

[1]*Federal University of Technology, School of Environmental Technology, Surveying and Geoinformatics Department, Minna, Nigeria*
[2]*Namibia University of Science and Technology, Faculty of Engineering and the Built Environment, Department of Land and Spatial Sciences, Windhoek, Namibia*
[3]*Federal University of Oye Ekiti, Faculty of Environmental Science, Department of Surveying and Geoinformatics, Oye Ekiti, Nigeria*

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Abstract

Soil erosion poses a significant environmental challenge in many developing nations, and critically evaluating the threat of soil erosion is paramount for sustainable land management practices. This study aims to identify the contributing factors to erosion and estimate the amount of soil loss in the Bosso Local Government Area of Niger State, Nigeria, using the Revised Universal Soil Loss Equation (RUSLE) model. Factors like rainfall erosivity (R), soil erodibility (K), topography (LS), cover and management (C), and support practices (P), were integrated into a Geographic Information System (GIS) environment to generate variable layers. The estimated values of $R, K, LS, C, and\ P$ ranged between 438.866 and 444.319 MJmmha-1 h-1 yr-1, 0.06 to 0.015 megajoules per hectare hour megajoules-1 hectare-1 millimeter-1, 0 and 572, 0 to 0.2, and 0 to 1, respectively. GIS raster calculations derived from these factors revealed a mean estimated soil loss rate of 0-6672.83t/h/yr-1 (tons per hectare per year). Notably, rainfall emerged as the most influential factor driving soil erosion within the study area. The study highlights the necessity for immediate intervention to mitigate soil erosion in the study area. Furthermore, to formulate effective conservation and management strategies, this study advocates for further research prioritizing severity analysis areas and estimating sediment loss across the region.

1. Introduction

The initial layer of organic and mineral components of the earth surface is known as soil (Roy et al., 2023). While its organic components come from the breakdown of living materials, its mineral components come from weathering processes (Strahler & Strahler, 2013). Soil is an essential part of the earth system that regulates hydrological cycles, and biogeochemical processes, and provides human civilizations with a wealth of resources, products, and services (Berendse et al., 2015). Soil has the most significant function and holds a central place in human connection with the physical environment, especially when it comes to economic and subsistence needs (Alewoye et al., 2020).

Soil is an abundant natural resource essential to agricultural productivity (Dutta et al., 2015). Therefore, the productivity of soil is crucial to the well-being of both the current and future generations, especially in a nation where agriculture is one of the primary sources of income for the populace (Pal & Chakrabortty, 2022b). But since humans first arrived on the planet, it has deteriorated dramatically (Adediji et al., 2010; Ugese et al., 2022; Balabathina et al., 2020; Yesuph & Dagnew, 2019). Land degradation puts pressure on the global economy and ecology, and it is also a menace to food production, food security, and the preservation of natural resources, especially in Africa (Balabathina et al., 2020; Belayneh et al., 2019). One of the problems the continents have faced is the loss of land's ability to produce due to the depletion of soil fertility, soil biodiversity, and other land surface resources because of the physical, chemical, and biological characteristics of soil deterioration (Egbueri et al., 2022; Getu et al., 2022).

These days, many natural and human-induced activities have negatively disrupted the ability of land to supply essential nutrients and sustain the development of plants. According to Pal et al. (2021), Chakrabortty & Pal (2023) and Pal & Chakrabortty (2019a), soil erosion caused by climate change continues to be one of the most dangerous problems facing the world's ecosystems in the twenty-first century. Hurni et al. (2015) estimated that erosion negatively affects around 50% and 80% of the world's pasture and agricultural land, respectively. While

***Corresponding Author**

*(adesinageoworldsolutions@gmail.com) ORCID 0000-0001-9526-4540
(oajayi@nust.na) ORCID 0000-0002-9467-3569
(joseph.odumosu@fuoye.edu.ng) ORCID 0000-0003-1604-4924
(abelillah56@gmail.com) ORCID 0009-0002-6315-2821

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soil erosion is a global concern, its effects are particularly noticeable in nations like India with dense populations and complicated topography (Pal et al., 2022a; Pal & Chakrabortty, 2019b).

In most of the third-world countries in Africa, anthropogenic forces such as deforestation, steep slope cultivation, overgrazing, over cultivation, and unsustainable use of land resources have had significant impacts on soil erosion (Pal et al., 2022b; Pal & Chakrabortty, 2019b; Roy et al., 2023). Estimates of the loss in agricultural output in Africa as a result of soil erosion range from 2 to 40% (Smaling & Oenema, 2020). Flooding and soil erosion-related land degradation is a common occurrence throughout Sub-Saharan Africa (Odumosu et al., 2014). According to Kiptoo & Mirzabaev (2014), erosion affects more than 61% of Tanzania's total land area, and it destroys 15% of Malawi's and Zambia's arable land.

A significant issue facing Nigeria, a developing nation in sub-Saharan Africa where agriculture is one of the primary sources of income for over 75% of the people, is the country's ongoing decline in agricultural output (Andualem et al., 2020; Tsegaye & Bharti, 2021). Soil erosion-induced deterioration of land resources is the primary cause of this. For example, in the study by FAO (2015), it was projected that during the previous 15 years, from 1985 to 2010, soil erosion cost the nation 1.9 billion US dollars. Deressa et al. (2020) estimated that Nigeria loses over 2 billion tons of productive topsoil per year or 8% of all land surface erosion. It accounted for around 1 mm of the vertical soil depth nationwide and cost the nation 3% of its Agricultural Gross Domestic Product (GDP) (Balabathina et al., 2020).

In addition to causing a decline in agricultural productivity, water-induced soil erosion has also led to an increase in sediment output and reservoir layering from sedimentation. As a result, Nigeria has the greatest rate of soil erosion in all of sub-Saharan Africa (Ayalew et al., 2020; Erol et al., 2015; Gessesse et al., 2015).

Despite having plans in place since 1980 to reduce soil erosion, the country has not been able to carry them out because of gaps and limitations with the implementing body as well as a lack of community-based discussion about land reforms and reclamation (Legesse et al., 2004; Getu et al., 2022). The issue in the Nigerian highlands became more severe due to poor and antiquated farming practices, mismanaged land cover degradation, a lack of community involvement, unmanageable planning units, and a lack of in-depth knowledge and expertise in the characterization of watersheds (Hurni et al., 2015).

The Nigerian highlands are susceptible to soil erosion, which causes an annual loss of over 1 billion tons of net soil and a 2.2% reduction in land productivity (Getu et al., 2022). Among the main driving causes in the Nigerian highlands are extensive deforestation to accommodate the increase of agricultural land and the resulting need for wood, grazing on steep slopes, population growth, and the ensuing strain on arable areas (Teshome et al., 2021). Some farm plots these days are in a condition that makes rehabilitation difficult. Similar to this, soil erosion has emerged as one of the main issues facing the Bosso Local Government Area in Minna, Niger State, Nigeria. This is due to a combination of the region's varied terrain, fluctuating climate, and human activity.

Soil erosion is currently a serious concern to food security for smallholder farmers due to the depletion of soil fertility and the ensuing decline in agricultural production. The main impacts of erosion in the Bosso Local Government Area of Minna, Niger State, Nigeria, include soil loss, productivity drop, soil depth decline, plot size reduction, soil color change, and gully development. The Bosso Local Government of Minna, Niger State, Nigeria has reduced the vulnerability of soil erosion; nonetheless, there is still a dearth of objectively measurable quantitative data on the extent of soil erosion, which could inform methodological choices for conservation planning.

Models are crucial in easing these restrictions since, even though field studies are highly helpful in characterizing the scope and size of field conditions, they are often expensive, time-consuming, and complicated (2020; Ghafari et al., 2017; Tsegaye & Bharti, 2021; Aneseyee et al., 2020). Even though several soil erosion models have been created since the 1980s, the majority of them are regionally restricted and challenging to extend (Bastola et al., 2019). It is a result of the models' internal data not taking into account universal standard circumstances during their evolution. Among the frequently utilized methods for estimating soil erosion and sediment loss are the Universal Soil Loss Equation (USLE) (Wischmeier & Smith, 1978), Soil Water Assessment Tool (SWAT) (Piniewski et al., 2019), Sediment Delivery Distributed Model (SEDD) (Ferro & Porto, 2000), Revised Universal Soil Loss Equation (RUSLE) (Renard, 1997), and Agricultural Non-Point Source (AGNPS) (Williams et al., 2008). The USLE has a few drawbacks despite being a strong empirical model that is very simple at both the regional and national levels.

According to Tesfaye (2015), a few of these restrictions are as follows: Its application in forest land, rangeland, and disturbed areas was limited. It was designed to predict soil loss from agricultural fields; it does not take into account gully and stream channel erosions; it assumes uniform runoff throughout the catchment; it is not designed to operate at large scales; it cannot handle undulating terrains; it does not examine the relationship between rates of infiltration and intensity of runoff; and it does not account for sediment deposition at the lowest point of concave slopes. However, the RUSLE model (Pal & Chakrabortty, 2019a) is an enhanced version of the first USLE model. According to Bombino et al. (2004) and Egbueri et al. (2022), the RUSLE model has several improvements when it comes to analysis of the factors that govern soil erosion, considering various Land Use Land Cover (LULC) scenarios, such as forestlands, and rangelands (Ashiagbor et al., 2013; Colman et al., 2018; Thapa, 2020).

According to Haile & Fetene (2012), the RUSLE model is a cost-effective soil loss assessment tool for successful conservation planning in locations where the necessary quantity and kind of data are sufficiently accessible. According to Belayneh et al. (2019), the RUSLE model is more effective at forecasting the long-term average yearly rate of soil erosion on-field slopes due to its simplicity, flexibility, compatibility, and application with the limited amount of data that is currently available (Zanchin et al., 2021).

Since each cell in a raster picture now represents a field-level event, the development of GIS technology has made it possible to compute the soil erosion equation (Ayalew & Selassie, 2015). Because of this, several studies have discovered that the GIS-integrated RUSLE model produces findings even for vast regions and is a cost-effective soil loss estimating tool for efficient conservation planning. Thus, the purpose of this study is to assess the yearly soil loss rate in the Bosso Local Government of Minna, Niger State, Nigeria, and to ascertain the relative impacts of erosion-controlling elements using the RUSLE model and Arc GIS.

2. Materials and methods

Data

The rainfall data used for this study was obtained from https://dsp.imdpune.gov.in/, while the soil data was downloaded from the Soil Grids website (https://soilgrids.org/). These datasets are publicly available (open source). The study also used the SRTM Digital Elevation Model (DEM) downloaded from the United States Geological Survey (USGS) Earth Explorer (https://earthexplorer.usgs.gov/) with a resolution of 30 m. Landsat8 imageries of the year 2023 was used to prepare land use land cover map and the NDVI map. Table 1 presents the data used for the study and their corresponding sources.

Table 1: Input data used and corresponding sources.

Input data	Data source
Daily rainfall	IMD stations and WRD stations (https://dsp.imdpune.gov.in/)
Soil	Soil Grids (https://soilgrids.org/)
DEM	USGS Earth Explorer
Landsat8	(https://earthexplorer.usgs.gov/)

Data processing and RUSLE factor generation

The study employed remote sensing and field data integrated into a GIS framework to generate the RUSLE input parameters for predicting soil erosion. The various RUSLE factor maps were designed using Arc GIS 10.4. The RUSLE model was used to integrate these factor images and determine the annual severity of soil erosion rates.

RUSLE model description

RUSLE is the most well-known and often-used soil erosion model for agricultural watersheds globally (Kebede & Fufa, 2023). It was selected for this study based on the recommendations of Renard (1997) and Wischmeier & Smith (1978). According to Moisa et al. (2022), RUSLE model is flexible enough to modify parameters and situations, making it easy to integrate with a GIS for geographical analysis. It also analyses soil erosion adaptively.

The model formulation considers five parameters: rainfall, soil, topography, LULC, and conservation practices. Renard et al. (1991) produced the general universal equation for soil loss, which is as follows:

$$A = R \times K \times LS \times C \times P \qquad (1)$$

where A is the average annual soil loss (tonnes ha-1 year-1), R is the rainfall-runoff erosivity factor (MJ mm ha-1 hr-1 year-1), K is the soil erodibility factor (tonnes ha-1 MJ-1 mm-1), LS is the slope which is defined as the ratio of soil loss from the field slope length under identical conditions, and Length of Slope Factor (defined as the ratio of soil loss from the field slope gradient under otherwise identical conditions), P is an abbreviation for the contributing conservation practice factor, and C stands for cropping management element. Secondary data acquired for the analysis included soil and meteorological data, satellite imagery, rainfall data, and SRTM DEM. Sections 2.1 through 2.6 provide information about the study area and the parameters of the soil-loss model.

2.1. Study area

Bosso Local Government Area of Niger State was used as the study area for this study. It covers about 72 km^2 and has a rocky environment with a typical middle belt zone climate (Adesina et al., 2023). The mean monthly temperature is 30-50^{0}C (83^{0}F) and the rainy season starts in April of every year. Literature suggests that gully development is influenced by the underlying geology, with rock types being key factors. According to Abdulfatai et al. (2014), the geological map of Niger State shows three main types of lithology: fine-grained biotite granite, porphyritic and biotite hornblende granite, and undifferentiated schist. Figure 1 presents the map of the study area.

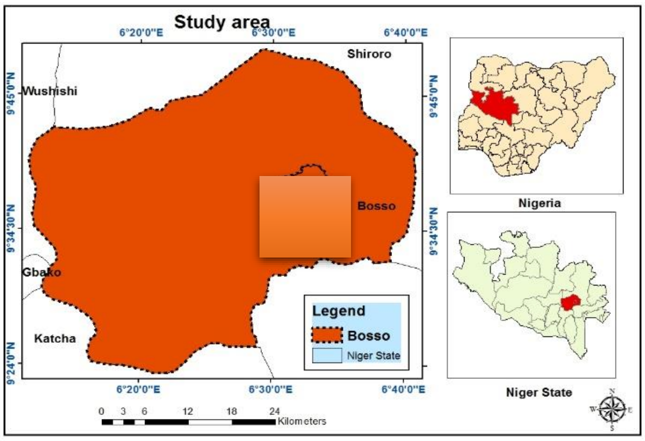

Figure 1. Study area map of Niger State's Bosso Local Government area

Data Analysis and Derivation of RUSLE Parameters

2.2. Rainfall erosivity factor (R)

The yearly average of the number and severity of individual rainstorms is known as rainfall erosivity (R), and it is proportionate to the total annual precipitation. R stands for the two storm components that are most crucial in determining a storm's erosivity: the amount of precipitation and the highest level sustained for an extended length of time. Previous studies have demonstrated a clear relationship between soil loss in agricultural regions and the strength and duration of each downpour (David Raj & Kumar, 2022; Yousuf et al., 2022; Kushwaha et al., 2022; Sharma et al., 2023). The rainfall erosivity factor in RUSLE must take into consideration the effect of raindrops as well as the expected amount and rate of runoff from the rainfall. According to Morgan et al. (1984), the formula in Equation 2 was used to determine the amount of rainfall in the study area.

$$R = 38.5 + 0.35P \tag{2}$$

where R= Rainfall erosivity factor, P = Mean annual rainfall in mm

2.3. Soil erodibility K-factor

The soil erodibility factor (K) quantifies how easily soil particles can be transported or carried away by rain and runoff. The K factor depends on the soil profile's permeability, organic matter content, and texture (Erencin, 2000). The quantity of soil loss per erosion index unit from the plot size unit is known as the soil erodibility factor (K) (Wischmeier & Smith, 1978). On a particular terrain, other factors that affect the pace of soil erosion include crop productivity, precipitation, and alternative land uses. The properties of the soil that affect soil erodibility include soil texture, soil structural stability, soil permeability and infiltration, organic matter, and soil mineralogy (Singh et al., 1992). Since it is expensive and time-consuming to directly measure K from an experimental run-off plot, Wischmeier & Smith (1978) developed a simple nomograph. Equation 3 was used to calculate the K factor for each grid point in the watershed of the study area (Reddy et al., 2016).

$$K = 0.2 + 0.3\exp\left(0.0256 * S_a * \left(1 - \left(\frac{S_i}{100}\right)\right)\right) * \left(\frac{S_i}{C_i + S_i}\right)^{0.3} * \left(1.0 - \frac{0.25 * C}{C + \exp(3.72 - 2.95C)}\right) * \left(1.0 - \frac{0.7 * SN}{SN + \exp(-5.51 + 22.9SN)}\right) \tag{3}$$

where Sa = Sand %; Si = Silt %; CL = Clay %; SN = 1-(Sa/100); C = Organic Carbon

Higher values indicate higher sensitivity, with potential k-factor values listed in Table 2.

Table 2. The different ranges of the K factor and their meanings

Soil types	K factor	Meaning
Rocky soil/deserted land	0-0.2	Very low erodibility
Silt or clay loam	0.2-0.5	Low erodibility
Sandy loam	0.5-0.8	Moderate erodibility
Sandy soil/ gravelly soil	0.8-1.0	High erodibility

The study area's soil erodibility factor was calculated by implementing Equation 3 in ArcGIS 10.4.

2.4. Slope length and steepness LS-factor

The topographic factor is the relationship between slope length (L) and slope steepness (S). It illustrates how topography affects erosion. The L and S variables show how vulnerable a particular site is to topographic erosion. The digital elevation model (DEM) from the Shuttle Radar Topographic Mission (SRTM) served as the source data for estimating the L and S components. We used the maximum downhill direction approach to determine the slope to get the LS values. The angle established between each 30 x 30 m raster cell and its lowest neighbouring cell was utilised to get the slope value for each cell. Tarboton (1997) developed the "D" (infinite directions) technique, which predicts the scattered or grilled flow from slopes to lower neighboring cells for each cell and used it to predict the flow direction. Using the flow direction raster, the computation of flow accumulation involved determining the number of cells that contributed flow to each cell. Using ArcGIS, it was possible to estimate the DEM sinks' filling, slope angle, flow direction, and flow accumulation. Moore & Burch (1986) gave the following formula for LS factor computation:

$$LS = \left(\frac{\lambda}{72.6}\right) m^{\times[}(65.41 \times \sin 2\theta) + (4.56 \times \sin\theta) + 0.065] \tag{4}$$

where λ= slope length in meters. θ= Angle of slope

m= dependent on slope: i). 0.5 if slope > 5% ii). 0.4 if slope is between 3.5% and 4.5% iii). 0.3 if slope is between 1% and 3% iv).0.2 if slope is less than 1%.

Using the raster calculator, the slope length and steepness factor equation from Moore & Burch (1986) was used for this study and it was implemented in the ArcGIS 10.4 environment.

2.5. Cover management C-factor

One of the most important RUSLE components which shows how easily controllable the soil conditions are to reduce erosion is the C-factor. The calculation of C factor is done using weighted average soil loss ratios (SLRs), which are calculated as the ratio of soil loss for a particular status of vegetative cover over a given period as compared to the soil loss that occurred on the unit plot during that period. This site-cover and site-management-related C-factor assesses the correlations between several factors. Several studies have experimented with soils covered in different kinds of vegetation types to study the C factor (Reddy et al., 2016) and the findings proved that several factors influence soil loss. Nonetheless, the slope's length, steepness, and vegetation cover factor are the most crucial factors. Assigning C values to various LULC classes based on field research or literature is necessary to obtain the C factor map.

Chalise et al. (2019) proposed that the cover management factor (C), which monitors the dynamics of plant development and rainfall, is the most spatiotemporally sensitive factor (Nearing et al., 2004). It takes into consideration the impact of cropping and other practices on erosion rates. This factor, which compares the similar loss from continuous bare fallow to the soil loss from precipitation erosion under certain land and vegetation circumstances, is defined as a non-dimensional number between 0 and 1 (Wischmeier & Smith, 1978). The study looked at several land use types, which were then integrated into a single class using ArcGIS 10.4 software after being transformed from a raster map to a polygon using the raster-to-polygon tool. Each land-use example has a C value, which runs from 0 to 1, according to sources (Erencin, 2000; Panagos et al., 2015a; Panagos et al., 2015b) (Table 3). A larger C value denotes significant odds of soil loss, whereas a smaller C value denotes no loss.

Table 3. Land use land cover and C factor

S/No.	LULC	C Factor
1	Water bodies	0.00
2	Forest	0.03
3	Flooded vegetation	0.01
4	Crop land	0.21
5	Barren land	0.45
6	Built up area	0.70
7	Scrub land	0.03

2.6. Support practice P-factor

The support practice component indicates the rate of soil erosion in accordance with agricultural practice. Three strategies are necessary to control erosion: terraces, cropping, and contouring (Heald et al., 2015). Kouli et al. (2009) stated that the contouring approach with P values is based on a scale of 0 to 1, where 1 represents a non-anthropogenic.
erosion facility and 0 represents suitable anthropogenic erosion.

Table 4. P factor values for slope (Kumar et al., 2016b

S/No.	Slope %	P Factor
1	0.0-7.0	0.55
2	7.0-11.3	0.60
3	11.3-17.6	0.80
4	17.6-26.8	0.95
5	>26.8	1.0

Conversely, the P factor is dependent on land management activities carried out by humans. According to Ganasri & Ramesh (2016), there is a relationship between the rate of soil erosion and straight-row upslope and downslope tillage farming techniques. Runoff is the primary cause of runoff-triggered soil erosion. Therefore, different conservation support techniques can lessen the hydraulic forces, runoff velocity, and runoff concentration. A P factor value between 0 and 1 indicates a strong conservation practice factor that helps to prevent soil erosion, while a value of 1 indicates a bad practice factor that causes soil loss.

The value of the P factor was assigned based on insights derived from the LULC as surveying the entire watershed was impractical. The RUSLE model parameters were integrated using the ArcGIS 10.4 toolbox, yielding the mean yearly soil loss for the research area map, as indicated by Equation (1).

3. Results and discussion

The rainfall erosivity factor (R) values ranged from 438.866 to 444.319 mm/ha/yr, whereas the topographic factor (LS) values ranged from 0 to 572, according to the obtained results. The range of values for the soil erodibility factor (K) was 0.06 to 0.015. Throughout the entire region, the values of the support practice factor (P) ranged from 0 to 1. The cover management factor (C) values fell between 0.01 and 0.25.

RUSLE, an experimentally based modelling approach, uses five variables to forecast the long-term average yearly rate of soil erosion on slopes. It computes soil loss under comparable topographical and climatic conditions, according to Prasannakumar et al. (2012). Five parameters that exacerbate site erosion were compounded using the ArcGIS raster calculator to produce a potential erosion map of the study area. Most of the land is in the low erosion hazard zone which amounted to about 6672.83 t/ha/yr, based on the information.

Using information from multiple sources, this study used ArcGIS software to compose a potential soil erosion rate map for the study area. Other research projects with similar geographic characteristics also used the same methodology (Prasannakumar et al., 2012; Panagos et al., 2015a; Panagos et al., 2015b; Kumar et al., 2016a). Considering the R-factor, LS-factor, K-factor, P −factor, and C-factor appropriately will help reduce the amount of uncertainty in erosion modelling.

Details of the obtained result which consists of the components of soil loss modelling used for the study and their discussions are presented in sections 3.1–3.6.

3.1. Rainfall erosivity factor (R)

The study area's average annual rainfall erosivity factor is shown in Figure 2.

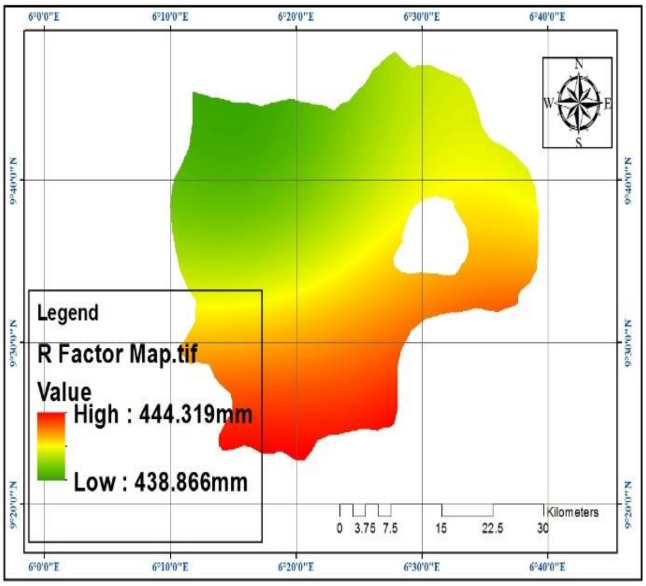

Figure 2. Rainfall erosivity factor map

Using a map of the rainfall erosivity factor, Figure 2 depicts the distribution of rainfall in the study area. This is particularly important because erosion cannot occur until the erosivity factor is greater than the erodibility factor. The runoff factor was found using the Climatic Study Unit Time Series (CRUTS), which includes monthly time series data on temperature, precipitation, cloud cover, and other variables and spans the Earth's surface from 1905 to 2022. Gridding the datasets to a resolution of 0.5 x 0.5 degrees is based on an analysis of over 4000 individual weather station records. The average yearly rainfall map in Figure 2 and the computation by Morgan et al. (1984) indicate that the study area receives between 438.866 and 444.319 MJmmha1yr1 (megajoules millimeter per hectare per hour per year). However, additional factors that might result in the loss of the soil surface and induce erosion, such as slope, vegetation cover, and rainfall intensity, also affect soil erosion. Put differently, when the rainfall becomes heavier and more intense such that it exceeded 25 mm per hour, it caused serious erosion.

3.2. Sol erodibility factor (K)

The key factor influencing the soil's ability to erode is its texture, which is determined by the various soil types. The K factor is impacted by a few more elements as well, such as organic matter and soil texture. Figure 3 shows a map with the soil erodibility factor of the study area overlaid on it while Table 5 displays the different soil types within the study area together with their corresponding volumes and erodibility factors (k).

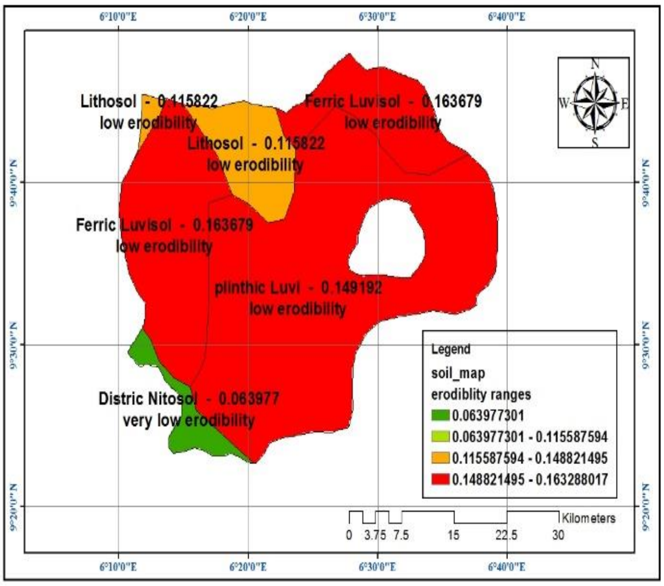

Figure 3. Map of the study area's soil erodibility factor

The Food and Agricultural Digital Soil Map of the World (DSMW), a digitalized version of the FAO-UNESCO soil map of the world produced in a paper edition at a scale of 1:5000000, provided the data necessary to compute the erodibility factor k. It displays 4931 soil associations, or mapping unit—sets of different soil types combined. According to Table 2, the erodibility of the soil in the study area ranges from 0.06 to 0.015 megajoules per hectare hour megajoules-1 hectare-1 millimetre-1. Table 5 shows the types of soil in the study area.

Table 5. Types of soil in the study area

Soil type	Sand %	Silt %	Clay %	OC %	(K) Factor
Distric Nitosol	38.9	17.6	43.6	1.57	0.06
Ferric Luvisol	74.6	9.6	15.9	0.39	0.16
Lithosol	58.9	16.2	24.9	0.97	0.12
Plinthic Luvisol	69.9	10.5	19.5	0.73	0.15

3.3. Slope length and slope steepness factor (*LS*)

The slope steepness and length that ArcGIS generates from the DEM served as the basis for this topographic component. Calculating the LS factor involves using the slope and flow accumulation percentages. Figure 4 shows the digital elevation map of the study area, while Figure 5 displays the slope length and steepness factor.

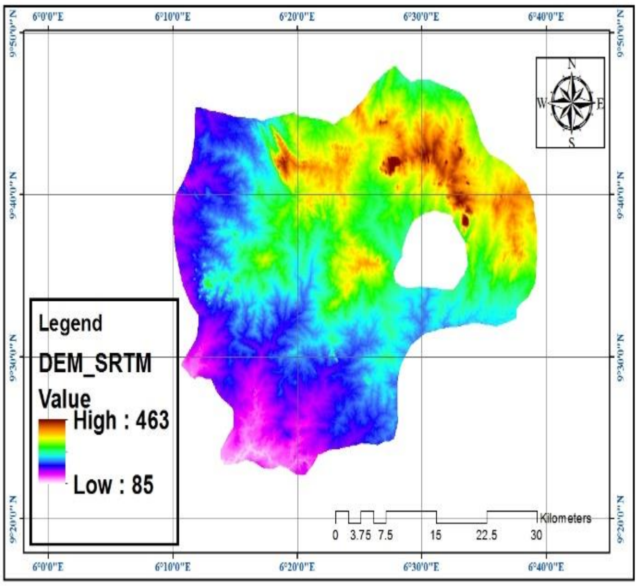

Figure 4. Digital elevation map (DEM) of the study area

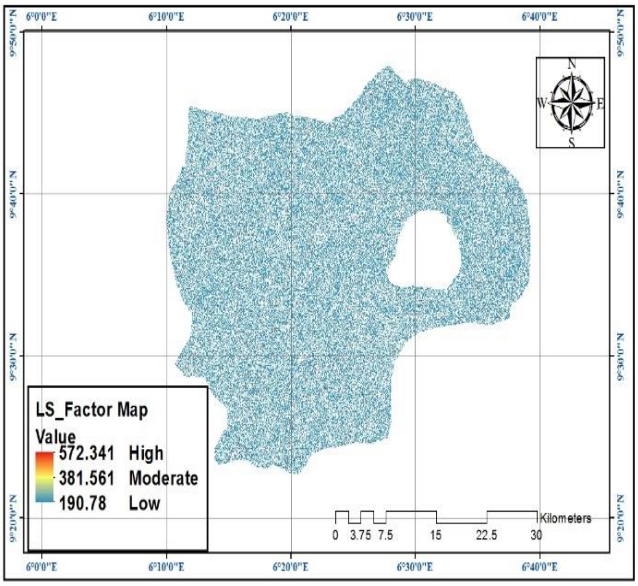

Figure 5. Slope length and steepness factor map of the study area

Using the 12.5 m resolution Digital Elevation Model (DEM) of the study area, the slope length and steepness factor were computed. The different support practice variables for conservation strategies are shown in Table 5. As seen in Figure 5, soil erosion affected topography through slope length and steepness, with steeper slopes resulting in more intense runoff, and this influence was most noticeable between 0 and 572. The higher number suggests that the deep valley and rough terrain are naturally erosive. The watershed's south and southwest, where the river valley is excessively wide and deep, have higher *LS* values. This area is especially susceptible to soil erosion in the study area due to its high runoff and topographic erosion. Table 6 lists the various LULC classes' *C* and *P* factors.

Table 6. *C* and *P* Factor value of different LULC

Catchment	*C* Factor	*P* Factor
River	0	0
Lake	0	0
Medium Dense Forest	0.05	1
Temperature Forest	0.2	1
Sedimentation	0.18	1
Agriculture Land	0.2	0.5
Fallow Land	0.18	1
Built-up Area	0	0
Waste/Barren Land	0.18	1

3.4. Cover and management *C*-factor

The Land Use and Land Cover data produced from Landsat 8 OLI data were used to estimate the *C* factor. The *C* factor had a value between 0 and 0.2. The four-land use and land cover classes assigned in this study are agricultural land, barren land, built up area, and vegetation (Figure 6). The land receives the highest value (0.2) because it is bare. While Figure 7 shows the Conservation factor map.

The higher numbers imply that there is either very little or no plant cover, which increases the rate of soil erosion and leaves the soil more susceptible to it. The lower *C* value (0.05) indicates a substantial plant cover that inhibits or stops soil erosion.

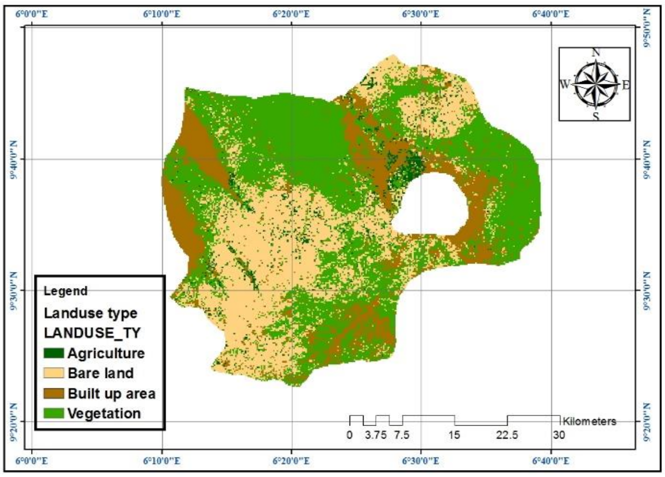

Figure 6. Land use map of the study area

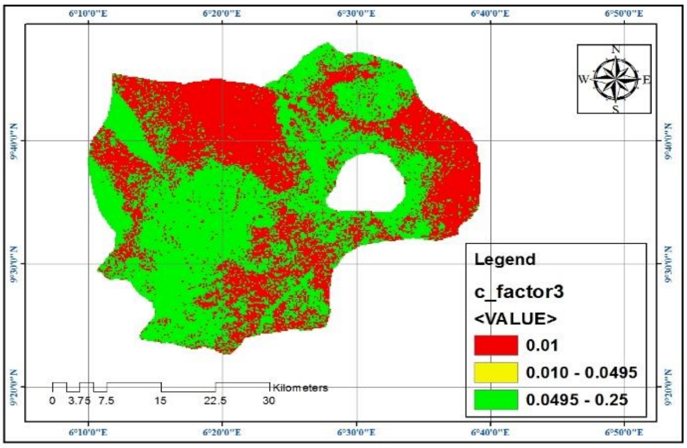

Figure 7. Conservation factor map

The conservation factors in Figure 7 span from 0.01 to 0.25, indicating that while efforts are being made to decrease the rate of soil erosion in the study area, they are still extremely inadequate. In the study area, green areas signify conservation initiatives that have reduced erosion, whereas red spots denote severe or high severity. Table 5, which is integrated into the GIS environment, displays the conservation factor value for various land use and land cover characteristics in the study area.

3.5. Conservation support practice factor *P*-factor

The source image for the *P* factor estimation is the same land cover and land use map. The *P* factor in RUSLE is the ratio of soil loss with straight-row upslope and downslope tillage to soil erosion with a particular support practice. The lower value denotes the implementation of conservation measures aimed at protecting agricultural land's soil. Gaining knowledge of the mechanisms underlying human-caused soil erosion raises the *P* factor. The study area's support practice component is shown in Figure 8, where values vary from 0 to 1. This is because conservation practices are seen in agricultural land. Table 7 presents the list of the different practice variables influencing support for different conservation initiatives.

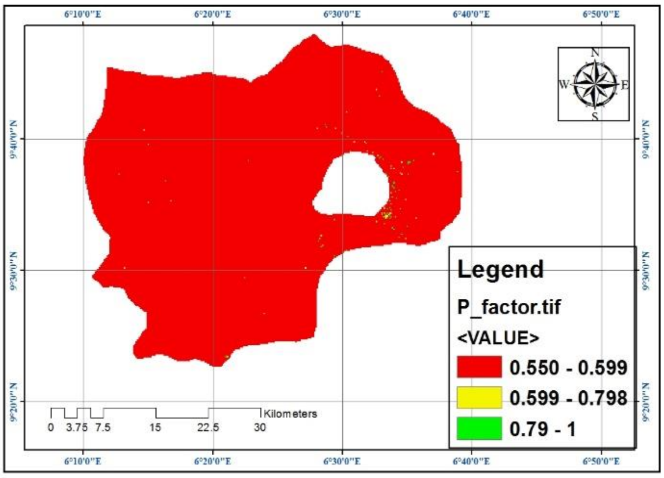

Figure 8. Support practice factor map of Bosso Local Government

Table 7. Support practice elements for various conservation practices (Singh et al., 1992)

Slope (%)	Contouring	Strip cropping	Terracing
0-7	0.55	0.27	0.2
7-11.3	0.66	0.3	0.12
11.3-17.6	0.8	0.4	0.16
17.6-26.8	0.9	0.45	0.18
26.8>	1	0.5	0.2

The Support Practice Element (SPE) of the RUSLE model is used to evaluate how well conservation practices reduce soil erosion; a score of 1 indicates a good result.

3.6. Soil loss estimation

The mean annual soil loss in the study area ranges from 0-6672.83t/h/yr-1 ((ton per hectare-1 per year-1). The loss rate, though significant, is still small compared to the larger expanse that is unaffected by the soil erosion in the study area as shown on the map (Figure 9), the red color depicts area with low erosion rate while the orange and green color depicts area with moderate and high soil loss rate, respectively, which is evenly spread across the study area.

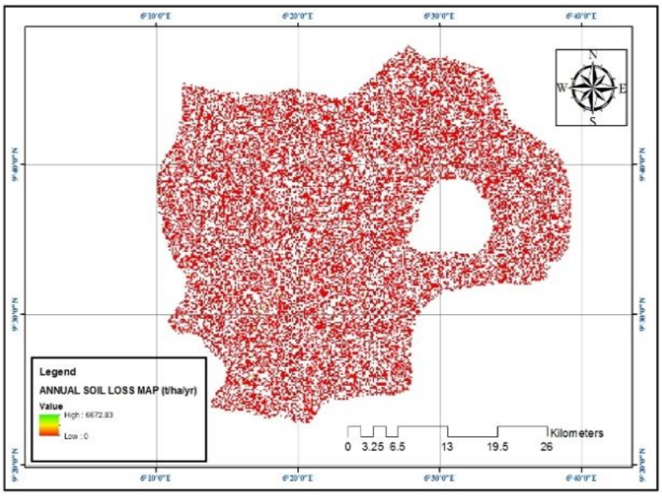

Figure 9. Mean annual soil loss map

4. Conclusion

Using remote sensing, GIS, and existing data sets in conjunction with the RUSLE model, this study has assessed the soil erosion rate of the study area. The study yielded practical outcomes that can facilitate focused attention towards an improved soil conservation strategy for the study area. It makes it possible to identify areas at high risk of soil erosion and provide soil conservation efforts with targeted attention.

This study examined the eroding properties of soil, the impact of cover and management techniques on the erosion process, the influence of rainfall and the runoff it generates, the magnitude of yearly soil losses, and the impacts of topography on erosion rates. The predicted yearly soil loss indicates that soil erosion poses a risk to the sub-catchment area's agricultural productivity and sustainability. It also highlights the possibility that if prompt corrective action is not provided, the issue may worsen in the future.

The study yielded significant results, such as thematic maps that illustrate the various factors that govern erosion and the estimated potential and actual soil loss rate. These maps can serve as a basis for developing appropriate strategies and action plans to protect soil and improve management. They will also guide the decision-making processes.

Furthermore, the RUSLE model's results offer first-hand knowledge to local government and non-governmental organizations, and land management specialists to help them create programs for immediate attention and long-term soil conservation structures, particularly in areas where soil erosion rates are high enough to become irreversible. Policymakers, development planners, local land managers, concerned NGOs, and other responsible authorities will find this study useful, especially if they are interested in creating soil conservation initiatives and sensible management plans for the sub-catchment region.

Our estimate of soil erosion gives a notional basis that the region needs rapid action to support the soil of the area given the extent of the watershed area, the severity of the problem, and the resources. To create workable strategies for conservation and management, more investigation into the severity analysis area prioritization and sediment loss estimation in this area is strongly recommended.

Author Contributions

The contributions of the authors to the article are as follows: **Author1**: Conceptualization, Investigation, Supervision, and validation. **Author2**: Visualization, study supervision, Writing-Reviewing and Editing. **Author3**: Visualization, Investigation and Draft Review. **Author4:** Data collection and processing, Software and methodology, writing original draft.

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

Research and publication ethics were complied with in the study.

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Comparative analysis of noise pollution in high traffic zones of Faisalabad and Lahore

Zain ul Abideen[1], Kanwal Javid*[1], Warda Habib[1], Saddam Hussain[1]

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Abstract

The chaotic and loud traffic in crowded and densely populated urban areas poses challenges for environmental and urban experts in developing more efficient transportation plans that enhance both quality of life and environmental conditions. Lahore and Faisalabad, being prominent industrial cities in Pakistan, attract a large population due to their industrial importance. However, they encounter significant traffic problems, leading to a noisy and unpleasant environment. Using a Mesteth digital sound meter, noise level samples were gathered from various locations in Lahore and Faisalabad. In Lahore, sites included Jail Road, GPO Mall Road, Badami Bagh Bus Station, Thokar Niaz Baig, Gajumata Bus Station, Shahdra Metro Station, Kalma Chowk flyover, Mochipura Mor, and Babu Sabu toll plaza. In Faisalabad, sites such as GTS Square, Clock Tower, Railway Station, Santayana Road, Allied Mor Bus Stop, Narwala Road, McDonald's Road, D Ground Park, and Chenab Club were sampled. Fieldwork spanned from May 20th to June 23rd, 2022, conducted during morning and evening hours to capture peak and low traffic periods. Measurements were taken at a height of 1.2 meters from the ground and 1 meter away from the traffic flow line as per ISO standards. Data encompassed various zones, including heavy traffic, commercial, semi-commercial, and residential areas. The collected data was organized into Microsoft Excel sheets and subsequently inputted into ArcGIS 10.5 for mapping using Inverse Distance Weighting. After comparing the noise level values of both cities, it can be concluded that Lahore is facing more noise pollution as compared to Faisalabad due to the high noise pollution on the scale. The minimum amount of noise pollution recorded in these cities is 70 dB and the highest amount of noise pollution recorded in these is near 90 dB. This condition is very dangerous because according to the WHO the standard noise level in Pakistan is 75dB.

1. Introduction

Noise pollution is an environmental threat that disrupts human activities and stability. The noise is a phenomenon that has both psychological and physiological impacts on people. It is a major problem for the environment in numerous metropolitan regions. Additionally, there are several types of sources of noise. Particularly, traffic noise has a significant impact on citizens near densely populated areas. Noise pollution is rapidly increasing because of heavy traffic on the roads, vehicle dysfunction, a lack of awareness, and escalating transportation demands. High noise levels can have a negative impact on humans' heart health and worsen the effects of coronary artery disease. In comparison to other environmental issues, noise pollution has not received the same level of attention (Ali et al., 2022).

Extreme growth in the industrialization and urban development is affecting the environment in many ways. As the development is increasing day by day the environment is affecting through it (Bouzir et al., 2017). In many countries, there is inappropriate implementation of law against such issues. Like the example of Nigeria where there is no law for harmful noise levels (Frederick et al., 2019). Population is affecting day by day through the harmful effects of the noise pollution. Noise pollution is a major issue in the developing countries of world (Baqar et al., 2018; Bello et al., 2019).

In Pakistan many researchers noticed the noise pollution due to the traffic on roads and they declared it as the most prominent cause of noise pollution. Many scholars agreed when they made research in Pakistan that noise pollution is created by traffic on roads, machineries in industries, music systems in houses, loud speakers in different ceremonies, sound of train on railway tracks and at public places (Esmeray & Eren, 2021). If we saw the situation of Karachi, then we noticed that the noise pollution is partially lesser in the transport's strike day than the normal day when different buses and rickshaws are active in city of Karachi. The noise level was 75 dB in Karachi and in normal days the noise level was 98 db. So, the buses,

***Corresponding Author**

(kanwal.javid@web.gcu.edu.pk) ORCID 0000-0002-8199-454X
*(kanwal.javid@web.gcu.edu.pk) ORCID 0000-0003-3143-8868
(wardahabib419@gmail.com) ORCID 0000-0002-1803-1572
(nzamwitasabbath@gmail.com) ORCID 0000-0001-8846-2733

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rickshaws, coaches, lorries and motorbikes are the cause of noise pollution in Karachi. If we minimize the number of rickshaws in country then we will notice a huge change in the noise level of our country.

Being unfamiliar with vehicle impairment, industrial growth, inadequate urban planning, transportation, and development activities are the primary causes of noise pollution in urban regions. Hearing loss, circulating blood pressure, increased hostility, headaches, migraine, higher fat levels, and irritability Noise pollution poses significant health risks such as insomnia, gastric ulcers, and psychological disturbance. A study was conducted to determine the variation in traffic equivalent noise levels as the distance from the road connection increased. Even people in Katchehry Bazaar (Faisalabad), the town's heart and commercial center, were subjected to an average noise level of 93.5 dB for 10 to 12 hours per day (Zia et al., 2022).

Lahore and Faisalabad are Pakistan's most populous cities, housing a variety of industries. The population of these cities is gradually increasing. Demand for transportation vehicles is also increasing as the population grows, and as a result, traffic density increases linearly with population density. According to earlier research, people living in this environment with such high traffic density are at susceptible to loss of hearing (Zahra et al.,2022).

Therefore, the comparative analysis of Faisalabad and Lahore is essential for addressing the challenges posed by noise pollution in urban areas and for promoting sustainable and healthy living environments. This research focuses on mapping in detail the extent of noise pollution in high traffic zones of Lahore and Faisalabad. Such study findings can lead to the development of a framework for a sustainable transportation system to reduce the negative impact on the residents.

2. Study area

Faisalabad's population is exceeding, more than 3.5 million people and ranked 3rd largest city of Pakistan with wide range of manufacturing and industrial enterprises, factories, small and large private business. That's why it is regarded as industrial hub of a country. Faisalabad is located on 31.418715 latitude and 73.079109 longitude. It has Chiniot and Sheikhupura on the northern side, Sahiwal in East, Toba Tek Singh in south and Jhang city in the west. Main crops that are cultivated in Faisalabad are wheat, Pulses, Maize, Bajara and Jawar. Climate of Faisalabad is semi-arid followed by very hot and humid summer and dry cool winters. June is the hottest month while minimum temperatures are recorded in January with a dense fog. Monsoon season starts in the month of July and August and average rainfall is about 375 mm. Faisalabad District covers an area of 5857 km^2.

Lahore is the 2nd largest city of Pakistan with respect to population. It is the capital city of Pakistan which is situated on 31.58045 latitude and 74.329376 longitudes. River Ravi lies down on the northern side of Lahore, wagha on East, Kasur District on south and Sheikhupura in western side of Lahore. Lahore District covers an area of 1772 km^2 (Figure 1).

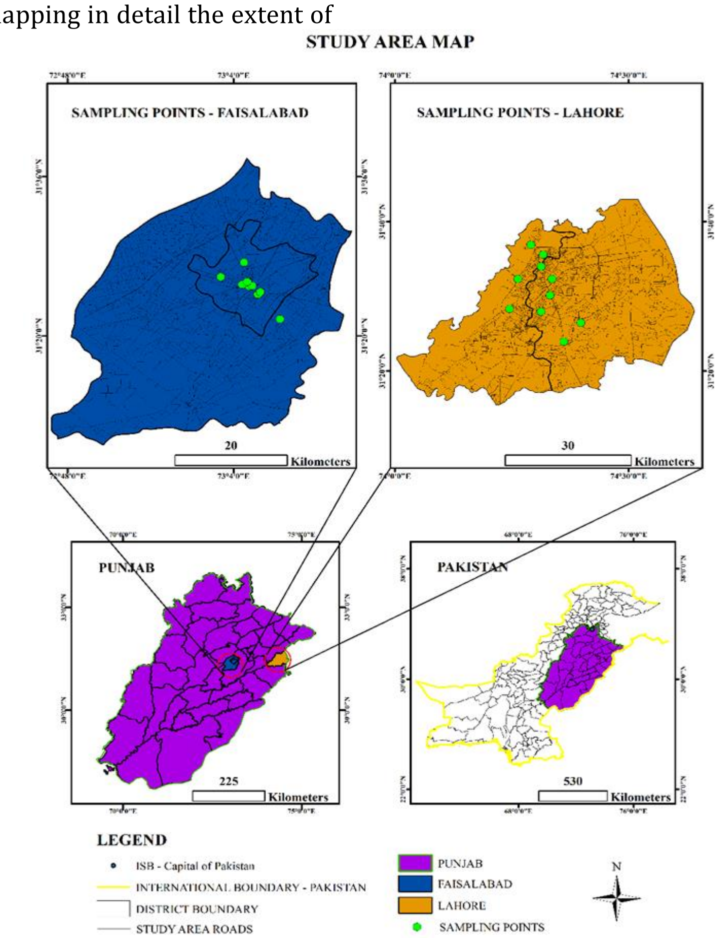

Figure 1. Location of Study Area

3. Methods and materials

A Mesteth digital sound meter was used to collect samples of noise levels in 2022 from different locations named as Jail Road Lahore, GPO Mall Road Lahore, Badami Bagh Bus Station, Thokar Niaz Baig, Gajumata Bus station, Shahdra Metro Station, Kalma Chowk fly over, Mochipura Mor and Babu Sabu toll plaza in Lahore and GTS square Faisalabad, Clock tower, Railway station, Santayana Road, Allied Mor Bus stop Faisalabad, Narwala Road Faisalabad, McDonalds Rd Faisalabad, D Ground Park Faisalabad and Chenab Club are sites in Faisalabad from where data was collected by Mesteth digital sound meter

The field work was carried out on consecutive days from 20th May 2022 to 23rd June 2022 on two different timings of the day. Morning and evening timings were selected to collect recordings from maximum to minimum in low and peak hours and data was collected by placing meter for 1 minute at height of 1.2 meter from the ground and 1meter away from the traffic flow line as it is suggested by ISO standard. Measurements were recorded in different zones from heavy traffic to commercial and semi commercial zones and residential areas.

Afterwards, this data was further inserted in Microsoft Excel sheet and database of noise levels were built. The Excel spreadsheet data which was collected from 18 locations of Faisalabad and Lahore as explained earlier, was inserted in ArcGIS 10.5 to use technique Inverse Distance Weighting to map different recordings of morning and evening. Figure no, 2 represents the methodological framework of this study which further elaborates the procedure of this research (Figure 2).

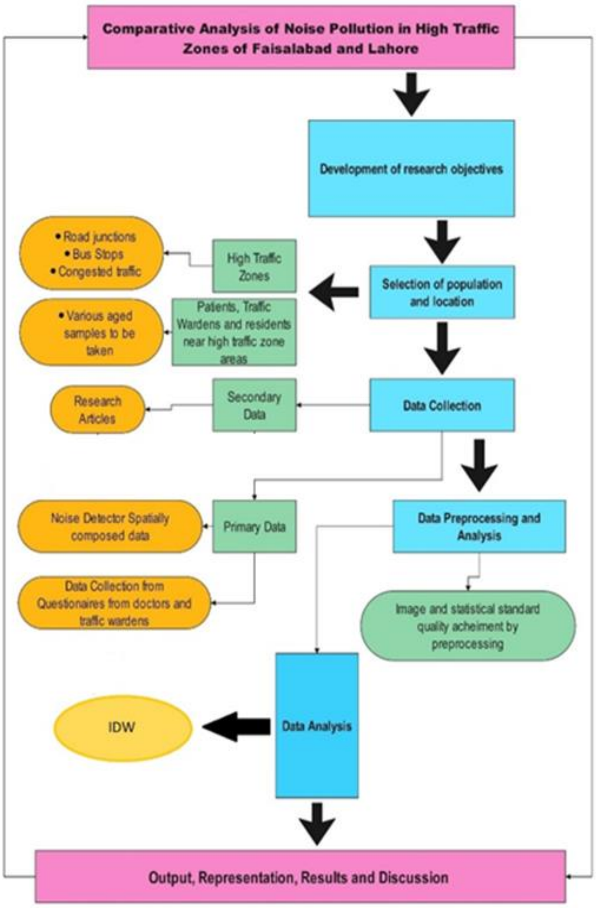

Figure 2. Methodology of the research

4. Results, analysis and discussion

4.1. First week analysis of noise pollution (Morning)

Comparing daily noise pollution values from May 20th to May 26th, 2022, reveals variations between Lahore and Faisalabad. On weekdays, Lahore exhibits higher pollution levels than Faisalabad, attributed to greater population density and traffic. Weekend days, May 21st and 22nd, show lower pollution levels due to reduced activity. However, on May 23rd, pollution rises in both cities with increased population movement. May 24th sees elevated pollution in traffic-heavy zones of both cities. On May 25th, noise pollution levels in Lahore and Faisalabad align more closely. By week's end, May 26th, both cities experience heightened pollution levels, yet Lahore consistently shows higher levels, especially during morning rush hours.

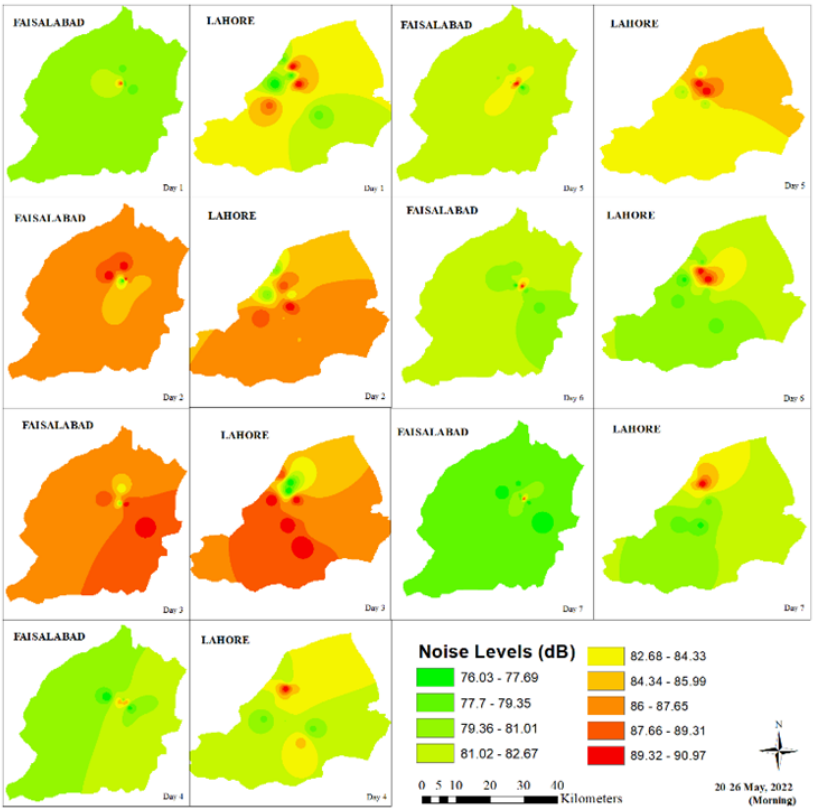

Figure 3. 20-26 May 2022 morning

4.2. First week analysis of noise pollution (Evening)

Figure 4 displays evening noise pollution data from high-traffic zones in Faisalabad and Lahore. On May 20th, Faisalabad shows higher pollution levels due to industrial activity, while on May 21st, Lahore records higher levels, likely due to weekend outings. Similarly, on May 22nd, Lahore's pollution surpasses Faisalabad's. On May 23rd, Lahore again records higher levels. Conversely, on May 24th, Faisalabad's pollution exceeds Lahore's. On May 25th, Lahore's pollution is higher, while on May 26th, Faisalabad's pollution surpasses Lahore's. Overall, from May 20th to 26th, 2022, Faisalabad consistently exhibits higher evening noise pollution levels than Lahore.

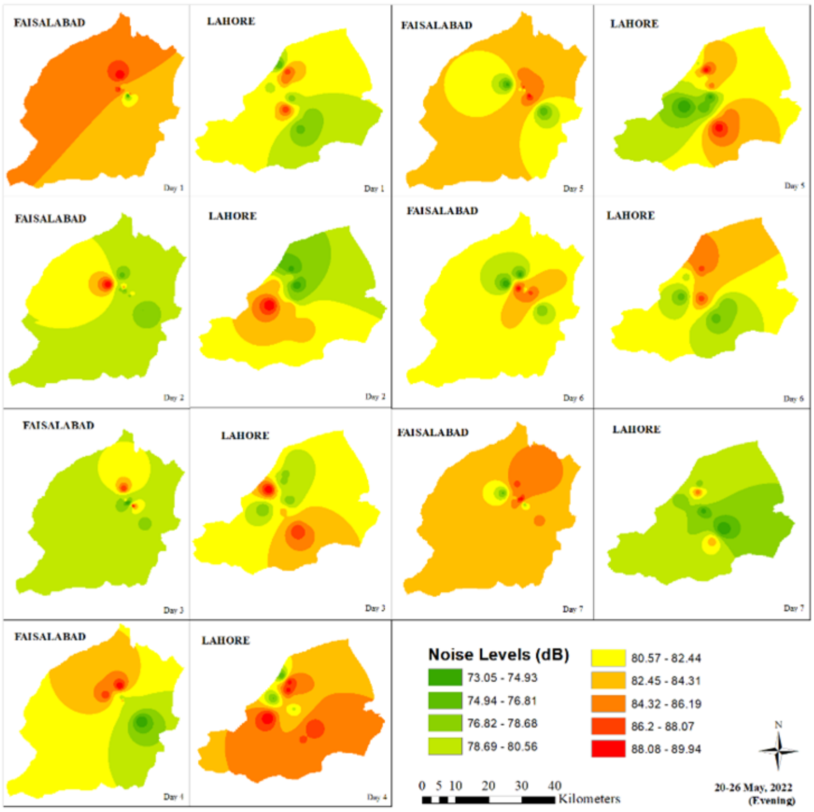

Figure 4. 20-26 May 2022 evening

4.3. Second week of analysis of noise pollution (Morning)

May 27th, 2022, both cities experience morning noise pollution. On May 28th, Faisalabad's high traffic zones face greater pollution than Lahore's. May 29th sees higher pollution levels in Lahore. May 30th shows Lahore with significantly higher pollution levels than Faisalabad. On May 31st, Faisalabad's areas exhibit higher pollution due to recording elevated noise levels. June 1st records higher pollution levels in Faisalabad compared to Lahore, indicated by intense colors in Figure 4. On June 2nd, Lahore's high traffic zones experience higher noise levels compared to Faisalabad. Overall, from May 27th to June 2nd, 2022, Lahore's high traffic zones are more affected by noise pollution than Faisalabad's.

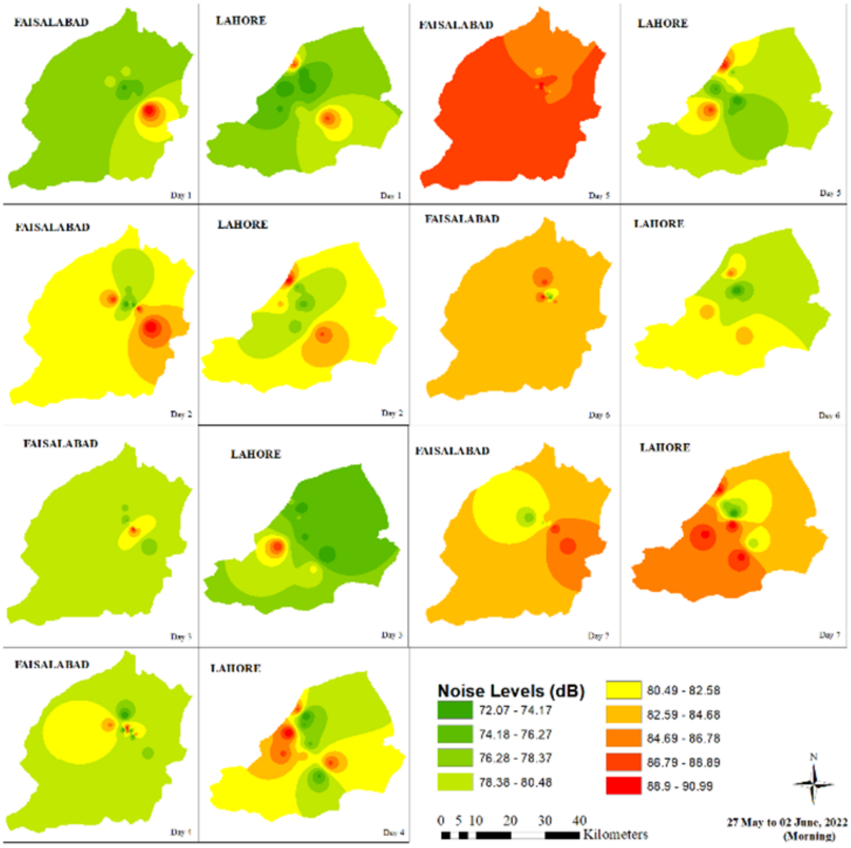

Figure 5. 27 May to 02 June 2022 morning

4.4. Second week of analysis of noise pollution (Evening)

Figure 6 depicts a map created using the Inverse Distance Weighting (IDW) technique in ArcGIS, illustrating evening noise pollution levels in the high traffic zones of Faisalabad and Lahore. Red areas indicate high noise pollution, while green areas indicate low pollution. Other colors represent varying pollution levels. On May 27th, 2022, Lahore's high traffic zones exhibit higher pollution levels compared to Faisalabad, though some points in Faisalabad also show elevated pollution. On May 28th, Faisalabad experiences higher pollution levels. Conversely, on May 29th, Lahore faces higher pollution. May 30th sees Lahore with greater pollution than Faisalabad. On May 31st, Faisalabad's high traffic zones experience higher pollution levels. June 1st and 2nd show Faisalabad with higher pollution levels. Overall, from May 27th to June 2nd, 2022, Lahore's high traffic zones consistently face higher noise pollution levels compared to Faisalabad's.

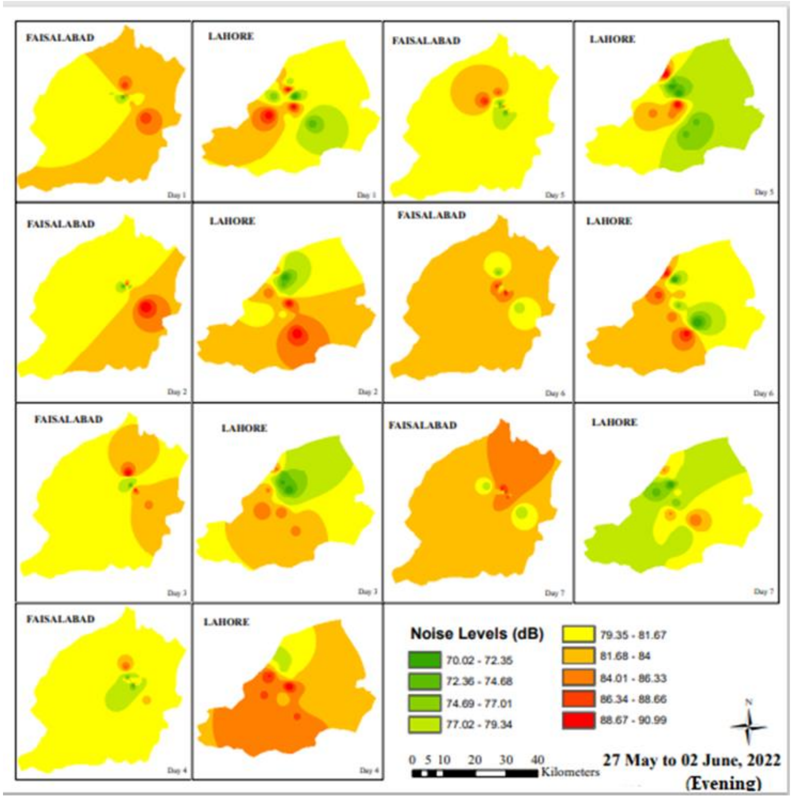

Figure 6. 27 May to 02 June 2022 evening

4.5. Third week of analysis of noise pollution (Morning)

Figure 7 illustrates a map generated using the IDW technique in ArcGIS, displaying morning noise pollution levels in the high traffic zones of Faisalabad and Lahore from June 3rd to June 9th, 2022. Red indicates high pollution areas, while green indicates low pollution. On June 3rd, Faisalabad experiences higher pollution than Lahore. Similarly, on June 4th, Faisalabad records higher pollution levels. Conversely, on June 5th, Lahore faces higher pollution. June 6th sees slightly higher pollution levels in Lahore. On June 7th, Lahore's high traffic zones have higher pollution levels. Conversely, on June 8th, Faisalabad experiences significantly higher pollution levels. On June 9th, Lahore's pollution levels exceed Faisalabad's. Overall, from June 3rd to June 9th, 2022, Lahore consistently faces higher morning noise pollution levels in its traffic zones compared to Faisalabad.

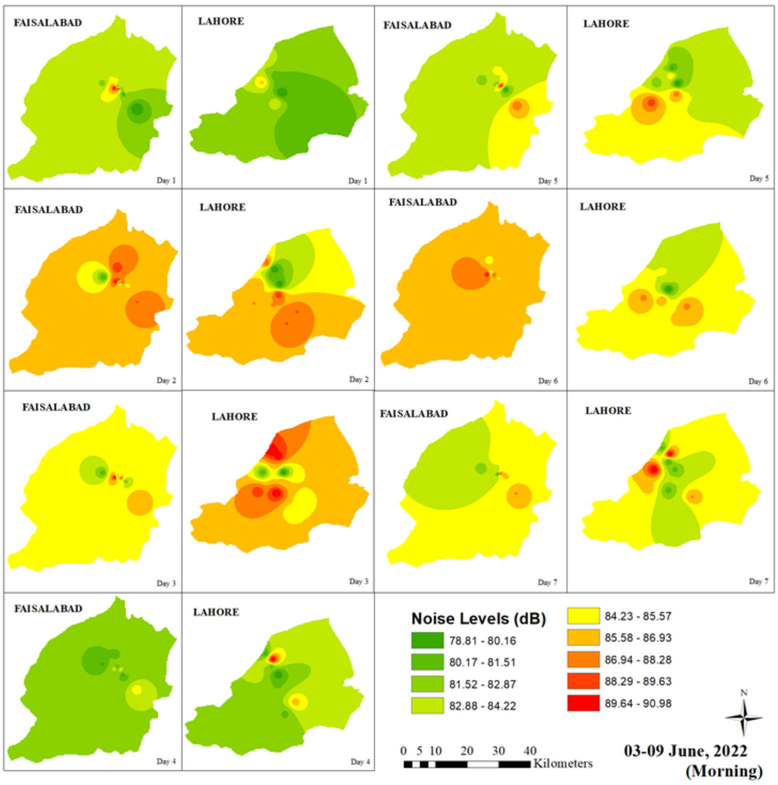

Figure 7. 03-09 June 2022 morning

4.6. Third week of analysis of noise pollution (Evening)

The evening of day 1 which is 03 June 2022 showing that the noise pollution in high traffic zones of Lahore is comparative more than the high traffic zones of Faisalabad. On the evening of day 2 dated 04 June 2022 the value of noise pollution is higher than the Faisalabad. On 05 June 2022, Day 3 the noise pollution in the evening is higher in the Lahore than the high traffic zones of Faisalabad. By comparing the noise pollution of evening of Day 4 that is 06 June 2022 the value of noise pollution is higher in the high traffic zones of Faisalabad. On the day 5th dated 07 June 2022 the value of noise pollution in the high traffic zones of Lahore is higher than the zones of Faisalabad. On the 08th June 2022 the value of noise pollution is higher in Lahore than Faisalabad. On the evening of day 7th dated 09 June 2022 the value of noise pollution is higher than Faisalabad. The figure 7 shows the value of noise pollution in the areas of high traffic zones of Lahore and Faisalabad. By comparing the value of both cities of whole days concluded that High traffic zones of Lahore faced the more noise pollution than the high traffic zones of Faisalabad (Figure 8).

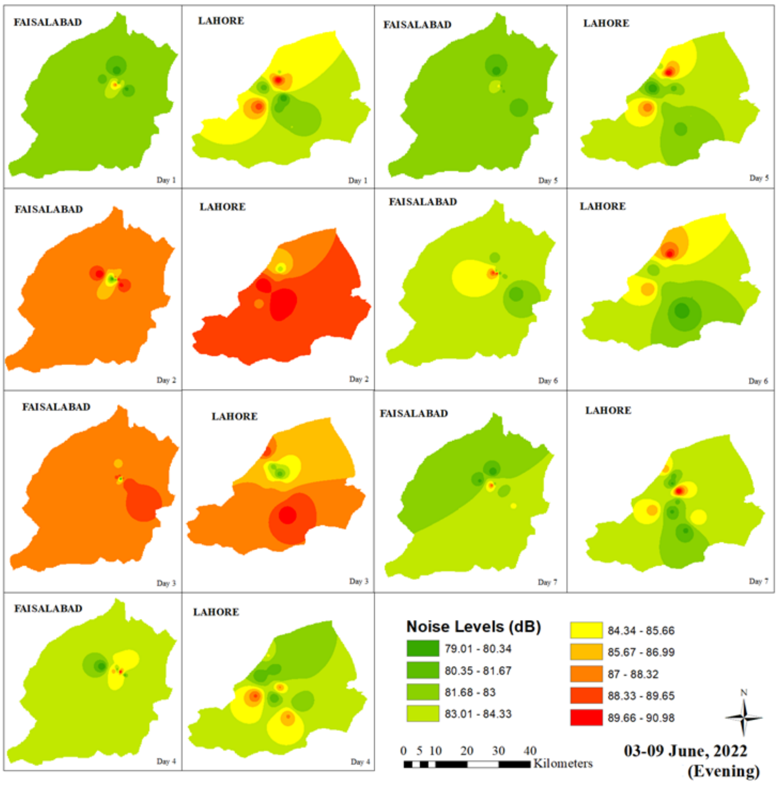

Figure 8. 03-09 June 2022 evening

4.7. Fourth week of analysis of noise pollution (Morning)

On the first day that is 10 June 2022 the map is showing the value of noise pollution high in the high traffic zones of Lahore than the high traffic zones of Faisalabad. Day 2 dated 11 June 2022 the value of noise pollution is high in the high traffic zones of Lahore in comparison of high traffic zones of Faisalabad. On the day 3 dated 12 June 2022 high traffic zones of Faisalabad faced much noise pollution than the high traffic zones of Lahore. Day 4 which is 13 June 2022 the areas of Lahore is facing much noise pollution than the areas of Faisalabad. On the day 5 which is 14 June 2022 the value of noise pollution is higher in the areas of Lahore than Faisalabad. Day 6 which is 15 June 2022 the value of noise pollution is higher in the areas of Lahore are facing the higher value of noise pollution than Faisalabad. 16 June 2022 which is the day 7 where map is showing the high number of noise pollution in the areas of Lahore in comparison of Faisalabad. Through comparison of values of days from 10 to 16 June 2022 concluded that the high traffic zones of the Lahore faced the more noise pollution than the high traffic areas of the Faisalabad (Figure 9).

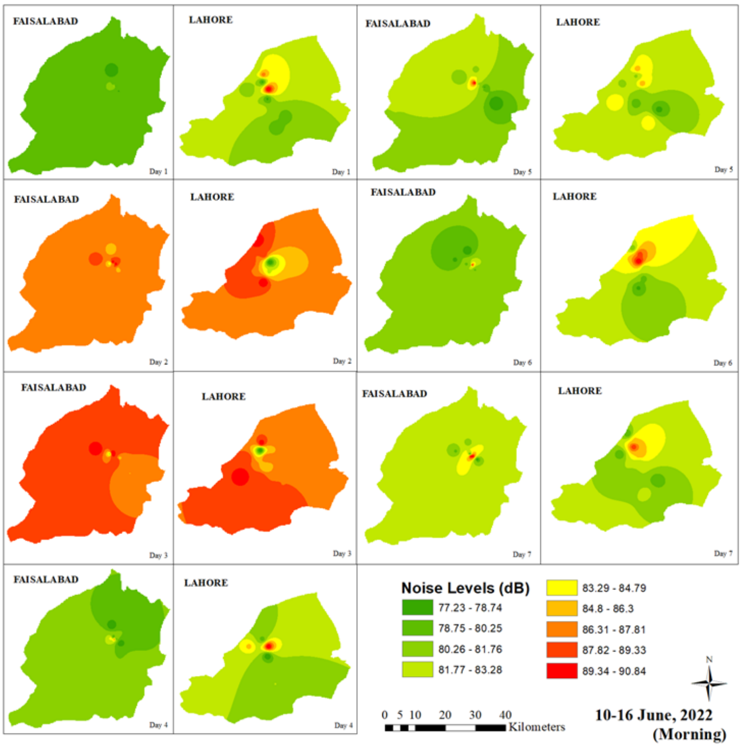

Figure 9. 10-16 June 2022 morning

4.8. Fourth week of analysis of noise pollution (Evening)

The evening of day 1 which is 10 June 2022 showing that the high traffic zones of Lahore faced much noise pollution than Faisalabad. Day 2 showing the evening of 11 June 2022 where the value of noise pollution in Lahore is higher than Faisalabad. On the evening of day 3 that is 12 June 2022, the figure showing the value of noise pollution is higher in Faisalabad than the high traffic zones of Lahore. The day 4 dated 13 June 2022 showing the value of noise pollution approximately same in both cities high traffic zones. Day 5 which is 14 June 2022 showed the value of noise pollution higher in the zones of Lahore than the Faisalabad. 15 June 2022 is showed by the day 6 where the noise pollution is higher in the high traffic zones of the Faisalabad in the comparison of Lahore. On the evening of 16 June 2022, the noise pollution is high in the high traffic zones of Lahore in comparison of Lahore. Through the comparison of all the values of High Traffic zones of Faisalabad and Lahore, the conclusion is the high traffic zones of Lahore are facing the high values of noise pollution than the high traffic zones of Lahore (Figure 10).

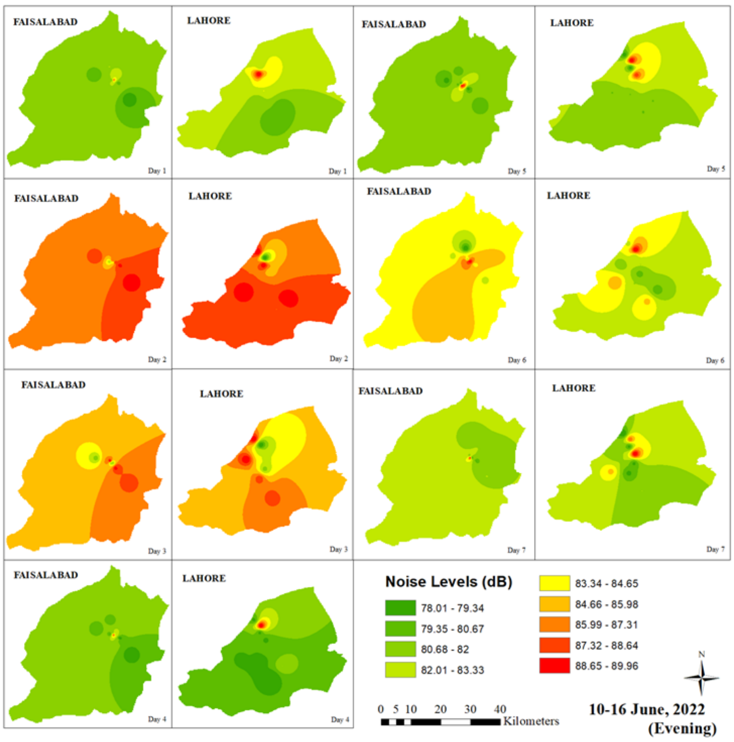

Figure 10. 10-16 June 2022 evening

4.9. Fifth week of analysis of noise pollution (Morning)

Figure 11 displays a map generated using the IDW technique in ArcGIS, illustrating morning noise pollution levels in the high traffic zones of Faisalabad and Lahore from June 17th to June 23rd, 2022. On June 17th and 18th, Faisalabad exhibits higher pollution levels than Lahore. Conversely, on June 19th, Lahore's traffic zones face higher pollution. June 20th sees higher pollution levels in Lahore. On June 21st, Faisalabad records higher pollution levels. Similarly, on June 22nd, Faisalabad experiences significantly higher pollution levels. On June 23rd, Faisalabad's pollution levels exceed Lahore's. Overall, from June 17th to June 23rd, 2022, Faisalabad consistently faces higher morning noise pollution levels in its traffic zones compared to Lahore.

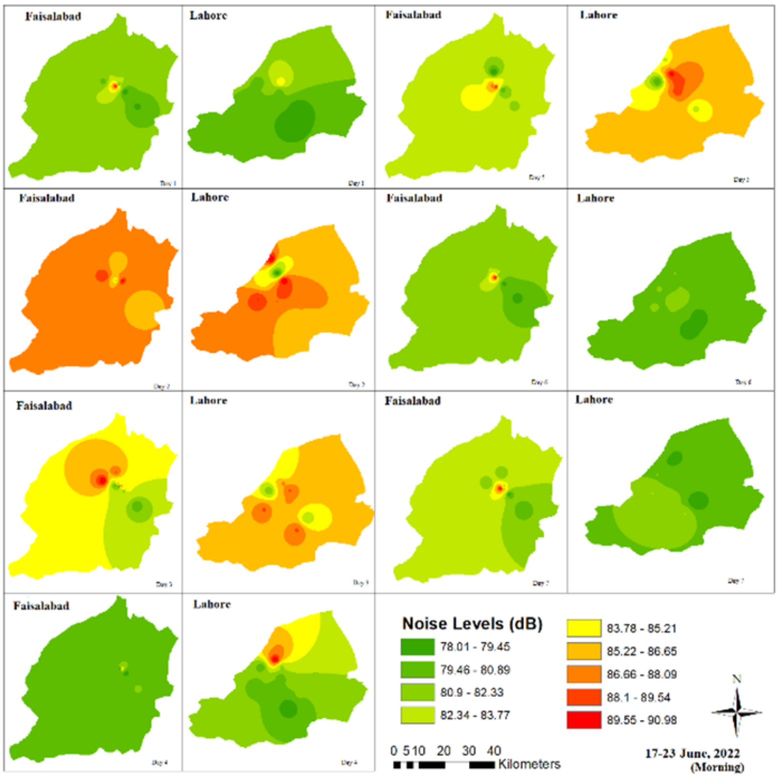

Figure 11. 17-23 June 2022 morning

4.10. Fifth week of analysis of noise pollution (Evening)

In Figure 12, Day 1 illustrates evening noise pollution levels on June 17th, 2022, with Faisalabad's high traffic zones showing higher pollution than Lahore's. Day 2, June 18th, records higher pollution levels in Faisalabad. Conversely, Day 3, June 19th, depicts higher pollution in Lahore's traffic zones. On June 20th, Day 4 shows higher pollution in Faisalabad. Day 5 highlights higher pollution levels in Faisalabad compared to Lahore. Similarly, Day 6, June 22nd, indicates higher pollution in Faisalabad. Conversely, on June 23rd, Day 7, Lahore experiences higher pollution levels. Overall, from June 17th to June 23rd, 2022, Faisalabad's high traffic zones consistently face higher evening noise pollution levels compared to Lahore's. Despite some close values, the collective comparison indicates that Faisalabad's traffic zones encountered more pollution than Lahore's during this week (Figure 12).

The IDW techniques portray the noise levels in high traffic zones of Faisalabad and Lahore. The colors of above maps showing the effects of noise pollution in those areas and al the areas where the noise pollution is high is in dangerous situation. The whole results are based upon the using the analytical technique that is showing the results that Faisalabad and Lahore both are under the dangerous conditions. This slow poison is dangerous for the lives of the people and environment. People taking this risk very low but after an age they can be affected by these problems. Lahore and Faisalabad, being major cities of Pakistan, both are the functional cities where a huge number of populations is living. They attract a large population seeking education, opportunities, and better living conditions. However, with this influx comes a significant challenge: noise pollution. Both cities struggle with high levels of noise due to heavy traffic, typical of densely populated areas. Faisalabad, known as the Manchester of Pakistan, hosts major industries contributing to the nation's progress. Unfortunately, inadequate facilities have adversely affected the health of residents and workers. Areas with heavy traffic, especially near markets, bear the brunt of noise pollution, primarily from trucks, rickshaws, and other vehicles transporting goods. In contrast, Lahore is renowned for its luxurious lifestyle, with many residents employed or studying. Morning traffic and high traffic zones experience elevated noise pollution, with bus stops particularly affected on weekdays and weekends. Residential areas generally experience lower noise pollution, but those near workplaces suffer adverse effects such as mood swings, headaches, and depression due to the impact on their nervous systems and daily lives, according to hospital data.

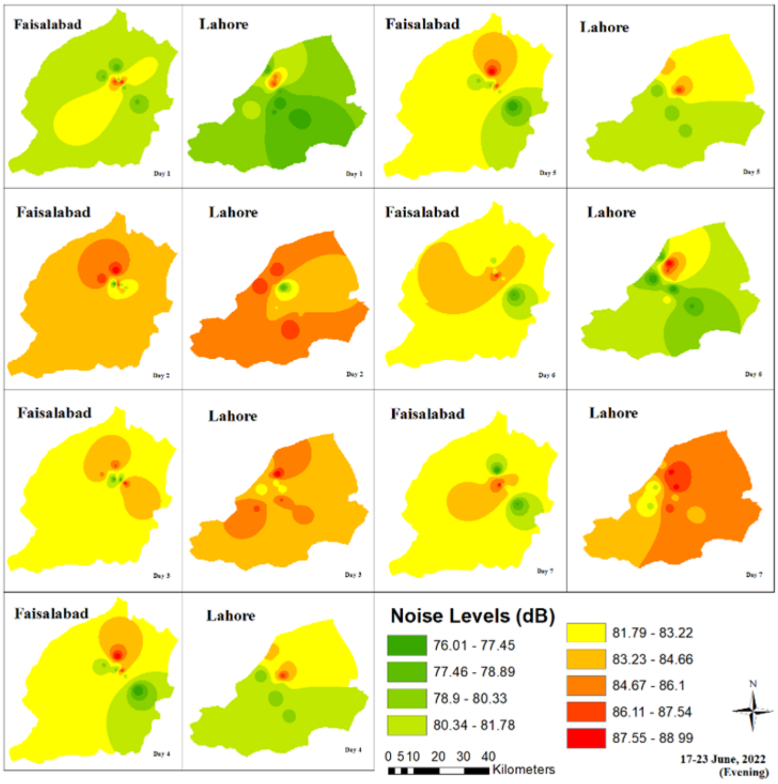

Figure 12. 17-23 June 2022 evening

In this study focusing on Faisalabad's sites, it is found that noise levels reached a peak of 85.9 dB(A) at two locations, with a minimum of 70.8 dB(A). The heavy usage of these roads by various forms of transportation, including public, commercial, loader trucks, and private vehicles, contributes to the elevated noise levels. The research also investigated traffic noise in Lahore, specifically at 18 busy intersections with high traffic flow during peak hours. It is observed that the average noise level during the day exceeded the permissible limit of 80 dB(A) in 90% of the city's busiest areas. The maximum average noise level recorded in Lahore was 90 dB(A). This heightened noise level is primarily attributed to vehicular traffic, particularly autorickshaws equipped with ineffective silencers, as well as the frequent use of pressure horns by buses, wagons, and lorries.

The researchers examined urban noise levels and traffic density in Chiniot and Jhang to assess the non-auditory health impacts of noise on residents. Urban noise data revealed that 82% of locations in Jhang exceeded Pakistan's National Environment Quality Standard (NEQS-Pak) and the World Health Organization's (WHO) noise limitations, with levels reaching 87 dB. In Chiniot, 95% of sites exceeded these standards, with noise levels peaking at 95 dB. The study attributed higher noise levels in Chiniot to excessive road traffic and dense population. Strategies such as vehicle maintenance and urban planning are recommended to mitigate urban noise pollution. The equivalent noise levels recorded at several places in Delhi ranged from 63 dB(A) to 83 dB(A) (Rahman Farooqi et al., 2017).

5. Conclusion

The growth of urban populations worldwide leads to greater demand for transportation. Consequently, more roads are constructed to accommodate this heightened need for mobility. This trend holds true for Pakistan as well, where increasing mobility necessitates expanded infrastructure. Lahore and Faisalabad are Pakistan's fastest-growing metropolitan cities, with several professional, industrial, educational, and medical organizations. Both cities are plagued by severe noise pollution from the noise of motorcycles, autorickshaws, cars, and increased traffic volumes. Utilizing a Mesteth digital sound meter, noise level samples were collected from various locations in both cities. Fieldwork conducted from May 20th to June 23rd, 2022, during morning and evening hours, aimed to capture peak and low traffic periods. The collected data underwent analysis and mapping using ArcGIS 10.5. Comparative analysis revealed that Lahore to have higher noise pollution levels compared to Faisalabad, with noise ranging from 70 to 90 dB, exceeding WHO standards. This study aims to pinpoint high-traffic zones to aid administration in formulating targeted strategies to combat noise pollution.

6. Recommendations

Noise levels recorded at all study sites surpassed the recommended limit set by the Punjab Environmental Protection Department (45-55 dBA). To mitigate traffic noise reaching residential areas, it is advised to install noise barriers. Options include tree plantations, precast reinforced cement concrete walls, and brick walls.

Among these, tree plantation emerges as the preferable choice due to its various environmental benefits. It is essential for the government to identify areas where sound pressure levels exceed the threshold and take appropriate measures to address this issue. People their selves should properly maintain their vehicles and install good silencer in their vehicles those are soundless. Thorough investigations into noise pollution across major cities in Pakistan would offer a comprehensive insight into its prevalence and variations. Such research could pave the way for tailored recommendations and policies specific to each region, addressing the distinct challenges encountered in various urban settings. Additionally, studying the design and materials used in noise barriers could offer valuable insights for effective noise mitigation strategies.

Author Contributions

The contributions of the authors to the article are equal.

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

Research and publication ethics were complied with in the study.

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The relationship between macroeconomic variables and oil prices and analysis of global oil prices

Merve Şenol*[1], Hüseyin Çetin[1]

[1]*Bursa Technical University, Faculty of Humanities and Social Sciences, Department of International Trade and Logistics, Bursa, Türkiye*

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Abstract
This study unravels the complex web of factors influencing OPEC crude oil prices, going beyond the immediate impact of isolated events. To this end, it has developed a multifaceted approach that uses nonparametric regression, correlation analysis, ARIMA forecasting, and spatial analysis with ArcGIS in a combined and integrated manner to reveal the interaction of variables that make up the family of macroeconomic factors and oil prices. The analysis confirms the expected positive correlations between oil prices and factors such as inflation, exchange rates (when the local currency weakens), and GDP (indicating increasing demand with economic growth). But it also explores the more complex relationship between oil production and price. Through the use of visualizations and forecasts, the study offers valuable insights into these relationships and provides projections for future price movements. This comprehensive approach provides a richer understanding of the multifaceted influences on oil prices, informing the decisions of policymakers, industry leaders, and investors navigating the complexities of the global oil market.

1. Introduction

Crude oil remains the epitome of great energy and is one of the most traded commodities in the world. Its price volatility has had a major impact on the macroeconomic stability of the country, both for oil-producing and non-producing countries (Berument et al., 2010). The formulation of a government's fiscal strategies is significantly influenced by oil price trends (Al Jabri et al., 2022). Most sectors of the economy, such as the automotive, transportation, and airline industries, link their operational success to fluctuations in the price of oil. Meanwhile, accurate oil price forecasting is considered essential for efficient planning and decision making in macroeconomics. This is because price forecasting is complicated by various factors such as political, economic, and regional stability in oil-exporting countries, economic sanctions, and trade conflicts (Xu et al., 2023). This simply shows the difficulty of predicting oil prices, as major events such as the drop in crude oil prices caused by the Covid-19 pandemic have occurred. Today, such oil prices have risen to levels not seen for many years, symbolizing a volatile face of the oil market (OPEC, 2024).

The relationship between oil price and macroeconomic variables has continued to mark an important area of study in economic studies, reflecting the proper role that oil plays in the international economy (Guo et al., 2022). Changing oil prices have been found to have far-reaching effects on everything from GDP growth rates to inflation, exchange rates, balance of payments, interest rates, and unemployment rates (Mukhtarov et al., 2020).

Starting from GDP, the movement of oil prices must have different effects depending on the conditions that exist for a country as an exporter or importer of oil (Charfeddine et al., 2020). Higher oil prices typically lead to higher production costs and more money for consumers to spend on energy, resulting in less spending on non-energy goods (Alsalman, 2021). In contrast, oil-exporting countries may experience an increase in GDP due to higher oil revenues. The impact on inflation is much clearer. Typically, higher oil prices lead to cost-push inflation, as the higher transportation and production costs are passed on in the final prices of most goods and services (Wen et al., 2021).

Another important area strongly affected by oil prices is the exchange rate. In oil-exporting countries, high oil prices can strengthen the national currency as foreign exchange earnings increase; however, in the case of oil-importing countries, it could leave their currencies worse off, most likely depreciating due to larger trade deficits (Kilian & Zhou, 2022). Exchange rates are also affected by such movements through changes in investor sentiment and speculative positions in global financial markets (Demirer et al., 2020). In general, the increase in

***Corresponding Author**
*(mrvaydgduu1@gmail.com) ORCID not available
(huseyin.cetin@btu.edu.tr) ORCID not available

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the price of oil causes the current account balance of oil importers to deteriorate and that of oil exporters to improve. However, the overall impact on a country's balance of payments is subject to the interaction that currently exists between the current account and the capital account (Chang et al., 2023).

In addition, the price of oil affects other macroeconomic variables such as interest rates and unemployment. Thus, the need for central banks to raise interest rates to combat high oil price inflationary pressures may lead to different shifts in employment in sectors that affect the energy, manufacturing, and transportation sectors. The net impact on unemployment will thus be determined by the balance between job creation in some sectors and losses in others, which in turn will depend on the ability of the economy to adjust to changes in energy prices and the effectiveness of policy responses (Kocaarslan et al., 2020).

Current estimates put global oil consumption at up to 95 million barrels per day (OPEC). The scope of crude oil price forecasting is wider than we think, the forecast used applies to large and small industries and countries that benefit from the predicted prices. Thus, a comprehensive analysis of oil price changes is highly needed to get a clear perspective on the changing global economic dynamics, especially regarding the critical place of oil in energy markets and national economies (Hong et al., 2024). Econometric models have been developed over time for this purpose: to accurately predict a complex and volatile oil price by applying different methodologies. Notable among these are nonlinear regression analysis (He, 2020), nonparametric regression analysis (Lin & Xu, 2021), and ARIMA models (Ariyanti & Yusnitasari, 2023), each of which attempts to capture the nuances of oil price movements with different analytical tools.

Nonlinear regression analysis, a very important tool in studies involving oil prices, can model very complex behaviors that the linear models might not capture (Safari & Davallou, 2018). The method does not assume linearity between variables; therefore, it has provided sufficient insight into the multiple factors that influence oil prices. Among these dynamics, studies have provided some insight into how market sentiment, geopolitical tensions, and economic indicators interact in complex ways to define the dynamics of oil price movements using nonlinear regression (Moshiri & Foroutan, 2006).

On the other hand, the nonparametric regression analysis brings out a very flexible framework where it does not assume a pre-specified functional form for the independent relationship between dependent and independent variables (Álvarez-Díaz, 2020). In particular, the method follows the natural structure of the data in cases such as the analysis of oil price fluctuations, without imposing a model assumption. Research using nonparametric regression has demonstrated its ability to reveal subtle patterns in oil price data, providing a nuanced understanding of market dynamics (Zhu, 2013). However, the method's strengths are offset by challenges in bandwidth selection and computational requirements, particularly for large datasets.

ARIMA models have been widely adopted for their effectiveness in forecasting time-series data, including oil prices (Ahmed & Shabri, 2014). By integrating autoregression, differencing to achieve stationarity, and moving averages, ARIMA models excel at capturing time dependencies and trends in oil prices. The literature is rich with examples of the application of ARIMA in oil markets, where it has been praised for its predictive accuracy (Tularam & Saeed, 2016). Nevertheless, ARIMA models are not without limitations, as they assume linearity and require the underlying data to be stationary, conditions that are not always met in the volatile oil market.

The following sections provide a more comparative look at the specifics of the advantages and limitations of these econometric methods, which certainly require a very careful choice of methods based on specific forecasting objectives and data characteristics. Recent developments in econometric modeling, integrating machine learning models and hybrid models, open very promising avenues for improving forecasting accuracy beyond what has been possible so far with traditional approaches (Safari & Davallou, 2018).

Geographic Information Systems (GIS) are an effective system for analyzing the distribution of data. GIS refers to a complex set of software and methodologies used to collect, store, manipulate, analyze, manage, and visualize spatial or geographic data (Erdogan et al., 2022). Essentially, GIS is a tool that visualizes the earth and its phenomena in a digital form so that raw data is transformed into something more understandable and accessible through eyes in a plane (McHaffie et al., 2023). This system supports the integration of statistical analysis and database technologies into an environment for spatial analysis and mapping (Ali, 2020).

These price changes are analyzed using GIS, a very sophisticated combination of technology and economics that provides a multi-dimensional view of a very complex market. This can be combined with economic indicators in spatial data to further show and analyze the geographic distribution of oil reserves, production facilities and transportation networks under fluctuating oil prices. In other words, such space-time analysis helps to detect patterns and trends that would otherwise be missed by conventional statistical methods (Erdogan et al., 2022). For example, it can help identify areas where political risks or logistical constraints may disrupt supplies and thus affect prices. In fact, overlaying environmental data predicts the impact of either regulatory changes or environmental incidents on oil production and thus its prices (Mahmood & Furqan, 2021). This is a powerful predictive tool to tell the future movement of price under different scenarios, including changes in demand, technological changes, and shifts in political landscapes, all due to the dynamic mapping and modeling capabilities of GIS (Balogun, 2021). In this way, GIS is one of the most powerful weapons in the arsenal of analysts and policymakers to make more informed decisions, as it provides a comprehensive and deep insight into the factors that drive changes in crude oil prices.

This connection between oil prices and various macroeconomic variables can be understood in a holistic manner. All these dynamics can be largely quantified using econometric models and empirical analysis, further shedding light on how economies deal with the problems posed by oil price volatility and change.

The aim of the study is to examine how the evolution of the world oil price is related to, and possibly influenced by, certain selected macroeconomic variables. This will identify the factors that make up the relationship, the parameters that affect them, and the reasons for changes from past to present in the oil price. For the change in oil price, the way and changes would be inquired, and the relevant method would be applied with the chosen method of analysis. In addition, the use of GIS map production techniques will enable the change in data over time to be revealed. It will thus explain the global effect on countries guided by the changes occurring in the prices of oil.

2. Method

In this study, we examine the major events that have occurred over the past four decades that could affect the crude oil market. To do this, daily closing prices for the benchmark crude oil price are obtained from online data-sharing platforms such as OPEC. It consists of opening, high, low and closing prices, but only the closing price is used in the analysis. The data is sorted from oldest to newest and outliers that may affect the data analysis are removed.

2.1. Data

This study uses monthly and annual oil price data provided by OPEC. The data are available from 1972 to 2022 (Figure 1).

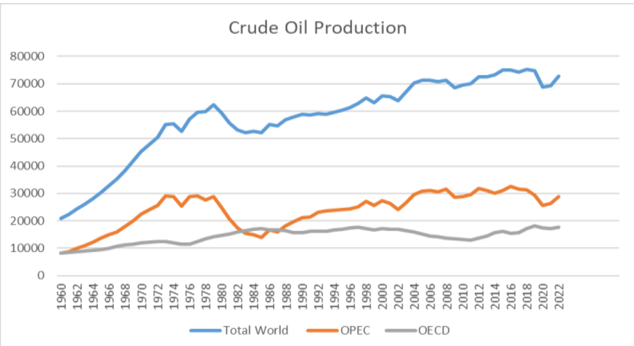

Figure 1. Crude oil production changes (produced from the OPEC data)

The collection and analysis of monthly crude oil price data, as well as related time series such as inflation rates, GDP growth, and exchange rates, is of great importance in various sectors of the economy (Figure 2). For economists and policymakers, these data are a benchmark for understanding economic trends and designing monetary and fiscal policies to stabilize and stimulate the economy. Fluctuations in crude oil prices have a direct impact on inflation, affect trade balances, and thus affect the overall health of the economy. By closely monitoring these changes, policymakers can adjust monetary policy in advance to counter inflationary or deflationary pressures.

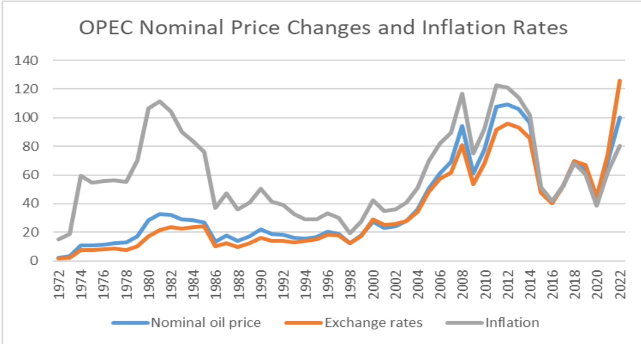

Figure 2. Price and Inflation changes in OPEC countries (produced from the OPEC data)

In addition, monthly crude oil prices are an investor's and financial analyst's toolkit for making wise decisions about various types of investments. Oil is so central to the global economy that its price fluctuations can reverberate through stock markets and investment portfolios to indicate broader economic trends. These price swings therefore have a direct impact on the energy sector, and investors in this industry must either change their strategies to hedge against potential losses or take advantage of emerging opportunities.

This data is needed by companies, especially those in sectors directly affected by oil prices, such as transportation, manufacturing, and agriculture. This forecasting capability helps companies to hedge against further price volatility and to better manage their costs to remain competitive.

In the same vein, monthly data are used to identify the causes of price changes, and annual data are used to analyze OPEC's spatial data on crude oil. Monthly data go back to 1983, while annual data go back to 1972. Therefore, monthly data will be a very good reference to identify geopolitical events that cause a sudden change in oil prices.

To follow this change analysis and relate price changes to historical events, the price change graph in Figure 3 is used.

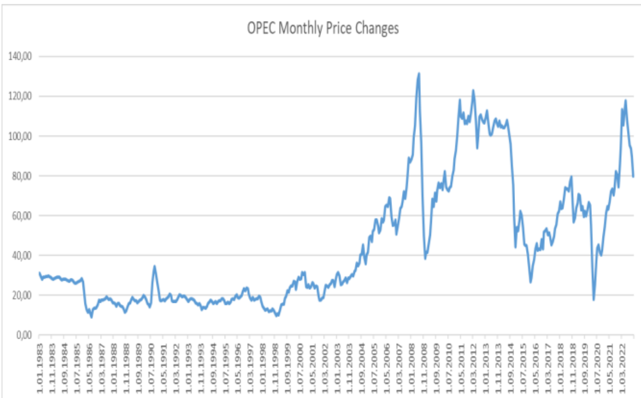

Figure 3. OPEC Monthly Price Changes (produced from the OPEC data)

2.1.1. October 1985 – April 1986

Crude oil prices ranged from $28 to as low as $9 during the period from November 1985 to April 1986.

The reasons that were attributed to such a massive drop were varied in nature, such as OPEC's change in strategy, large production of oil, weak global demand for oil, and technological advancement with alternative sources along with geopolitical factors. OPEC decided to increase production, while Saudi Arabia increased its own production to levels far beyond what was necessary to maintain its market share. Rising economic growth and an increased focus on energy efficiency reduced demand, while the discovery of new fields and the development of alternatives added supply to the system. At this point, the geopolitical conjunctures may be smooth, but very strong indirect impact on the global economy and repercussions on the respective energy policies. All of this combined to create a serious oversupply that caused prices to fall sharply and had a very deep impact on the global oil markets.

2.1.2. June 1990-November 1990

Between June and November 1990, the price of crude oil shot up from $14 to a monstrous $34 due to Iraq's invasion of Kuwait on August 2, 1990. There were many reasons for this, including the disruption of oil supplies from Kuwait and Iraq, heightened geopolitical tensions in the Middle East and international reactions, and uncertainties caused by U.S. speculation and market psychology. Other important reasons include insufficient strategic reserves and supply adjustments, as well as OPEC's limited effectiveness in managing the crisis. These factors caused oil prices to rise rapidly and raised fears of supply disruptions in the market. In January 1991, the outbreak of the Gulf War exacerbated the situation. However, this was really a period of rapidly rising prices, especially with the shock of the invasion and the uncertainties it created.

2.1.3. November 1990-March 1991

The decline in crude oil prices from $34 to $17 between November 1990 and March 1991 is closely linked to the end of the Gulf War and the reduction of immediate threats to oil supplies from the Middle East. During this period, the quick victory of the U.S.-led coalition and the absence of major damage to Kuwaiti oil production facilities reduced fears of an expected prolonged disruption of oil supplies. Factors such as Kuwait's resumption of oil production, the use of the Strategic Petroleum Reserve, reduced demand, and economic stagnation, reduced speculative activity, and OPEC countries adjusting production all contributed to lower prices. These factors helped to stabilize the market and return prices to levels that better reflect global supply and demand dynamics.

2.1.4. January 1997-January 1999

As a result, crude oil prices fell from $23 a barrel in January 1997 to $10 a barrel in January 1999, in part due to the Asian financial crisis, which caused economic contractions in Thailand, Indonesia, South Korea, and Malaysia, as well as sharp declines in regional oil demand. Meanwhile, non-OPEC oil production increased, and OPEC itself faced challenges in establishing production discipline. At the same time, supply received a technological boost from oil exploration and production, and these gains coincided with a lack of sufficient demand due to a strong US dollar and warm winters in the northern hemisphere. This also pushed prices down through market speculation and a delayed response from OPEC. This was a period of great sensitivity to global economic conditions and technological improvements.

2.1.5. February 1999-September 1999

Between February 1999 and September 2000, a confluence of events drove crude oil prices from $10 to $30 per barrel. Key developments that have been cited as the most important causes of this price movement period include OPEC cuts, economies recovering from the AFC, strong global economic growth, increased demand for heating oil and diesel, and market speculation. Other important factors include technical and investment factors within the oil industry and geopolitical tensions. Prices were higher, driven by a cocktail of factors that included decisions by OPEC and some non-OPEC producers to cut production, the economic recovery in Asia, and global economic growth that boosted energy demand. A cold winter and higher demand for diesel, speculators entering the market, geopolitical uncertainties, and the decline in exploration and development investment that has delayed new supply have all pushed prices higher. These are the sophisticated dynamics that underlie the speed at which price changes occur in energy markets and how many factors can have a very strong impact on prices.

2.1.6. November 2000-November 2001

Between November 2000-November 2001, the fall in crude oil prices from $31 to $17 was a result of several combined factors such as the global economic slowdown, the September 11 terrorist attacks, growth in oil production and OPEC's below-average production, improvements in energy efficiency and technology along with market sentiment and speculation along with the possibility of strategic exploitation of oil reserves. This would lead to reduced demand for oil at a time when it was falling in the USA and slowing in different major economies. Economic uncertainty also increased after the attacks, and the reduction in air travel affected the demand for jet fuel, and thus crude oil. Major increases in production, to which OPEC's initial response was inadequate, would have put too much supply on the market, while technological advances and improvements in energy efficiency would also have put downward pressure on oil prices. Speculative trading and outflows from the Strategic Petroleum Reserve would have exerted more pressure than necessary at the level of demand indications. This chain of events led to a significant decline in crude oil prices.

2.1.7. May 2003-October 2004

Between May 2003 and October 2004, the price of crude oil rose by $25 to $45 due to a massive combination of factors. Economic growth around the world was more widely felt, with the U.S. and China experiencing tremendous growth, creating massive demand for oil. Increasing geopolitical tensions, most acute in the Middle East and other oil-producing regions, had raised concerns about supply disruptions. Other factors that contributed to the rise in prices included limited spare capacity and market speculation. In addition, there was the fact of the depreciation of the US dollar, OPEC's production policy and, apart from all this, concerns about refining capacity. This period vividly illustrates the dynamics of supply and demand, combined with geopolitical and economic factors, and how they can sometimes affect oil prices.

2.1.8. December 2004-August 2006

Between December 2004 and August 2006, crude oil prices rose from $35 to $69. The rise was the result of a cocktail of factors, including global economic growth, political tensions around the world, limited spare production capacity, and increased investment and speculation in the markets. Others include supply disruptions and concerns over Iran's nuclear program, energy and investment policies, and market dynamics and psychological factors. This period, characterized by continued expansion in the advanced economies along with Chinese growth, boosted oil demand, while geopolitical events in Iraq, Nigeria and Venezuela raised supply concerns. Large oil price spikes during this period followed the events of September 11, 2001, and were catalyzed by natural disasters such as Hurricane Katrina and international tensions over Iran, which increased supply risks. In addition, such high prices raised further questions about the security of energy supply and the level of investment in new production capacity. In addition, the combination of rising demand, supply constraints and market speculation exacerbated the upward pressure on prices.

2.1.9. January 2007-July 2008

From January 2007 to July 2008, a cocktail of factors caused the price of crude oil to rise from $50 per barrel to $131 per barrel. During this period, a new wave of strong economic growth, particularly in China and India, fueled increased demand. Geopolitical tensions, as well as the lack of spare production capacity in the Middle East or Nigeria, have increased supply concerns, which could push prices higher. The fall in the US dollar means that oil is cheaper in other currencies, increasing demand for the fuel. Speculative trading activity drove prices higher, with both futures markets and market sentiment acting in tandem. The main factors that pushed prices to their highest levels ever by mid-2008 were technical problems, which, in addition to political instability, led to supply disruptions and ever-increasing production costs. However, in the second half of 2008, it was the global financial crisis that triggered a sharp drop in demand and, consequently, in prices.

2.1.10. July 2008-December 2008

Between July and December 2008, the price of crude oil fell from $131 per barrel to $38 per barrel, influenced by a sharp decline in economic activity and oil demand. Prices had fallen sharply due to several other factors, including the impact of the financial crisis in world and economic recession and the resulting strengthening of the U.S. dollar, which led to a flight from commodities. OPEC's delayed response, coupled with a sharp rise in oil production and inventories, also had a devastating effect on market psychology and led to a destruction of demand. These factors illustrate how quickly the oil markets can react to changing economic conditions, market sentiment and geopolitical developments, and how quickly the price can change.

2.1.11. January 2009-April 2010

From January 2009 to April 2010, the price of crude oil rose from $40 per barrel to $82 per barrel due to several factors. These include economic stimulus from the global financial crisis, rising demand, OPEC production cuts, the weakness of the U.S. dollar, speculative investment, and other factors such as inventory adjustments, geopolitical tensions, and improvement in financial markets. The period highlighted the impact on oil prices: the fragile recovery in the global economy, OPEC's production policy and speculative investments that may have helped shape market expectations. It has shown a sharp increase from the sharp fall in prices witnessed in the second half of 2008, therefore global economic conditions and supply and demand dynamics are the key determinants of price movements.

2.1.12. July 2010-April 2011

Between July 2010 and April 2011, the price of crude oil rose from $72 to $118 based solely on global supply and demand, geopolitical tensions, market dynamics, and speculative investment that accumulated around it. During this period, the recovery of the global economy, particularly the growth of China and India, boosted oil demand, while anti-government protests, also known as the Arab Spring, depressed production, especially in oil producer Libya, raising supply concerns. The weakness of the U.S. dollar increased the demand for oil against other currencies and thus its price, as the dollar is the world's currency in oil denomination. Speculative investments put upward pressure on prices by influencing market dynamics. Geopolitical factors and supply concerns in the MENA region, along with OPEC's production policies, pushed prices significantly higher. This period is well represented in the sense that the price of oil can really spike when a number of different reasons combine to push prices up; no single reason for the spike.

2.1.13. March 2012-June 2012

Between March 2012 and June 2012, crude oil prices fell from $123 to $94 per barrel. In addition to global economic concerns, such as the European debt crisis and slowing growth in China, other important factors included a stronger US dollar against other currencies, increased oil supply, strategic releases of oil reserves and easing geopolitical tensions, changes in market sentiment and speculative trading, technical factors, and price corrections. These developments, together with lower demand expectations and perceptions of adequate or increasing supply levels, have thus driven prices lower, reflecting the sensitivity of oil to changes in the economic outlook, geopolitical developments, and market dynamics.

2.1.14. June 2014-January 2016

Crude oil prices plummeted from $108 per barrel to $26 per barrel between June 2014 and January 2016, one of the steepest selloffs in modern history. Some of the reasons include increased shale oil production in the United States, a market share strategy by OPEC, as well as weak global demand and the strengthening of the U.S. dollar. All these factors have, to some extent, affected the global economy, energy companies and oil-dependent countries in ways that will lead to adjustments in the energy sector and a rebalancing of the market in the coming years.

2.1.15. January 2016-October 2018

Between January 2016 and October 2018, crude oil prices rose from $26 to $79 per barrel, driven by several factors. These include OPEC and non-OPEC production cuts, global economic growth, declining US shale oil production, geopolitics, market sentiment and speculative trading. Lower global growth will also be reflected in global oil inventories, fluctuations in the U.S. dollar, and increased investment in oil infrastructure. This period has been indicative enough of how oil markets operate in cycles and how the price level is significantly affected by the supply/demand imbalance, geopolitical conditions, and the general pulse of the markets.

2.1.16. October 2018-April 2020

Between October 2018 and April 2020, the price of crude oil fell from $79 to $17 per barrel. This was a massive drop due to a combination of several factors, such as a global economic slowdown, fears of oversupply, trade disputes between the US and China, concerns about storage capacity, and of course the price war between Saudi Arabia and Russia, in addition to negative oil prices due to COVID-19. With the global economy sluggish and trade tensions already in place, oil demand was subdued, but the new wave of the novel coronavirus has hit it like never before around the world. In addition, a price war between Saudi Arabia and Russia, at a time when storage capacity was already being stretched to the limit, further tightened the market. All of this has led to one of the most volatile periods in the history of the oil market, pushing prices to historic lows that show vulnerability as the market shifts with changes in global demand and geopolitical tensions or market dynamics.

2.1.17. April 2020-June 2022

Between April 2020 and June 2022, crude oil prices rose from $17 to $117 per barrel. The support came from a cocktail of factors, including the post-COVID-19 economic recovery, OPEC+ production cuts, various types of supply disruptions, and robust demand for transportation fuels. There was also inflationary support from geopolitical tensions and investment concerns around the energy transition. As a result, the introduction of the vaccine, the easing of quarantine measures and the lifting of travel restrictions eased the pace of economic activity and supported oil demand. Decisions by OPEC+ countries on production cuts and geopolitical events put pressure on the supply side, while on the other hand, the general upward trend in commodity prices and speculative trading also contributed to pushing prices higher. This period consolidated how dynamic the oil market could become and the complexity associated with managing the economic recovery coupled with the supply-demand balance in the post-COVID period.

2.1.18. June 2022-December 2022

Between June 2022 and December 2022, crude oil prices fell from $117 to $80 per barrel due to various factors. This was mainly due to fears of global economic slowdown, increase in oil supply, unbridled oil reserves and strategic COVID-19 restrictions in China, among some other geopolitical events, currency exchange and market speculations. All these factors combined to pull oil prices due to the interaction of several dynamics, such as fears of reduced demand, production increases by OPEC+ and non-OPEC countries, release of oil from strategic reserves by countries, particularly the US, lockdown in China and conflict in Ukraine, and market sentiment at a time when the US dollar strengthened with speculative trading in futures markets.

2.2. Application

The study tracks annual data on crude oil prices, production, reserves, and demand, and links them to key historical events to determine their impact on the global oil market. This research therefore adopts a multifaceted econometric approach that seeks to analyze the dynamics in the OPEC data using an Excel package called XLSTAT.

Predicting the future of oil prices is a crucial exercise that usually falls under the cluster of time series analysis techniques. Historical price data has been used to identify patterns and predict future movements using models such as ARIMA or nonparametric regression. These are typically forecasts in econometric models such as VAR with external variables, including geopolitical events, technological developments, and changes in global supply and demand. These models provide a nuanced view of how different factors interact to influence oil prices.

Complementing these quantitative methods, forecasting focuses on looking at the likely range of certain future events and how they may affect oil prices. This approach is therefore flexible and useful in preparing stakeholders for many possible situations in a volatile market. The forecasting process is dynamic and needs to be constantly reviewed and modified with new data and information. At this point, stakeholders should be able to interpret the complexity of the oil market. Through in-depth analysis and a range of forecasting tools, they should be able to make informed decisions to mitigate risks and capitalize on market opportunities. It also reemphasizes the importance of monthly crude oil price data in economic planning, investment strategies and operational decision-making processes on a sectoral basis within boards of directors.

Our main dataset consists of annual records from the OPEC database. Secondary data sources are used to enrich our analysis. These sources will include data from international financial institutions, supplemented by historical archives that reference original OPEC data, thus providing a robust dataset suitable for use in this study.

The analysis of price volatility, a key indicator of the global energy market, provides insight into supply and demand dynamics, geopolitical tensions, and economic trends. Evaluation of production data reveals OPEC's role in market equilibrium and explores how strategic production adjustments affect global oil supply. Reserves represent the long-term sustainability of oil production and influence future market strategies and investment decisions. Demand analysis emphasizes consumption patterns that reflect economic growth, technological advances, and shifts toward renewable energy. The inclusion of inflation as a variable allows for an examination of how oil prices relate to broader economic indicators, affecting purchasing power and economic policy.

This paper formulates models and obtains forecasts using the XLSTAT an Excel package, known for its advanced capabilities in econometric analysis and time series forecasting. The reason for this choice is that XLSTAT can be used to efficiently handle very large data sets and difficult and complex econometric models. This allows for an intensive analysis of the relationships between the variables under study. First, descriptive statistics are calculated to get an idea of the distribution, central tendencies, and variability of the data. This step aims to reveal any anomalies, trends, and patterns in the data set and to provide a basis for more detailed econometric modeling.

The core of our analytical methodology involves multiple regression and time series analysis to explore the dynamics between crude oil prices and key economic indicators such as production volumes, reserve estimates, demand figures and inflation rates. Non-parametric regression analysis is used to quantify the impact of each variable on crude oil prices, while time series models such as ARIMA are used to identify trends, cyclicality, and seasonal variations in the data. These econometric models will provide the basis for forecasting and identifying underlying patterns in the oil market.

An important aspect of our methodology is the study of historical events, which involves a systematic approach to identifying and categorizing significant historical events based on their expected impact on the oil market. For each selected event, market indicators before, during and after the event are examined through a comparative analysis using interrupted time series analysis and counterfactual scenarios to isolate the impact of the event from other variables.

2.3. The relationship between macroeconomic variables and description of the methods

Understanding the relationship between macroeconomic variables and OPEC crude oil prices is critical to understanding global economic dynamics. As one of the largest groups of crude oil producing countries, OPEC sets oil prices through quotas and effects the global supply level. Prices are the result of the interaction of various macroeconomic variables such as GDP growth, exchange rates and inflation. For example, global GDP growth means that there will be greater demand for energy from developed and emerging economies, and thus oil prices will rise. On the other hand, during periods of economic recession, demand for oil tends to decline, putting downward pressure on oil prices.

Exchange rates have an indirect but very important effect on OPEC oil prices. This is because most oil-related transactions are denominated in dollars, so any change in the value of currencies can affect the affordability of oil in some markets that use other currencies. A weak dollar makes oil cheaper for countries with stronger currencies, potentially increasing demand and thus prices. On the other hand, a stronger dollar in the medium term could reduce demand for oil, which could lead to lower prices. This shows that monetary policies and currency valuations in major economies are interrelated with the energy sector and thus affect OPEC's pricing strategies and even the revenues it generates. Information on all these variables is presented in Table 1.

Table 1. Changes in OPEC nominal oil prices and macroeconomic data by years (assembled using OPEC data)

Date	Nominal Oil Price ($)	Exchange Rates	Inflation	GDP	Oil Production (1000 b/d)	Oil Demand (1000 b/d)
1972	2,29	1,8	14,87	78774,42	25592,052	844,7132686
1973	3,05	2,16	18,6	106362,7	29023,138	971,0353584
1974	10,73	7,67	59,23	203017,8	28827,615	1064,043914
1975	10,73	7,45	54,78	218723,6	25412,581	1239,07646
1976	11,51	8,27S	55,57	275364	28724,135	1484,599384

Table 1. (Continued)

Date	Nominal Oil Price ($)	Exchange Rates	Inflation	GDP	Oil Production (1000 b/d)	Oil Demand (1000 b/d)
1977	12,39	8,56	56,28	314419,3	29152,263	1704,479023
1978	12,7	7,77	55,11	330183,8	27680,694	1906,348939
1979	17,25	10,19	70,33	431881,1	28801,423	2104,636821
1980	28,64	17,04	106,39	575304,2	24834,709	2494,867231
1981	32,51	21,69	111,55	600923,4	20518,12	2625,324862
1982	32,38	23,73	104,67	595770,6	17441,068	2819,617591
1983	29,04	22,39	89,87	602225,5	15521,164	3051,017954
1984	28,2	23,71	83,51	577870,7	14808,722	3261,914773
1985	27,01	24,01	76,26	478332,3	13966,467	3400,555356
1986	13,53	10,37	37,22	448529	16660,718	3468,273016
1987	17,73	12,59	47,23	458950,3	15999,725	3496,268137
1988	14,24	9,87	35,93	458535,1	18198	3689,16028
1989	17,31	12,52	40,92	462226,6	19667,047	3677,096006
1990	22,26	16,17	50,38	483492,7	21220,323	3660,372019
1991	18,62	14,15	41,29	483891,9	21357,169	3831,529455
1992	18,44	14,03	39,14	527047,7	23091,562	4059,943568
1993	16,33	13,13	32,77	480853,6	23519,741	4202,108068
1994	15,53	14,15	28,86	453561,2	23927,832	4273,144326
1995	16,86	14,9	29,04	535153,6	24021,569	4289,927986
1996	20,29	18,31	33,47	595559,4	24313,114	4390,430571
1997	18,68	17,76	30,03	616349,5	25074,938	4540,301377
1998	12,28	12,14	19,42	578635,9	27194,056	4686,377291
1999	17,48	17,34	27,41	630100,7	25662,436	4669,327627
2000	27,6	28,78	42,47	734686	27227,118	4891,949761
2001	23,12	24,99	34,8	737377,4	26458,592	5058,143917
2002	24,36	26	36,04	738746,6	24224,377	5194,984114
2003	28,1	28,02	40,66	830790,3	26691,44946	5341,879067
2004	36,05	34,58	50,71	1054929	29533,63181	5703,082627
2005	50,64	48,05	69,54	1337571	30772,308	6075,356705
2006	61,08	57,51	81,85	1611337	31014,20769	6410,460859
2007	69,08	61,85	89,61	1929021	30514,893	6678,457474
2008	94,45	80,81	116,87	2415450	31505,957	7044,066044
2009	61,06	53,83	74,86	2030800	28491,886	7272,69502
2010	77,45	68,04	92,16	2581341	28829,806	7645,370292
2011	107,46	91,46	122,62	3081477	29646,867	7986,857429
2012	109,45	96,04	121,19	3369941	31924,78	8336,357459
2013	105,87	93,39	114,17	3230116	31024,734	8640,126915
2014	96,29	85,62	101,56	3221916	30075,003	8807,185121
2015	49,49	47,72	51,51	2696360	31061,71	8886,477558
2016	40,76	40,39	41,69	2627045	32467,373	8873,695279
2017	52,43	52,43	52,43	2782931	31636,264	8810,460159
2018	69,78	69,87	67,8	2801984	31216,587	8691,884596
2019	64,04	67,18	60,39	2711519	29375,778	8769,314034
2020	41,47	44,29	38,38	2332772	25659,265	7878,295258
2021	69,89	74,41	62,42	2766706	26363,078	8273,598838
2022	100,08	125,85	80,14	3374636	28894,931	8842,402753

It seems that inflationary pressures and interest rates are the key factors. In terms of cost-push inflation, an increase in oil prices should increase in cost-push inflation. Such an event usually encourages central banks to change monetary policy, under which there is the potential of interest rate pressure. Higher interest rates could strengthen the national currency, making oil more expensive in other currencies and potentially reducing demand. In addition, geopolitical events and shifts in energy policy toward sustainability and efficiency can affect the global supply and demand balance by affecting demand for OPEC oil. Understanding these relationships is critical to analyzing oil market trends, as it highlights the sensitivity of OPEC oil prices to broader economic forces and policy decisions.

To analyze the data and interpret the results, nominal oil prices and macroeconomic variables are analyzed using various statistical methods.

To examine the relationship between macroeconomic variables and OPEC crude oil prices, we first use nonparametric regression analysis. This method allows us to model these relationships without assuming a specific functional form for the underlying data distribution, making it particularly useful for analyzing complex, non-linear patterns that may exist between oil prices and macroeconomic indicators. Non-parametric regression is implemented through the kernel smoothing technique, where the regression function is estimated locally for each point x:

$$f(x) = \frac{\sum_{i=1}^{n} K_h(x-x_i)y_i}{\sum_{i=1}^{n} K_h(x-x_i)} \quad (1)$$

where $K_h()$ is the kernel function, a weighted function that assigns weights to observations near the point x, h is the bandwidth parameter that controls the width of the kernel, x_i are the independent variable observations and y_i are the dependent variable observations (Tibshirani & Wasserman, 2013).

To further understand the interdependencies between the variables, we conduct a correlation analysis, generating both correlation maps and matrices. Correlation coefficient, r, calculates the strength and direction of relationship between two values, calculated as:

$$r_{xy} = \frac{n(\sum xy)-(\sum x)(\sum y)}{\sqrt{[n\sum x^2-(\sum x)^2][n\sum y^2-(\sum y)^2]}} \quad (2)$$

where n is the number of observations, x and y are the individual observations of the two variables (Asuero et al., 2006). This analysis helps visualize the relationships and identify potential predictors for inclusion in the regression model.

AutoRegressive Integrated Moving Average (ARIMA), a time series model, will be used to predict the future of nominal oil price. The model is written as ARIMA (p, d, q), where p is the autoregressive terms value, d is the differences required to render the series stationary, and q is the lagged forecast errors. The model is formulated as:

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (3)$$

where y'_t differenced series (if d>0), c is a constant value, ϕ_i are autoregressive terms parameters, θ_i are moving average parameters, and ε_t is noise (Sahai et al., 2020).

ARIMA's integrated approach, combining autoregression, differencing, and moving averages, allows for an accurate capture of time dependencies and trends within the oil market, making it an ideal choice for this study. Its effectiveness is further evidenced by its widespread adoption and success in previous oil market forecasts, where it has demonstrated predictive accuracy and reliability.

Moreover, the inherent flexibility of the ARIMA model to adapt to the stationary requirements of time series data, by differencing, addresses the challenge posed by the volatile nature of oil prices. This adaptability is crucial for accurately forecasting oil prices, given their susceptibility to abrupt changes due to geopolitical events, supply-demand imbalances, and other exogenous shocks. This approach not only enhances the understanding of oil price dynamics but also contributes to more informed and strategic decision-making in the face of market volatility.

This comprehensive methodology, which combines nonparametric regression, correlation analysis, and ARIMA forecasting, allows for a nuanced understanding of the dynamics between macroeconomic variables and OPEC crude oil prices, as well as the prediction of future price movements based on historical trends.

Along with all these analyses, data on World Oil Production and Demand from OPEC data are positioned by country. They were then analyzed with the help of Kernel Density Analysis in GIS environment. In this way, it was revealed in which regions the data are concentrated. The following formulas define how the kernel density for points is calculated and how the default search radius is determined within the kernel density formula.

The predicted density at a new (x,y) location is determined by the following formula:

$$Density = \frac{1}{(radius)^2}\sum_{i=1}^{n}[\frac{3}{\pi} pop_i (1 - \left(\frac{dist_i}{radius}\right)^2)^2] \quad (4)$$

Where i = 1,…,n are the input points. Only include points in the sum if they are within the radius distance of the (x,y) location. pop_i is the population field value of point i, which is an optional parameter. $dist_i$ is the distance between point i and the (x,y) location.

The calculated density is then multiplied by the number of points or the sum of the population field if one was provided.

3. Results

Although crude oil price changes show sudden changes due to the impact of periodic events, analyzing these price changes can provide a better understanding of oil price changes with different indicators. In this regard, it is important to interpret oil prices and macroeconomic indicators together and analyze their relationship. In this way, price reactivity can be calculated, and future price forecasts can be made.

Our comprehensive analysis, which includes nonparametric regression, correlation, ARIMA forecasting, assessment of the impact of historical events, and spatiotemporal examination using ArcGIS and kernel density analysis, provides deep insights into the complex interplay between macroeconomic variables and OPEC crude oil prices. The results underscore the multifaceted influence of economic indicators, geopolitical events, and the spatial distribution of resources on the oil market, providing valuable perspectives for understanding future price movements and policy implications.

Nonparametric regression analysis examines various macroeconomic variables in relation to the nominal oil price. The inflation-based regression chart shows the relationship between inflation and nominal oil prices. A positive trend would suggest that as inflation rises, so do oil prices, which could be due to a decline in the purchasing power of the currency or cost-push inflation, where rising oil costs drive up the prices of a wide range of products (Figure 4).

The exchange rate-based regression chart plots the exchange rate against the nominal price of oil (Figure 4). If you observe that the red prediction points form an upward trend as the exchange rate increases, this implies that there is a positive relationship between the exchange rate and oil prices. An upward trend suggests that as the value of the currency falls, the nominal price of oil also rises.

The GDP-based graph correlates gross domestic product with the nominal price of oil (Figure 4). Typically, a positive relationship would indicate that higher GDP is associated with higher oil prices, which could reflect greater demand for oil as the economy expands.

In the graph based on oil production, you are looking at how the amount of oil produced affects its nominal price. The relationship can be more complex, as increased production can lead to both a decrease in the price of oil due to a supply glut, or an increase if production is associated with higher costs or risk factors. In the case of oil demand, the graph analysis shows how changes in oil demand are related to changes in the nominal price of oil. A positive trend, where projected oil prices rise with demand, would be consistent with basic economic principles of supply and demand - higher demand for oil typically leads to higher prices, all else being equal.

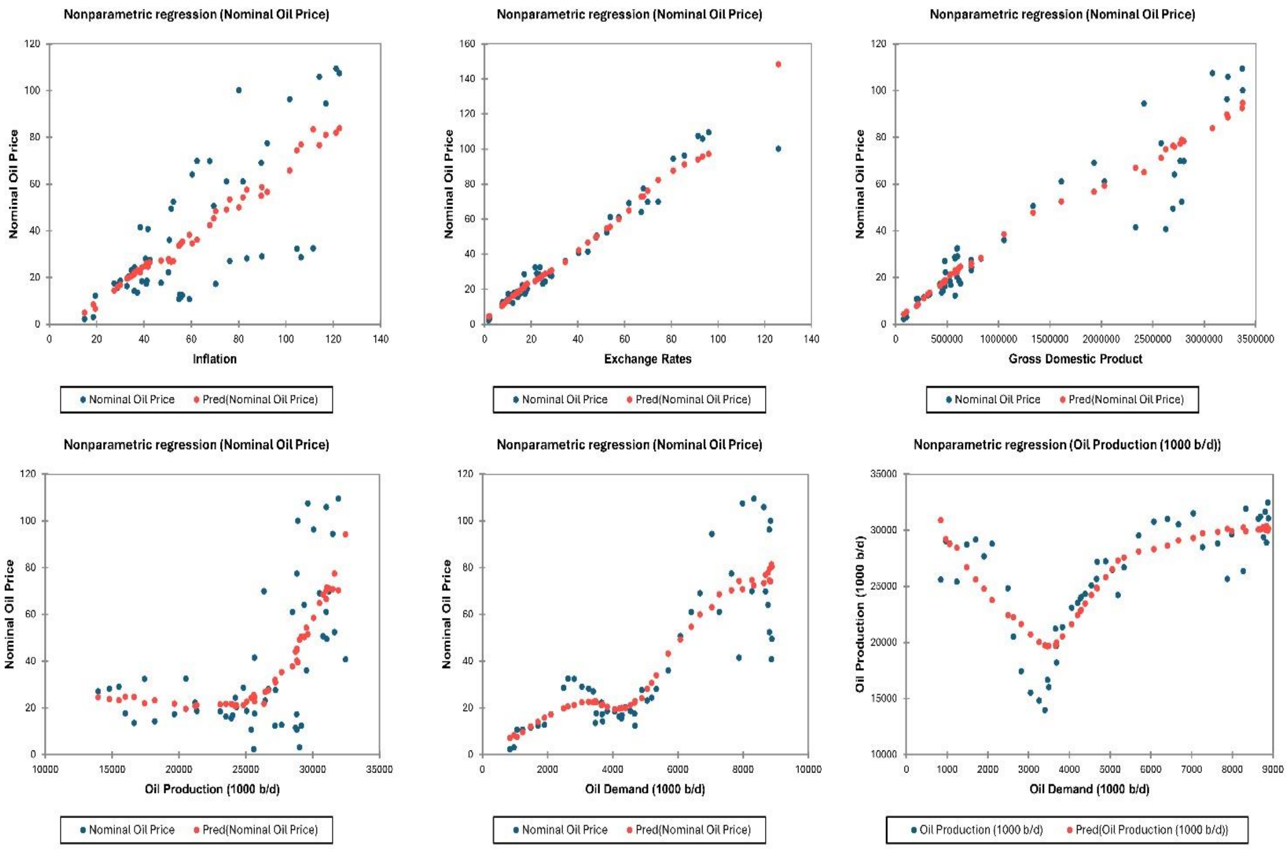

Figure 4. Non-parametric regression analysis results

In addition to nonparametric regression analysis, correlation analysis was performed, and a scatterplot graph was created to examine the relationship between the data. Correlation analysis analyzes the distribution of oil prices and other macroeconomic data. The scale on the side of the correlation matrix corresponds to the correlation coefficients. If the value is close to 1 that means a strong positive relationship, if the value is close to -1 means a strong negative relationship, and around 0 means no relationship (Figure 5). Taken together, the scatterplot graph (Figure 6) allows you to quickly assess the potential relationships among multiple variables and identify patterns that may warrant further statistical testing or inclusion in predictive models.

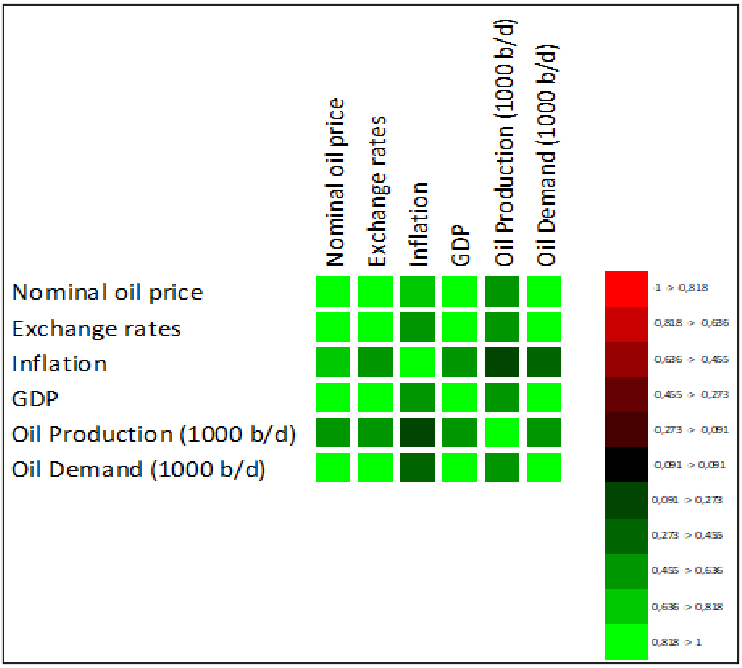

Figure 5. Correlation matrix

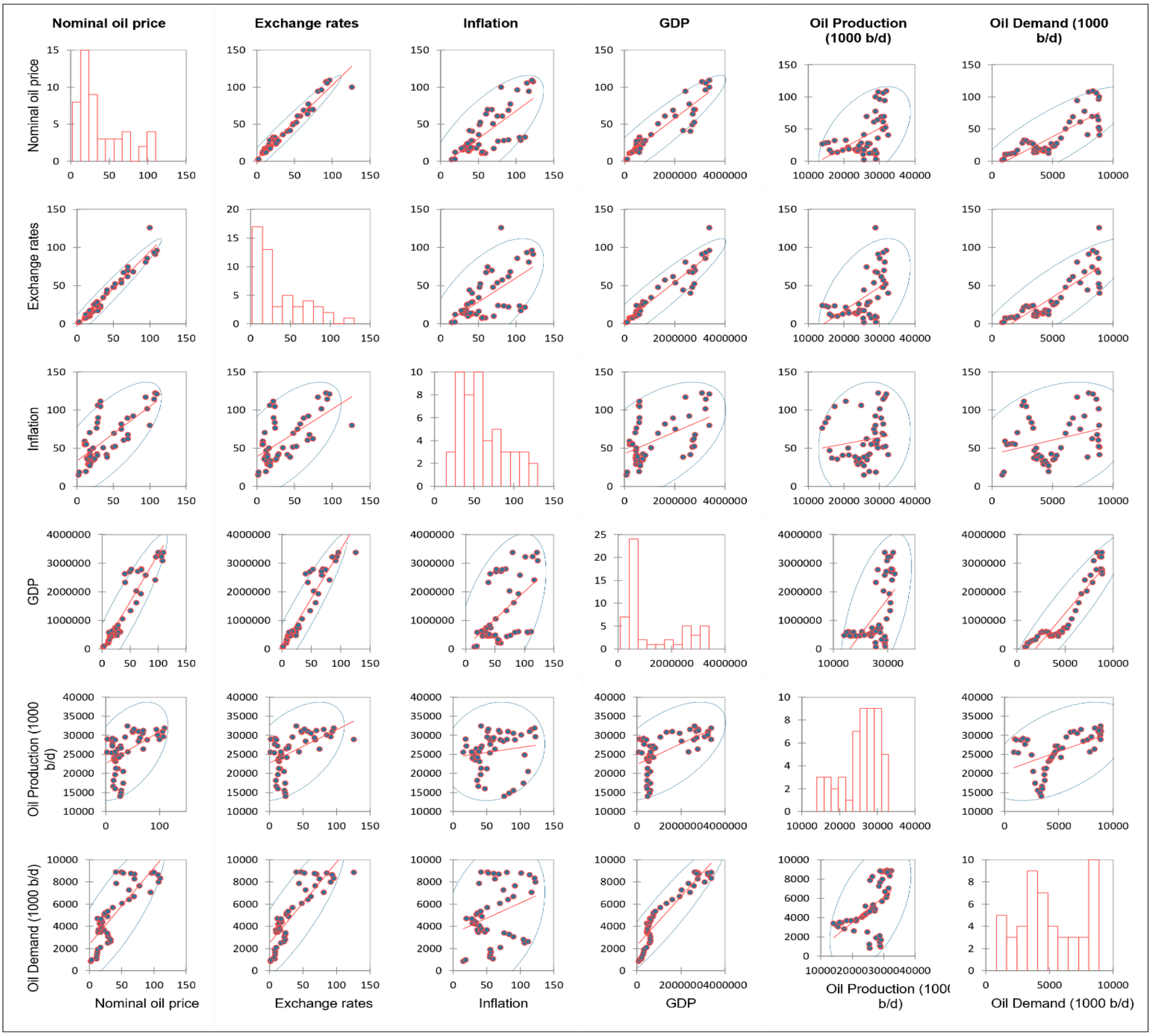

Figure 6. Scatter plot graph for correlation

In addition to nonparametric regression analysis and correlation analysis, time series analysis was used to understand the trend of each of the data and to estimate the direction of movement. ARIMA was selected as the most appropriate time series analysis. In the ARIMA analysis, the relationship of the data over time and the changes in macroeconomic changes and oil prices are calculated for the period 1972-2022 and the future forecasts are expressed in Figure 7.

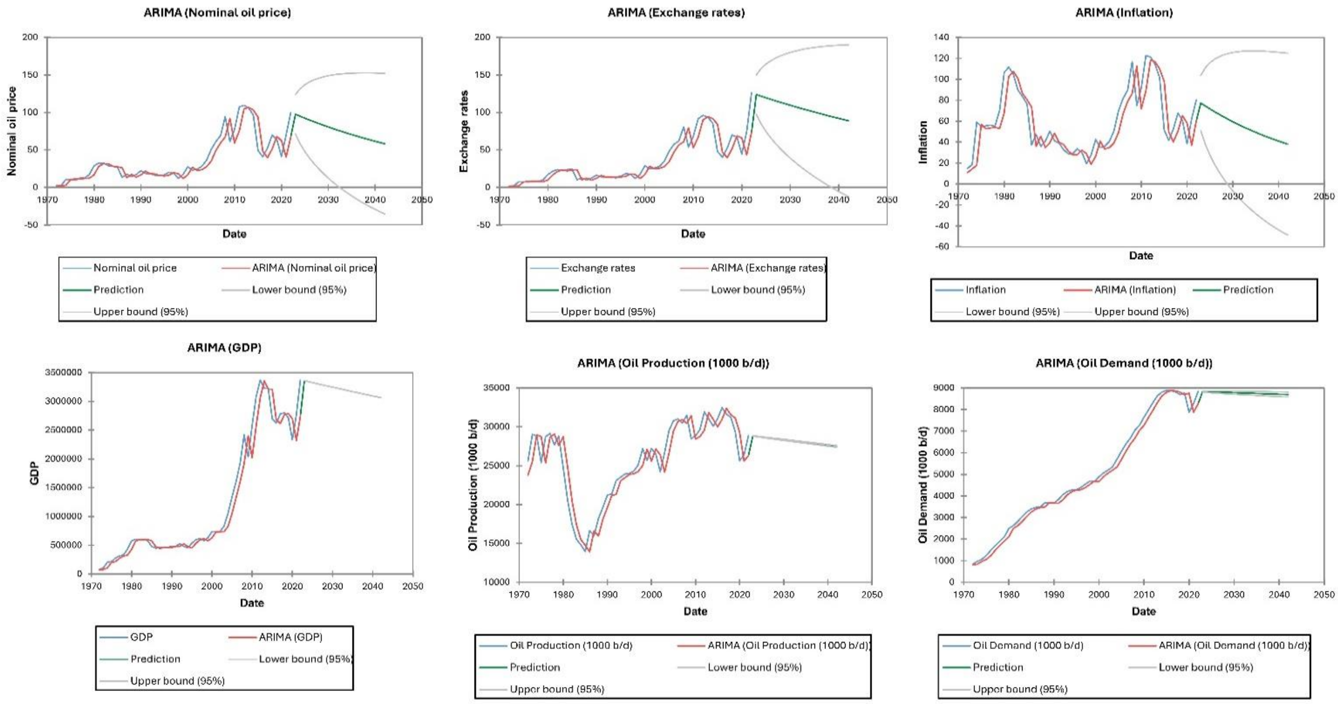

Figure 7. ARIMA analysis for nominal oil price and macroeconomic variables

The Nominal Oil Price chart includes history and forecasts for oil prices. The forecast may include history, seasonality, and past shocks. On the other hand, "Exchange Rates" always shows the relative value of one's own currency against the other, usually against the U.S. dollar. The forecast trend reflects expected economic conditions, policy changes and trade dynamics of countries. The "Inflation" chart reflects a trend showing a rate of increase in the general level of prices for goods and services, followed by a decline in purchasing power. Inflation forecasts are important inputs for monetary policy and economic planning. The GDP graph shows the market value of all final goods and services produced by a nation each year. Forecasts of GDP trends help to understand likely future economic health and possible policy interventions. The Oil Production graph shows the amount of oil produced over time. Forecasting production can help inform discussions not only about resource depletion, but also about investments and technologies for extraction and energy policy. The "Oil Demand" graph shows the willingness of consumers to buy oil at different prices. Its forecast helps to manage the supply aspect.

The ARIMA analysis of crude oil prices, in conjunction with nonparametric regression and correlation analysis, yields substantial insights into the intricate interrelationship between oil prices and macroeconomic variables, including inflation, exchange rates, GDP, oil production, and oil demand. The results indicate a strong positive correlation, confirming that as inflation and GDP rise, so do oil prices. This reflects higher demand and cost-push inflation. The analysis also elucidates the intricate relationship between oil production and prices. It reveals that increased production can result in either price declines due to oversupply or price increases if associated with higher costs. The geospatial analysis, conducted using GIS, adds a valuable dimension, demonstrating the geographic shifts in oil production and demand. This underscores China's growing economic influence. These findings provide a comprehensive understanding of the factors driving oil prices, offering policymakers and industry leaders critical insights for strategic decision-making in the global oil market.

In addition to all statistical analyses, country-based data from OPEC were recorded in their locations on GIS and a different perspective was tried to be put forward in the analysis of oil-related variables through spatial analysis. A GIS-based analysis following the temporal and spatial criteria of the paper is presented in the sequel. The time series variation is correlated with the spatial data of the macroeconomic variables crude oil production and crude oil demand. In this context, the kernel density function of the density tool of the ArcGIS Pro application is applied to these data, which have been recorded since the 1960s and allow us to obtain information on the production and demand of crude oil in the subject countries. Without these statistical and spatial analysis capabilities of ArcGIS, we would not be able to reveal the distribution of oil production and demand in the world. The following series of maps, shown in Figure 8, allows us to observe the changes in the intensity of crude oil production from the 1960s to the 2020s. In Figure 9, we look at the change in crude oil demand intensities from the 1960s to the 2020s in a series of maps. It also shows changes that have a global impact and further changes in prices.

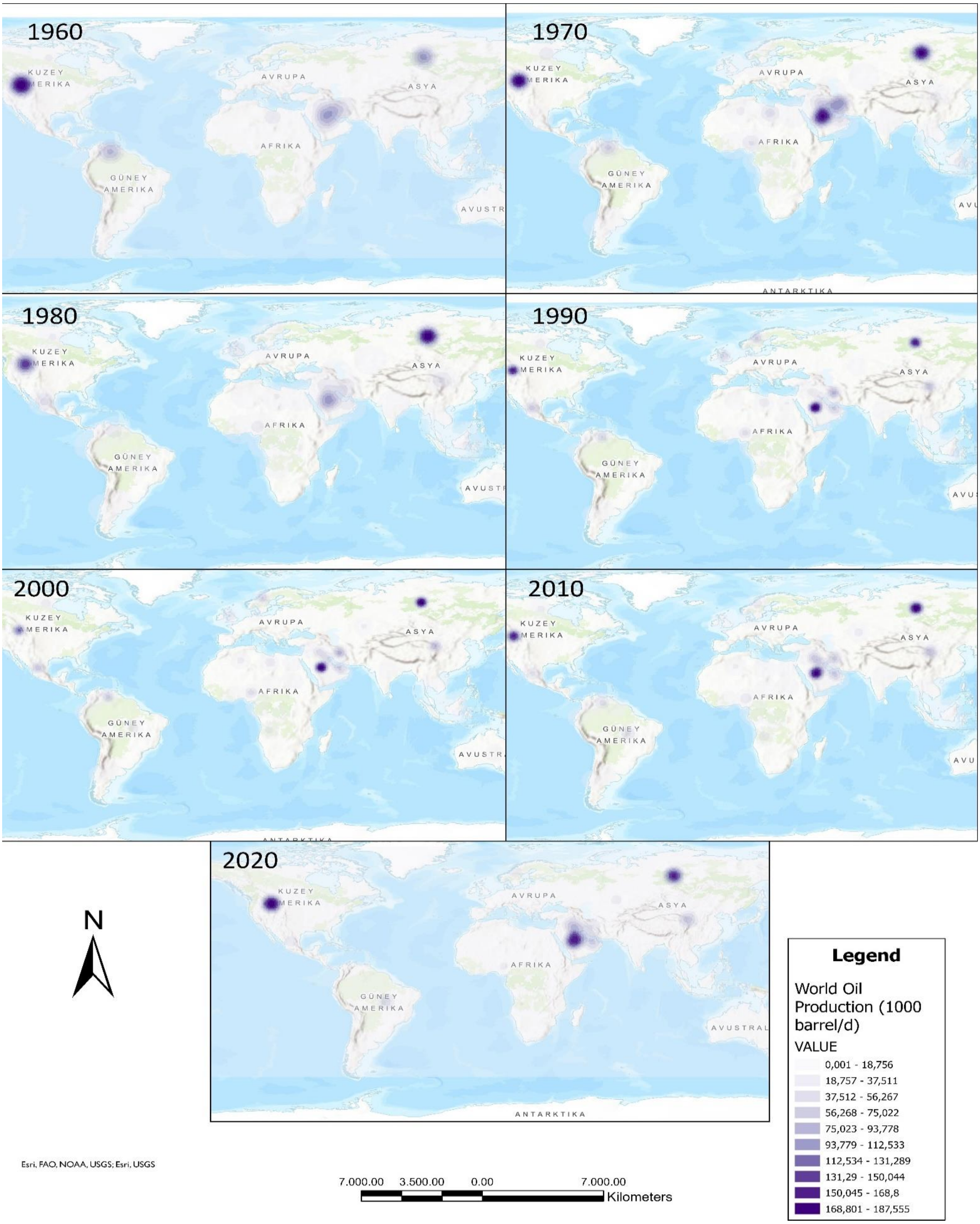

Figure 8. 1960s to 2020s global crude oil production

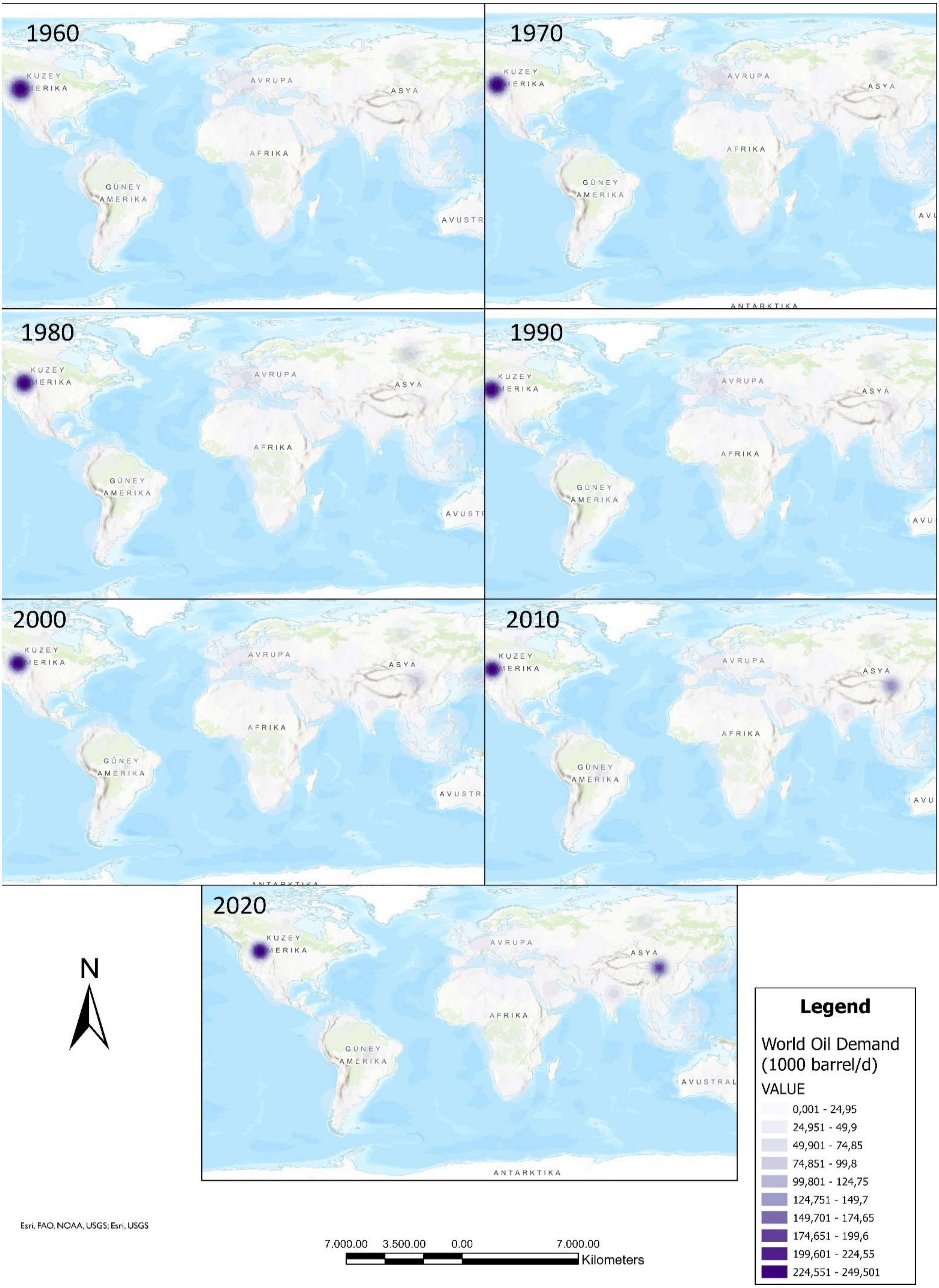

Figure 9. 1960s to 2020s global crude oil demand

4. Discussion

This study examines the relationship between certain macroeconomic indicators and OPEC crude oil prices. It follows a multifaceted approach that includes nonparametric regression, correlation analysis, ARIMA forecasting, assessment of the impact of historical events, and spatial analysis using ArcGIS.

The analysis confirmed the expected positive correlations between oil prices and factors such as inflation, exchange rates (when the local currency weakens), and GDP (indicating rising demand with economic growth). One interesting finding was the complex relationship between oil production and price. Increased production can lead to both price declines due to oversupply and price increases if production becomes more expensive or risky. The correlation matrix and scatter plots provided a quick way to visually assess potential relationships between oil prices and various economic factors. The ARIMA forecasts were particularly valuable as they provided insight into the projected trends of oil prices and key macroeconomic variables. This allows stakeholders to anticipate future market conditions.

Spatial analysis using ArcGIS revealed how geographic shifts in oil production and demand intensity over time contribute to global price fluctuations. This will be a major strength of the study, as it will provide a comprehensive view of the factors that influence the determination of oil prices. There was a time in the 1960s when much of the oil demand dominance belonged to the United States. Today, this leadership in oil demand is observed by China (Figure 10). This shows how economically powerful China has become and how influential it will be on price changes in the future.

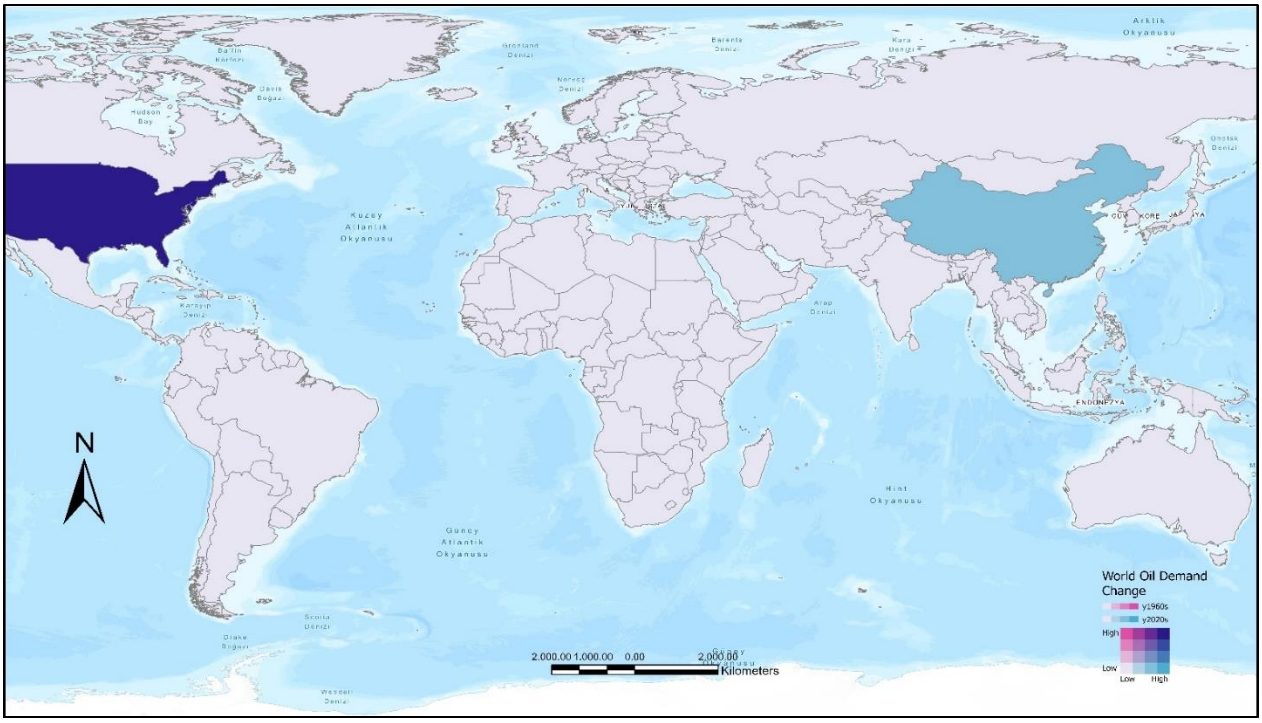

Figure 10. Global crude oil demand change between 1960s to 2020s

5. Conclusion

This study makes a significant contribution to the oil economics literature by employing a multifaceted analytical framework that captures the complexity of the oil market. Its findings are invaluable to stakeholders across the global oil industry, providing a richer understanding of oil price dynamics and guiding decision making in a volatile market environment. The research combines various analytical approaches, including ARIMA forecasts and spatial analysis, to anticipate future market conditions and develop effective strategies. This comprehensive methodology not only confirms the relationship between oil prices and macroeconomic variables but also introduces a spatial component that provides a more detailed landscape of oil market dynamics.

As discussed above, this research has proven useful in unraveling some of the very many opaque factors that influence OPEC crude oil prices. What makes it valuable is the fact that the research combines so many of the analytical approaches and thus makes it really have some relevant insights for the stakeholders in the global oil market. It considers the expected trends from the ARIMA forecasts and spatial analysis of production and demand patterns, in fact providing one of the most powerful means to anticipate future market conditions and effective strategies.

By comparing our findings with those of the existing literature, our study extends the understanding of the complex dynamics between macroeconomic variables and oil prices through its comprehensive methodology. While previous research, such as the work of Kilian & Vigfusson (2013) and Cologni & Manera (2008), has primarily focused on the linear impact of economic indicators on oil prices, our multifaceted approach reveals nuanced interdependencies and spatiotemporal dynamics that have not been previously highlighted. For example, our use of ARIMA forecasting and GIS-based spatial analysis has revealed patterns of global oil demand shifts and production intensities that provide a more granular view of market fluctuations. Moreover, our findings on the predictive value of macroeconomic variables for oil prices are consistent with the incorporation of spatial analysis to illustrate geographical shifts in oil production and demand. Thus, our research not only confirms the consensus on the relationship between oil prices and macroeconomic variables found in studies such as Mukhtarov et al. (2020) and He et al., (2010), but also introduces a spatial component that improves predictive accuracy and provides a richer, more detailed landscape of oil market dynamics.

The integration of GIS analysis and macroeconomic data analysis offers a synergistic approach that significantly enhances the understanding of the factors influencing crude oil prices. By integrating GIS's spatial visualization capabilities with traditional econometric models, such as ARIMA, the study provides a more nuanced and comprehensive view of how geographic patterns and economic variables interact. This integrated approach enables more accurate predictions, enhanced risk management, and informed decision-making for policymakers and industry leaders. GIS analysis reveals geographic trends and spatial dependencies that are crucial for anticipating the impact of regional economic changes and geopolitical events on global oil prices. This offers a powerful tool for navigating the complexities of the oil market.

On the other hand, there are some limitations. The accuracy of ARIMA forecasts can be affected by unforeseen events and changing market dynamics. In addition, the study focused on OPEC oil prices, and further research could explore how the findings apply to other oil benchmarks.

Some of the limitations of the study also point to further exploration, such as the possibility that actual events may have had an impact that can disrupt the forecasts and the OPEC price focus. Further research could also be done on price changes and isolated historical events. Third, a larger set of variables alternative to energy sources and climate policies could also be included in the forecasting models. Extending their approach to a more global scale, including non-OPEC oil benchmarks in the analysis, would provide a more comprehensive picture of the relationship between different market segments. This needs to be further developed to help researchers provide policymakers, industrialists, and investors in the global oil market with knowledge on how to operate and invest their resources most effectively and efficiently within this dynamic.

For future studies, there are several promising directions. Researchers could delve deeper into the impact of specific historical events on oil price fluctuations by developing more complex forecasting models that include additional variables, such as alternative energy sources and climate policies. Expanding the analysis to include non-OPEC oil benchmarks would provide a more comprehensive view of the global market. Additionally, integrating machine learning models with traditional econometric approaches could improve forecasting accuracy. By continuing to build on these insights, future research can enhance the understanding of oil price dynamics, empowering stakeholders to navigate the global oil market more effectively.

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Author Contributions

Merve Şenol: Conceptualization, Data curation, Methodology, Analysis, Writing-Original draft preparation, **Hüseyin Çetin**: Validation, Editing

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

Research and publication ethics were complied with in the study.

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Spatial association in students' residential apartment property characteristics around a university

Oladotun Peter Binuyo[*1], **Victoria Amietsenwu Bello**[1]

[1]*The Federal University of Technology, Akure, Nigeria*

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Abstract

This study aimed at examining the presence of spatial association in residential property characteristics. It considered self-contained residential apartments around a public university in Akure, Nigeria. It is a survey research where data was collected through the use of questionnaires administered to the occupants of the self-contained apartment within a 500-meter radius of the 'Southgate' axis of the university. Data collected was analyzed with the use of ArcGIS software where spatial regression was carried out as well as the Anselin Local Indicator of Spatial Association for Cluster/outlier analysis. The result of the analysis revealed that some of the property characteristics have multicollinearity which led to dropping some of them that are represented by their collinear attribute. Distance from the university was observed to have an inverse relationship with the rental prices while other property attributes have a positive influence. From the cluster/outlier analysis, it was revealed that there are significant clustering/outlying in the central and northwestern parts of the study area. The property physical attributes such as kitchen quality, bathroom quality, toilet quality, window quality, and wall quality are high in the northwestern parts where there are new and modern designs while the central part of the study area has low quality of these attributes. The results of the analysis show that the clustering/ outlying, otherwise known as spatial association, among the property attributes are not the same across a particular place and the assumption of a uniform spatial association across the area would be misleading. It is therefore recommended that analysis of real estate investment around an academic institution in Nigeria should consider the property characteristics that influence prices and also adopt spatial clustering analysis to know the specific property characteristics that are to be improved upon on the quality that should be provided to have the best prices with reference to locations. The originality of this research comes in the use of a relatively smaller study area in examining spatial associations among property characteristics. It also considers the clustering/outlying analysis of the qualities of the property characteristics with reference to specific locations which would help real estate developers and analysts on the quality of finishing that should be given to each property attribute at different locations around a university campus in Nigeria.

1. Introduction

The early adoption of the hedonic approach in real estate studies can be traced to studies such as Lancaster (1971), Griliches (1971) and Rosen (1974). There has since been its wide application in the field, especially in respect of mass appraisal for taxation and mass property valuation (Erath et al., 2009). This model allows the determination of property value, as a bundle of utilities including the property characteristics such as the quality and size, location and neighbourhood factors (Wilhelmsson et al., 2021). Wilhelmsson, et al. (2021) further emphasized that considering real estate spatial reference, real estate values vary spatially across geographic space and there has been the adoption of spatially varying models. This informs the need to ensure that spatially homogenous or heterogeneous factors should be taken into consideration when modeling real estate values as there are possibilities of submarkets which is not uncommon due to the location and neighbourhood factors, which could influence the level of development and the property characteristics (Rosen, 1974). Budziński et al. (2016) adduced that such a phenomenon is attributable to the fact that the spatial association in residential property data is linked to residential sorting, where choices of environmental goods influence people's choice of where to live which makes their preferences for the property utility-components to have high correlations. Spatial autocorrelation thereby shapes the spatial extent of the local real estate market, where the properties have similar values, dependent on special location (Li et al., 2020).

***Corresponding Author**

*(dotby2007@yahoo.com) ORCID 0000-0003-0744-4352
(opbinuyo@futa.edu.ng) ORCID 0009-0003-5571-6356

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One of the theories that create the framework of developing objective explanations for spatial association is the Alonso-Mills-Muth urban space model (Gwamna et al., 2015). It assumes that residential property renters make decisions as informed by the trade-off between property values and the cost of daily commuting where people of low-income class are closer to the CBD while the high-income class is commonly found in the suburban areas (Gwamna, et al., 2015; Kim & Kim, 2016). Properties of similar characteristics therefore develop in clusters due to the similarity of their neighborhood which could also influence their designs (Lo et al., 2022). Kim & Kim (2016) emphasized that properties within a school would have a positive correlation in their characteristics with an increase in the school qualities and high housing qualities. There could therefore be a level of homogenous development in terms of aesthetics and structures for clusters of properties within a neighbourhood that could have agglomerated around a particular homogenous function (Lo et al., 2022).

One of the utility components of the hedonic model is the structural qualities of properties, which Shen & Karimi (2015) explained to exist in homogenous groups, as a neighbourhood factor, to influence the predictability of property value models (Budziński, et al., 2016). An example of neighbourhood factors that can attract a class of people and which contributes to the nature of demand and indeed the types of residential properties developed is a university campus where students and staff are attracted, thus influencing the real estate investment nature and type in the neighbourhood.

The preferences of students to housing have not received sufficiently conclusive attention in the literature and most often in Nigeria, students have limited resources to spend which reduces their choices, thus the assumed needlessness of conducting research in that regard. Meanwhile, in an antithesis to the study of Thomsen (2007) on the preferences of students for accommodation where it was stated that there is less emphasis on the quality of the apartments because of the temporary nature of stay of students and their modal low economic status, Tavares et al. (2019) discovered the quality of apartment to be the major factor that attracts students to accommodation in the selected public universities in Portugal. An emphatic conjecture by Khozaei, et al. (2014) to accentuate the need to ensure quality housing for students was that, not only is student accommodation a place where they stay for one to four years and above of their young adult life, it is also a time of consequential phase of their lives, hence the need to make it positively contributing to the students' entire live.

The study of Park & Kim (2023) supports those residents have certain behaviors on their preferences for characteristics of residential properties which have spatial connotations. This implies that their choices have a relationship with the physical characteristics of the properties and this can be reflected in the spatial aggregation of the property characteristics and this was also established in Aluko (2011), a Nigeria study which was on a broader spectrum of analysis on neighborhood effect of location of residential properties.

While the presence of phenomena such as spatial association, spatial autocorrelation, and spatial dependence have been discovered in literature, such as Li et al. (2020), Morenikeji et al. (2017), and Park & Kim (2023), only few studies have considered similar phenomena around a university. Examples of such studies are Yunus et al. (2018) on the spatial arrangement of different off-campus student hostels around Bayero University, Kano, Nigeria, Mei et al. (2019) on travel-to-school distance as a factor of association, and Agostinelli et al. (2022) which considered access to education as a factor of the spatial association.

However, the consideration of the spatial association of qualities of housing is not readily available in the existing literature, and to emphasize the need for a study in this regard and the obvious scantiness of scholarly works on preferences for off-campus student accommodation especially where private real estate investors are involved, giving attention to the qualities of the structural characteristic of the accommodation in terms of possible spatial associations within the university environment thus creating 'micro-submarkets' would not be unnecessary.

One of the methods used in spatial analysis of local association of property data is the Local Indicator of Spatial Association (LISA) by Anselin (1995) to explore clustering spatial data and it is expressed as:

$$I = \frac{n(x_i - \bar{x}) \ \sum_i W_{ij}(x_j - \bar{x})}{\sum_i (x_i - \bar{x})2} = Z_i \sum_j W_{ij} Z_j \qquad (1)$$

where Z_i and Z_j are normalized x_i and x_j. When I_i is positive, it shows a statistically significant local clustering of the data where there is a similarity in the value of the local space and it could be when high values cluster or when low values cluster. When I_i is negative, it shows significant outliers, where there is clustering of low values around high data or high values around low data.

To further the LISA of Anselin (1995), the study of Basu & Thibodeau (1998) is one of the earliest geostatistical methods applied in examining the presence of associations among spatial data in a particular location. The approach of the study was to model the covariance matrix within the referenced location, denoted by $s_i = (x_i, y_i)$ and $s_j = (x_j, y_j)$, to which the Generalized Least Squares can be applied

$$y = X\beta + \varepsilon \qquad (2)$$

This gives room for the use of local parameter estimation where the weighted least squares method of weighting matrix is applied to locations and diagonal matrices of w_ij is measured by the distance locations ith and jth and the local parameters for each other are given as $\beta(x_i, y_i)$

$$\hat{\beta}\,(x_i, y_i) = (X^T W_{(i)} X)^{-1} \,.\, X^T W_{(i)} y \qquad (3)$$

For each of the locations,

$$\hat{y_i} = x_i \,.\, \beta\,(x_i, y_i) \qquad (4)$$

For the residuals at all locations (x_i, y_i)

$$\varepsilon_i = y_i - \widehat{y_i} = y_i - x_i \cdot \beta(x_i, y_i) \quad (5)$$

The application of local statistics in real estate values/prices in Nigeria is scanty and examining the property characteristics that influence students' choice of residential accommodation around a university campus has not received a local examination which informs this research. Existing literature has not extensively researched the clustering of property characteristics in influencing property values, especially with reference to residential properties around a university campus. This study, therefore, aims at using self-contained apartments occupied by students around a university in a developing country, to examine the spatial clustering and association of property physical attributes around the University. In this, the study uses a smaller geographic space in the examination of spatial clustering contrary to the convention of using a large study area when analyzing spatial association and property submarkets as observed in some existing studies.

2. Literature review

2.1. Student housing preferences

According to Khozaei, et al. (2014) student housing is such that provides accommodation for students during their time in the school and Ghani (2018) expressed that student accommodation provides the basis for the interaction between the students and their environment in determining their happiness, productivity and success while in school. Dizaj & Khanghahi (2022) affirmed that student housing is important in university students' lives after their education, as it serves the purpose of being their home for the time, they are in school which makes it necessary for it to meet the needs of the students while also responding to their social lives. Dizaj & Khanghahi (2022) therefore stated that student housing is expected to be properly planned as it has a direct impact on their behaviour, leadership traits, citizenship, academic performance, social and psychological attributes and sense of solidarity.

In the same light as the opinion of Dizaj & Khanghahi (2022), Najib & Abidin (2011), maintained that student accommodation should be provided by higher institutions so as to enhance their intellectual abilities but in some cases especially in developing countries there is inadequate accommodation for students by the Institutions. Therefore, Yunus et al. (2018) consented that many students in situations where there is inadequate accommodation on campus are constrained to seeking off-campus accommodation mostly within the proximity of the university.

Owing to the need for seeking off-campus accommodation by such students, different designs have emerged to cater for their specific needs at the time in school. The minimalist perspective for design has however affected the quality of designs of student accommodation by some of the private real estate investors through the use of inferior materials of design (Dizaj & Khanghahi, 2021). Meanwhile, in the view of Nijënstein et al. (2015), differences in taste bring about varying housing preferences that are reflected in the quality of materials of construction and designs, where the taste of students in a university might have been motivated by factors that are consistent with their purpose of being in school, which is to pursue a level of education that makes their preferences different from other categories of housing consumers. Moreover, housing preferences could often serve as the basis for measuring housing satisfaction derivable by students which could also vary by individuals.

The study of Khzaei et al. (2014) on the preferences of students on the design of their halls of residence revealed that students have preferences for accommodation of suite-style and single rooms. Along this line of research, the study of Nijënstein et al. (2015) discovered that factors that determine the decision of students as regards accommodation are travel time to the university, size of the room, sharing the kitchen with other students and the aesthetics of the housing, The study of Verhetsel et al. (2017) on the preferences of Belgian students as regards housing showed more preference for the size of the property, and rent payable before they make their choice which constraints them to prefer studio flat that provides privacy to the student. The finding of Verhetsel et al. (2017) was also confirmed in a study by Yunus, et al. (2018) carried out in Kano, Nigeria where privacy was emphasized as an important factor considered by students in making their housing choices.

As regards off-campus accommodation, the study of Edwards (2019) adopted a quantitative research approach to the preferences of students of a University in Cape Town, South Africa and discovered that their choices of housing are dependent on the presence of Wi-Fi, round-the-clock security and the presence of computer lab in the building. Noraini et al. (2017) however emphasized the need to conduct location-specific research as students' housing preferences could vary based on the location and other peculiar factors with respect to different areas. To this end, the study of Zubairu et al. (2018) in Nigeria discovered that distance from the school is the major preference by the students in choosing housing in the study area.

There are few studies that directly considered the finishing of the housing accommodation as part of the factors motivating the choices of students (Chiwuzie, et al., 2019; Bello & Binuyo, 2020). While there is evidence of preferences for aesthetics, the individual housing structural qualities have not been thoroughly examined in the available literature and the possibility of spatial association of these structural qualities around a university environment is conspicuously scanty in available literature, hence a need to start filling this gap.

The Nigerian situation is such that there is low funding for university education, which has implications on the availability of adequate dormitories for the students on campus, leading to the involvement of private developers to build student hostels, majorly off campus (Edwards, 2019).

2.2. Physical Property Characteristics/Attributes

In terms of accommodation qualities, Khzaei et al. (2014) stated that student housing is often configured such that toilets and bathrooms are used by one, two, three or four students and the rooms are designed such as to provide sleeping and study spaces. These relate to the structural or physical characteristics of the properties and generally in Nigeria, Chiwuzie, et al., (2019) expressed that structural attributes that affect the demand and values of residential properties are the number of living rooms, bedrooms, type and quality of floor finishes, perimeter fencing, interior and exterior decoration, number and quality of toilet and bathrooms, size of both bedrooms and living rooms, which also forms the basis for the attributes considered by students when making residential choice in the country.

Meanwhile, the characteristics mentioned in Chiwuzie, et al., (2019) define the quality of life of the people who live within a particular housing, making households in Nigeria particularly give preference to the aforementioned housing characteristics when choosing residential accommodation. Studies like Buys et al. (2005), Sitar & Krajnc (2008), Anthony (2012) and Okorie (2015) also established that structural attributes determine the demand and price paid for residential accommodation. The structural qualities considered in the study of housing and neighbourhood characteristics by Jiboye (2014) are building outlook, features of floors, windows, wall finishes, ceiling type, type of wall, and roof. Other facilities considered in the study of Jiboye (2014) are privacy, lighting, kitchen, toilet and bathroom.

The study of Amole (2009) on four universities in Nigeria discovered that the property characteristics considered by students before choosing an off-campus hostel are the number of people to be staying in a bedroom, the sharing size of the kitchen, sharing size of the bathroom, the floor on which the accommodation is located, presence of balcony and where to study. Sodiya, et al. (2016) however established that there are a few research works on the influence on building finishes like the use of aluminum roofs, glazed windows, floor tiles, security floors, and UPVC ceilings on rental values of properties unlike other infrastructure like, access to road, types of toilet and bathroom, electricity and water supply which is one of the motivations of this study to consider the influence of some of the former property characteristics mentioned in Sodiya, et al. (2016) on rental prices of residential accommodation around a university in Nigeria.

2.3. Spatial Autocorrelation of property characteristics

Spatial autocorrelation stems from the classical Tobler's (1969) first law of geography which states that everything is related to everything else but near things are more related than distant things, which establishes relationships among things that are within a geographic space as they influence one another. Studies such as Can (1990), Kim & Shin (2016) have suggested the presence of spatial autocorrelation in the prices of properties, where there are spatial interrelationships among properties within a particular location. Some of the variables that constitute spatial autocorrelation are crime rate (Collins et al., 2006), population density (Hong & Shen, 2013; Morenikeji, et al., 2017) which could influence the values and prices of house. Kim & Kim (2016) further stated that one of the factors that are responsible for spatial autocorrelation in property values is accessibility in terms of roads within the neighbourhood. Neighbourhood characteristics could also be the factor of attraction, while the time and nature of real estate investment could influence the structural attributes and values of properties within a confined location. The mode of real estate development in Nigeria which is majorly through individual ownership, with a large percentage through equity finance except in large-scale development where a large percentage of the funds is through debt financing.

Most often, real estate development by individuals is gradual and incremental, with funds inflow to the project. This also makes people of similar socioeconomic status to be found within a defined location and this is reflected in the type, attributes and nature of the properties in the area, where property development concentrates in different aggregates of locations within a particular area (Collins et al., 2006; Sipan et al, 2018). It is therefore not unusual to have undeveloped or less developed portions within a developed area that is proximate to a particular development attracting neighborhood factor. In most of such instances, values of properties within the confinement of each congregate of developments often correlate spatially (Sipan, et al., 2018).

In a developing country like Nigeria where funds are scarce for property development and there are no effective structures for housing provision and development, people often resort to self-help, which makes the morphology of properties to be similar within defined areas in terms of quality and standard. This might also be explained by existing urban theories like the classical Burgess theory and the Alonso-Mills-Muth theory although spatial autocorrelation considers what happens in different segregates of the city. These make properties in proximity have similarity in their structural attributes which could also be related to similarity in the time of development and the socio-economic status of the population of the people in the area, leading to spatial autocorrelation in the values of the properties that could disappear with distance (Clapp et al., 2002). This phenomenon is emphasized in Lin et al. (2014) and Barreca et al. (2018) that found spatial autocorrelations in the demographic and socio-economic characteristics of different ethnic groups.

Therefore, several factors can be responsible for spatial autocorrelation in a housing area and in the light of this study, considering real estate development and investment in Nigeria that is still evolving and majorly through equity finance, coupled with unguided development due to ineffective urban planning and development tools, it is not impossible to have different submarkets within a relatively small geographical space, in proximity to a neighbourhood factor.

Sipan, et al., (2018) conducted a study on the spatiotemporal neighbourhood-level house price index. It developed a standalone GIS statistical application of

Geographically Weighted Regression (GWR) for the analysis and the result shows a visual variation of house price based on neighbourhood, which was used in developing the price index. Lo, et al., (2022) examined the factors that affect spatial autocorrelation in residential properties considering both the vertical and horizontal dimensions of spatial autocorrelation. The spatial autoregressive hedonic model was used to analyze data from open market transactions. The result of the analysis linked market liquidity and market volatility with spatial autocorrelation in housing prices for properties within the same building in terms of vertical autocorrelation and that market liquidity increases vertical spatial autocorrelation.

2.4. Submarkets in real estate data

Song et al. (2021) observed that the factor of heterogeneity brings about segments of housing submarkets that are defined by different locations, neighborhoods and physical structures. This engenders more accurate property valuations and aids the formulation of strategy for policymaking in terms of household demand and housing market structure (Xiao et al. 2020). Following the study of Goodman & Thibodeau (1998), Song et al. (2021) submarkets housing market analysis helps in establishing the geographical boundaries of submarkets where properties of the same characteristics are bounded together. Can (1990) earlier differentiated the factors that constitute neighbourhood effects to be accessibility, physical environment, social, economic and demographic context and public-service provision. However, Can (1990) did not explicitly consider how a major neighbourhood function like academic or administrative can contribute to the values of surrounding properties, thus creating a separate housing market. Within this market, there is a likelihood of different submarkets which could be created by the factors considered in Can (1998).

It is also possible that the housing submarket would be categorized in terms of structural attributes. Cox & Hurtubia (2020) found that the structural attributes categorization could be in terms of the size of the properties, age of the properties, and number of bedrooms. This could also be in terms of accessibility to the housing neighbourhood considering the central business district or road accessibility which could influence housing location choices thus creating subgroups of housing markets, necessary for decision-making and a factor for real estate investors to consider (Can, 1990; Cox & Hurtubia, 2020).

Song et al. (2021) constructed segmented rental housing indices in Beijing, China using the hedonic model and clustering analysis was used to identify the submarkets in the study area. The findings of the study revealed that housing submarkets are distributed along administrative boundaries and there was identified rental housing spatial heterogeneity within the study area. Sipan, et al. (2017) retorted that neighbourhood which is an important definition of location shows spatial differentials with localized property markets within a restricted geographic space. This could get into micro-level value differentials up to streets and layouts, thus creating submarkets.

2.5. Spatial analysis with the Geographic Information System (GIS)

GIS comprises tools that are used in the collection, storage, retrieval, transformation, manipulation and display of spatial data from the real-world phenomenon for a particular purpose (Burrough & McDonnell, 1998). More than a combination of software and hardware, it is a process that uses data with geo-references and can handle issues of spatial manipulation and analysis which could be helpful in decision-making (Sipan et al., 2018). Unwin (1996) established that GIS can manipulate spatial data with the use of deterministic functions like spatial buffering, queries, overlays and the ability to carry out map algebra and this differentiates it from other database management systems. Can (1990) also maintained that the GIS enhances the management of geographic data by taking advantage of the location information to support spatial statistical and econometric analysis. Can (1990) further stated that there is a level of neighbourhood effect in the spatial data especially in real estate and it is dependent on spatial location which the GIS can analyze.

One of the recent developments in the application of GIS in real estate spatial analysis is the modeling of geographical constructs in real estate prices and the factors that contribute to the values of real estate. This has been discussed in Sipan et al. (2018) to explain property value changes within a given geographical space across neighborhoods thus creating submarkets of micro-level property prices are. When this is neglected, however, it could constitute misleading predictions at the local level for real estate investment decision-making and discountenance the possible effects of the heterogeneous nature of property characteristics. Hamid et al., (2012) expressed that there has been a rapid development in GIS with capabilities and support that are applicable to property-related spatial analysis

Spatial data analysis examines the distribution of such data and explains the process that produced the distribution, which assists in finding patterns in the data and would provide meaningful relation to the domain of knowledge (Unwin, 1996). GIS gives the opportunity for the use of a large geographic data set, the assumption that such global spatial analysis can be applied to smaller geographic data sets is unrealistic because it would be established on a faulty foundation of spatial homogeneity, which is inconsistent with location-specific characteristics of property data. This necessitates the use of local spatial statistics, where individual data in relation to a particular location is compared to other values in neighboring locations. Moreover, Zhang et al. (2015) maintained that the characterization of heterogeneity and spatial features of data is achievable through the use of GIS, where prices can be placed on a property to develop empirical models.

3. Study area and reconnaissance survey

The immediate neighbourhood of the Federal University of Technology, Akure is considered as the study area for this research. The Federal University of Technology Akure, is owned by the Federal Government of Nigeria. It is located in a medium-sized city in the southwestern part of Nigeria and the number of undergraduate students in the university is fifteen thousand five hundred and thirty-three (15,533) where only one thousand nine hundred and twenty-three (1,923) bed spaces are available in the hotels provided on-campus for student accommodation (FUTA, Giant Strides, 2016). This shows a huge bed-space deficit of thirteen thousand six hundred and ten (13,610) for off-campus accommodation provided by private real estate investors and owners. The accommodation deficit keeps growing with an increasing number of students admitted into the university every year as the study of Bello & Adebisi (2014) had earlier revealed on ten thousand six hundred and thirty-three (10,633) students in the university in the year 2013. Therefore, most of the students live in the 'Northgate', 'Southgate' and 'Westgate' axes of the university in off-campus hostels provided by private real estate developers.

There are few commercial properties in the study area. While some of them are being converted to residential properties, others provide retail and support functions to the residential accommodation for the students and other owner-occupied houses. The trend of development in recent times in the area is such that commercial and old-fashioned residential properties are being converted to self-contained (Studio) apartments, especially within a 500-meter radius of the university. This radius is also in tandem with the buffer established in Koster & Rouwendal (2012) on the impact of mixed land uses on residential properties. This radius is also adopted in this research in delineating the distance-decaying boundary of the impact of the university on neighboring residential properties occupied by students.

Most students prefer the self-contained (studio) apartment to other design types because it gives them a sense of privacy where they are able to make individual academic plans, with access to personal conveniences and a kitchen. Meanwhile, in order to minimize the cost of securing the accommodation due to the dwindling economic condition of the country, some of the students engage the idea of having one or two roommates, with whom they share the accommodation and the cost of securing it. Notwithstanding the affordability factor that brought about the roommate idea, most students would not want to be too far from the university and the number of available off-campus accommodations would not accommodate the growing student population if each unit of the apartment is occupied by only one student.

There are different layouts with different classes of roads running through the study area and the distance influences the amount which students are willing to commit to secure the apartment. Also, the quality of finishing of the apartment, the number of units in the building and the quality of the environment determine the desirability for the students and the rent passing in different locations. Most of the off-campus private residents are in the 'Southgate' axis of the university which is adopted in this study, and development of self-contained residential apartments started close to this 'Southgate' which continues to extend outwards with new and modern development found as one moves away from the 'Southgate', notwithstanding pockets of redevelopment activities at different part close to it.

A reconnaissance survey was carried out in the study area to analyze the perception of the students on the quality of different physical attributes of self-contained apartments. The physical qualities of the property thus assessed are kitchen quality, bathroom quality, toilet quality, wall finishing, floor finishing, window quality, and door quality. Other factors assessed are the quality of the environment and the number of floors of the building. After a delineation of the study area, where a 500-meter radius from the 'Southgate' axis of the university was measured on Google Earth software, a physical count was adopted in determining the total number of self-contained residential properties in the study area. The result of the physical count revealed that there are Two hundred and Seven self-contained buildings which is within the total census and all the properties that are the target population are considered in eliciting data.

Different observed designs and quality of the various attributes of self-contained apartments were included in the reconnaissance survey questionnaire where the respondents gave their preference in terms of quality and desirability in their accommodation. The data was elicited from the respondents using a Likert scale on the desirability of such quality and subsequently analyzed using a weighted mean score for the weighted average analysis of the responses from the respondents. The results of the analysis of how the students rate the presence of the physical attribute qualities presence in their apartments are presented in Table 1.

Table1. Results of a reconnaissance survey of factors influencing self-contained rental prices

Physical Attributes	5	4	3	2	1	Mean Score	Mean Score Ratio
Kitchen Quality							
Washing sink with tap	137	47	11	0	0	4.65	0.93
Floor tiled	133	46	12	4	0	4.58	0.92
Wall tiled	124	55	12	4	0	4.53	0.91
worktop	112	47	4	16	16	4.14	0.83
Water heater	31	4	0	43	117	1.92	0.38

Table1. (Continued)

Physical Attributes	5	4	3	2	1	Mean Score	Mean Score Ratio
Bathroom Quality							
Flowing tap	138	47	4	8	0	4.59	0.92
Shower	86	101	8	0	0	4.40	0.88
Floor tiled	116	63	0	8	8	4.39	0.88
Wall tiled	89	72	8	19	7	4.11	0.82
Shower tray	8	67	114	3	3	3.38	0.68
Water Heater	30	54	7	68	36	3.13	0.63
Jacuzzi	24	18	32	66	55	2.44	0.49
Toilet quality							
Floor tiled	100	79	8	8	0	4.39	0.88
Wall tiled	68	95	16	16	0	4.10	0.82
Special WC	189	54	24	24	12	3.86	0.77
WC	22	129	32	12	0	3.83	0.77
Wall quality							
Emulsion painting	75	83	12	11	8	4.15	0.83
Texcote painting	8	8	44	81	44	2.21	0.44
cement rendered	0	16	4	58	117	1.58	0.32
Floor quality							
Ceramic tile	91	88	8	8	0	4.34	0.87
PVC tiles	0	0	48	80	67	1.90	0.38
Cement creed	4	4	7	88	92	1.67	0.33
Window quality							
Aluminum glazed sliding window	68	55	60	12	0	3.92	0.78
Aluminum glazed casement window (swing)	23	120	40	8	4	3.77	0.75
Louvre blades	4	4	84	99	4	2.51	0.50
Door quality							
Imported steel door	106	77	8	4	0	4.47	0.89
Metal door	95	95	4	0	0	4.46	0.89
Panel door	4	4	54	117	16	2.30	0.46
Flush door	4	0	48	86	57	2.02	0.40

3.1. Measure of property characteristics

PCM = C_1 * Mean Ratio C_1 + C_2 * Mean Ratio C_2+,…, C_n* Mean ratio C_n

where PCM is the property characteristics measure which is the value contributed by a particular property characteristic as indicated by each respondent. C_1 , …, C_n are the features of the property characteristics. The mean ratio is determined from the ratio of the weighted mean score from the responses from the reconnaissance survey on the desirability of each property characteristic in the study area to the maximum weighted mean score from the ordinal scale adopted.

4. Method of data analysis

One of the preliminary data analyses conducted was to examine the presence of spatial association among the property characteristics that were identified to influence rental values of self-contained apartments in the study area. For this analysis, the Local Indicator of Spatial Association (LISA) which performs the Cluster/outlier analysis on each of the property characteristics was conducted. Multicollinearity test was however carried out among the variables to prevent overinflation of results that could arise from statistically significant spatial association among variables that give the same explanation. In this instance, where there is discovered statistically significant multicollinearity among variables, one of the variables is chosen to also explain the contribution of other variables within the association. In carrying out multiple regression analysis of spatial data, there is a need to examine the presence of collinearity among the independent variables. According to Shrestha (2020), collinearity shows where two variables are in perfect combination in their contribution to the dependent variable and this becomes multicollinearity when several independent variables have this significant correlation. The implication of the inter-correlation is a skewed result as an outcome of redundancy in the variables. Apart from correlation coefficients and eigenvalue methods indicated by Shrestha (2020) in detecting collinearity among the independent variables, the Variance Inflation Factor (VIF) suggested in Belsley (1991) has also been considered a method for detecting multicollinearity. VIF is used in measuring how much variance of the coefficients of the regression is inflated due to correlation among the variables. VIF is given as:

$$\frac{1}{1-R^2} = \frac{1}{Tolerance}. \quad (6)$$

After the collinearity test, the resulting variables are then regressed against the annual rent collected of the property.

The Local Indicator of Spatial Association is given as:

$$l_i = \frac{Z_i-\bar{Z}}{\sigma^2} = \sum_{j=1}^{n} j \neq i \left[W_{ij}(Z_j - \bar{Z})\right] \quad (7)$$

Where is the mean value of $\bar{Z}$ ith the sample number of n; Z_i is the value of the variable at location i; zj is the value at other locations (where $j \neq i$); σ^2 is the variance of Z; and W_{ij} is a distance weighting between Z_i and ; Z_j, which can be defined as the inverse of the distance. The weight W_{ij} can also be determined using a distance band: samples within a distance band are given the same weight while those outside the distance band are given the weight of 0.

To measure the relationship between the selected independent variables (property characteristics and dependent variables (rental prices), the multiple regression model is adopted which is given as;

$$RV = b_0(i) + b_1(i)KQ + b_2(i)BQ + b_3(i)TQ + b_4(i)DQ + b_6(i)WQ + b_7(i)FF + b_8(i)WF + b_9(i)DFUTA + e \quad (8)$$

where RV = rental Value, KQ = Kitchen quality; BQ = Bathroom Quality; TQ= Toilet Quality; DQ = Door Quality; FF = Floor finishes; WQ = Window Quality; WF = Wall Finishing; DFUTA = Distance from FUTA; e = error term; I = ith observation.

Table 2. Calibration of variables

Variable	Scale	Measurement	Category
Rental Price	Interval	Actual Price in ₦	Dependent
Distance from FUTA	Interval	Actual distance in meters	Independent
Location	Interval	Longitude and latitude (x and y)	Independent
Kitchen quality (multiplied by the mean ratio from the reconnaissance survey on each characteristic)			Independent
Washing sink with tap	Binary converted to Scale using equation 1	1 = Present 0 = Absent	Independent
Floor tiled	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Wall tiled	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
worktop	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Water heater	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Bathroom quality (multiplied by the mean ratio from the reconnaissance survey on each characteristic)			Independent
Flowing tap	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Shower	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Floor tiled	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Wall tiled	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Shower tray	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Water Heater	Binary converted to Scale using equation 1	1 = Present 0 = Absent	

Table 2. (Continued)

Variable	Scale	Measurement	Category
Bathroom quality (multiplied by the mean ratio from the reconnaissance survey on each characteristic)			Independent
Flowing tap	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Shower	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Floor tiled	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Wall tiled	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Shower tray	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Water Heater	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Jacuzzi	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Toilet quality (multiplied by the mean ratio from reconnaissance survey on each characteristic)			Independent
Floor tiled	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Wall tiled	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Special WC	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
WC	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Door quality (multiplied by the mean ratio from reconnaissance survey on each characteristics)			Independent
Imported steel door	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Metal door	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Panel door	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Flush door	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Floor quality (multiplied by the mean ratio from reconnaissance survey on each characteristics)			Independent
Ceramic tile	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
PVC tiles	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Cement creed	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Window quality (multiplied by the mean ratio from reconnaissance survey on each characteristics)			Independent
Aluminum glazed sliding window	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Aluminum glazed casement window (swing)	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Louvre blades	Binary converted to Scale using equation 1	1 = Present 0 = Absent	
Wall quality (multiplied by the mean ratio from the reconnaissance survey on each characteristic)			Independent
Emulsion painting	Binary converted to Scale using equation 1		
Texcote painting	Binary converted to Scale using equation 1		
cement rendered	Binary converted to Scale using equation 1		

5. Data Analysis, result presentation and discussion

5.1. Questionnaire administration and retrieval

From a reconnaissance survey where the physical count of the self-contained (studio) apartments was done, in 2022, there were 207 of such residential apartments within a 500-meter radius off the Southgate axis of the Institution. Each of the self-contained apartments was physically administered the questionnaire, where the coordinates of the properties were also taken to enhance the spatial analysis.

The result of the questionnaire administration is shown on Table 3. The result indicates that 94.2% of the total number of self-contained properties that were administered gave sufficient responses that are usable for the analysis in this study, which is a high percentage and could be relied upon for generalization to the entire population of self-contained properties in the study area.

Table 3. Questionnaire administration and retrieval

Total Number of questionnaires administered	207 (100%)
Total Number of questionnaires retrieved	195 (94.2%)

Within the radius of 500 meters from the 'Southgate' axis of the University, the self-enumeration done to show that there are two hundred and seven (207) self-contained residential buildings and all these buildings were administered questionnaire where one questionnaire was assigned to each building to provide data that shows the quality of the self-contained apartment, rent paid per annum and the distance from the 'Southgate' is determined with the aid of the coordinates taken at the survey beacon location of each building. As the difference between the administered and the properly retrieved questionnaire is not high, it gives more reliability and accuracy to the model.

Table 4. Collinearity Test

Coefficients[a]

Model	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
(Constant)	10362.928	10227.313		1.013	.312		
KITCHEN_QU	413.679	3235.370	.007	.128	.898	.440	2.271
BATHROOM_Q	8992.874	2883.057	.194	3.119	.002	.299	3.339
TOILET_QUA	13189.800	2562.945	.303	5.146	.000	.333	3.003
WINDOW_QUA	13242.707	3053.649	.267	4.337	.000	.305	3.284
DOOR_QUALI	4965.551	3431.783	.070	1.447	.150	.487	2.054
WALL_FINIS	10986.165	3406.534	.170	3.225	.001	.415	2.411
FLOOR_FINI	2581.114	3979.255	.031	.649	.517	.510	1.959
DISTANCEFR	-15.038	10.995	-.053	-1.368	.173	.755	1.324

The VIF analysis was carried out using SPSS and the result shows that there is no multicollinearity among the variables in their relationship with the rental prices, and this suggests the possibility of relying on the result for the rental price estimates in the study area. However, this analysis was carried out without recourse to spatial reference of property data but with an assumption of global uniformity. This was proved using spatial multiple regression analysis, using the spatial analyst tools of ArcMap with the ordinary least square function. However, this analysis was not possible to run on ArcMap due to spatial multicollinearity meanwhile non-spatial regression analysis had a misleading result which indicated that there was no collinearity among the variables from the VIF results.

Therefore, to further identify the variables with high multicollinearity that prevented the spatial regression analysis on ArcMap, the pairwise scatter plot was used to observe the variables' relationships with respect to the locations of each property. From the scatter plots, there was observed a positive spatial correlation in the following pairs: window quality and door quality', 'floor quality and wall quality', and 'bathroom quality and toilet quality. Therefore, one variable from each of the spatially inter-correlated pairs was selected and used to perform the spatial regression on ArcMap with the ordinary least square tool.

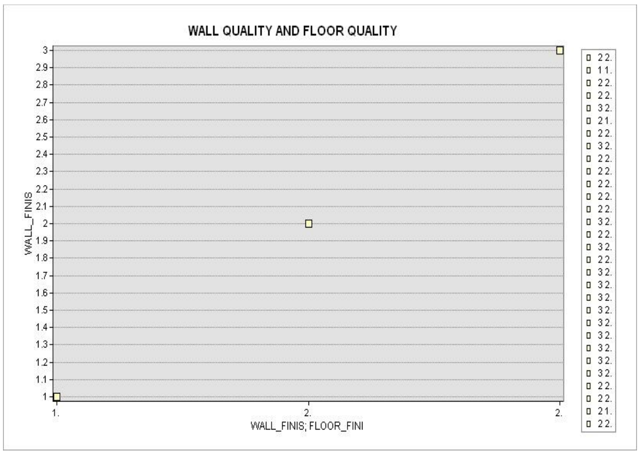

Figure 1. Scatter plot of wall quality and floor quality

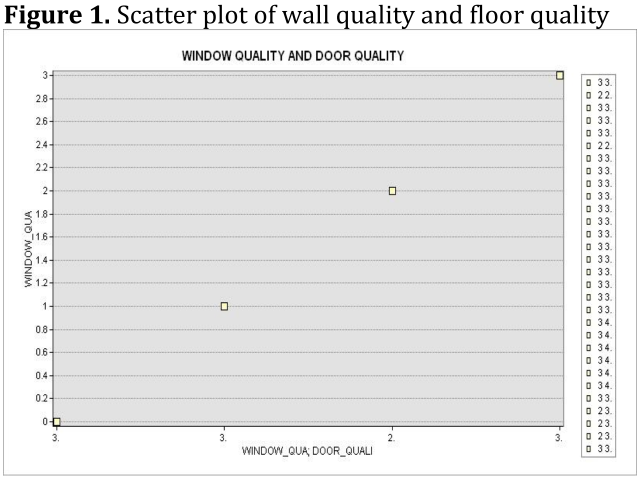

Figure 2. Scatter plot of window quality and door quality

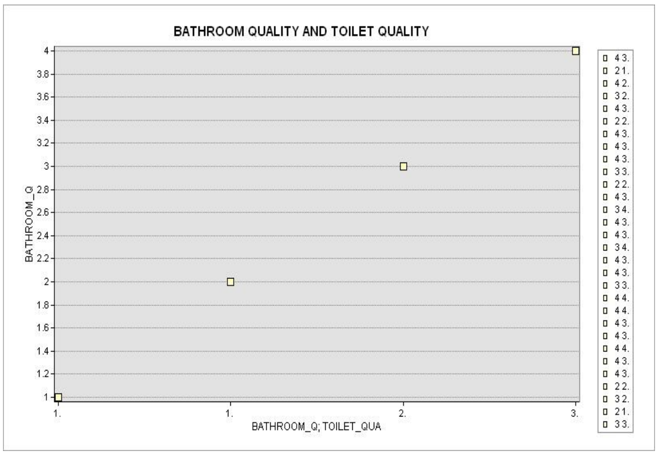

Figure 3. Scatter plot of bathroom quality and toilet quality

5.2. Spatial ordinary least square regression on ArcMap

The Ordinary Least Square Regression was carried out to examine the relationship between the rent paid by the occupiers (students) of the properties and the property characteristics (without spatial collinearity) that were discovered from literature to influence rents of residential apartments occupied by students in Nigeria, taking the peculiarity of FUTA into consideration.

Table 5. Spatial Ordinary least square Regression results

Variable	Coefficient(a)	Std. Error	t-Statistics	Probability (b)	Robust_SE	Robust_t	Robust_Pr (b)	VIF
Intercept	21596.78	8355.68	2.5847	0.0105*	8008.01	2.6969	0.0076*	-
DISTANCEFRO M FUTA	-14.93	10.57	-1.4121	0.1596	10.64	-1.4029	0.01623*	1.2294
KITCHEN_QU	1065.62	3193.43	0.3337	0.7390	3581.11	0.2976	0.7664	2.2209
BATHROOM_Q	12013.97	2421.56	4.9612	0.0000*	2560.53	4.6920	0.0000*	2.3650
TOILET_QUA	13351.51	2515.53	5.3076	0.0000*	2126.17	6.2796	0.0000*	2.9041
WINDOW_QUA	12571.32	2904.15	4.3287	0.0000*	3116.11	4.0343	0.0001*	2.9816
WALL_FINIS	12003.87	3336.57	3.5977	0.0004*	3127.09	3.8387	0.0001*	2.3220

Input Features: SELF-CONTAINED PROPERTI	Dependent Variable: RENT
Number of Observations: 195	Akaike's Information Criterion (AICc) [d]: 4408.956469
Multiple R-Squared [d]: 0.783890	Adjusted R-Squared [d]: 0.776993
Joint F-Statistic [e]: 113.654857	Prob(>F), (6,188) degrees of freedom: 0.000000*
Joint Wald Statistic [e]: 1521.338543	Prob(>chi-squared), (6) degrees of freedom: 0.000000*
Koenker (BP) Statistic [f]: 20.161757	Prob(>chi-squared), (6) degrees of freedom: 0.002592*
Jarque-Bera Statistic [g]: 10.623622	Prob(>chi-squared), (2) degrees of freedom: 0.004933*

Property characteristics that are therefore responsible for the determination of rental prices of self-contained residential properties around the university are Distance (-14.93, p< 0.016), Bathroom quality (1065.62, P< .050), Toilet quality (13351.51, p <0.050), window quality (12571.32, p <.050) and wall finishing (12003.87, p <.050). the coefficient of kitchen quality was not significant for the prediction.

The result on Table 5 shows the self-contained residential property attributes that do not have global spatial autocorrelation which are used in modeling the relationship between rental prices and the implicit contribution of each of the property characteristics. The result shows that out of the six predictors (independent variables), only kitchen quality does not have a statistically significant contribution using a 95% confidence level. The result further shows that Distance from FUTA has a negative effect which indicates that the rental prices of the self-contained apartment reduce with distance away from the university.

Meanwhile, other property characteristics like bathroom quality, toilet quality, window quality and wall quality have statistically significant positive implicit contributions to the rents paid by the occupants who are mostly students of the university. However, this result does not indicate the spatial reference of the contribution of each of the property characteristics which could be skewed to different locations severally across the property characteristics. This is therefore examined through the use of the Local Indicator of Spatial Association (LISA).

To examine the possibility of spatial patterns in the impact of the property characteristics that form the independent variables, the Local Indicator of Spatial Association (LISA) was assessed using the ArcGIS 10.2© software.

Table 6. LISA analysis results

Property Characteristics	HH significant spatial clustering (p<.050)	LH significant spatial clustering (p<.050)	HL significant spatial clustering (p<.050)	LL significant spatial clustering (p<.050)	Total Significant spatial clustering points	Percentage significant
Kitchen Quality	21 spatial locations (31.3%)	8 spatial location (11.9%)	3 spatial locations (4.5%)	37 spatial locations (55.2%)	67 spatial locations	**34.4%**
Window Quality	19 spatial locations (28.8%)	4 spatial locations (6.1%)	8 spatial locations (12.1%)	35 spatial locations (53%)	66 spatial locations	**33.8%**
Wall Quality	22 spatial locations (41.5%)	2 spatial locations (3.8%)	0 spatial location	29 spatial location (54.7%)	53 spatial locations	**27.2%**
Bathroom Quality	29 spatial location (58%)	5 spatial locations (10%)	1 spatial location (2%)	15 spatial locations (30%)	50 spatial locations	**25.6%**
Toilet Quality	7 spatial locations (14.9%)	3 spatial locations (6.4%)	8 spatial locations (17%)	29 spatial locations (61.7%)	47 spatial locations	**24.1%**

An analysis on the local spatial association was carried out using the Anselin Local Moran's I spatial model at a p-value of 0.050. This is to identify spatial points on the Gaussian field where properties within the neighbourhood using adaptive kernel bandwidth, exhibit statistically significant clustering in the property characteristics which are the independent variables that determine the annual rental price of the self-contained apartment in the study area. The spatial associations observed in the study are:

i. where a high-quality spatial point is surrounded by high qualities of the property physical attribute denoted by HH.
ii. Where a low-quality spatial point is surrounded by high quality of the property physical attribute denoted by LH.
iii. where high high-quality spatial point is surrounded by low quality of the property physical attribute
iv. where low quality spatial point is denoted by low quality of the property physical attribute.

5.3. Kitchen quality Local Spatial Association

From this analysis, it was shown that 64 spatial locations which is 34.4% of the 195 spatial points of the study area have significant spatial association in the kitchen quality. It shows that spatial locations where there is low quality of kitchen quality are surrounded by low kitchen quality have the highest spatial location. This shows that the quality of the kitchens of most of the self-contained apartments in the study area is low. Meanwhile, 31.3% of this significant kitchen quality spatial location has high kitchen qualities that are surrounded by high-quality kitchen qualities. This result can be explained by the fact that most of the property owners and developers in the study area used similar materials for their kitchens, which are significantly low or high. Those of low quality often have a wash hand basin and water while those of high quality have, in addition to the features of the low quality, wall and floor tiles, cooker unit, kitchen cabinet and water heater. Results of the interpolated p-value of the spatial association are shown on Figure 4 where the statistically significant spatial association is observed in the central part of the study area close to the south gate as well as the northwestern part of the University. Statistically significant spatial associations are also observed in the southwestern part. There are local points where low kitchen quality is surrounded by properties with low kitchen quality, which could be responsible for the spatial association in the central part of the study area where residential development started. The significant spatial association in the farther northwest and southwest parts could be due to new residential development and those experiencing redevelopment where newer kitchen facilities are installed and such properties are also surrounded by others that have high kitchen-quality installations.

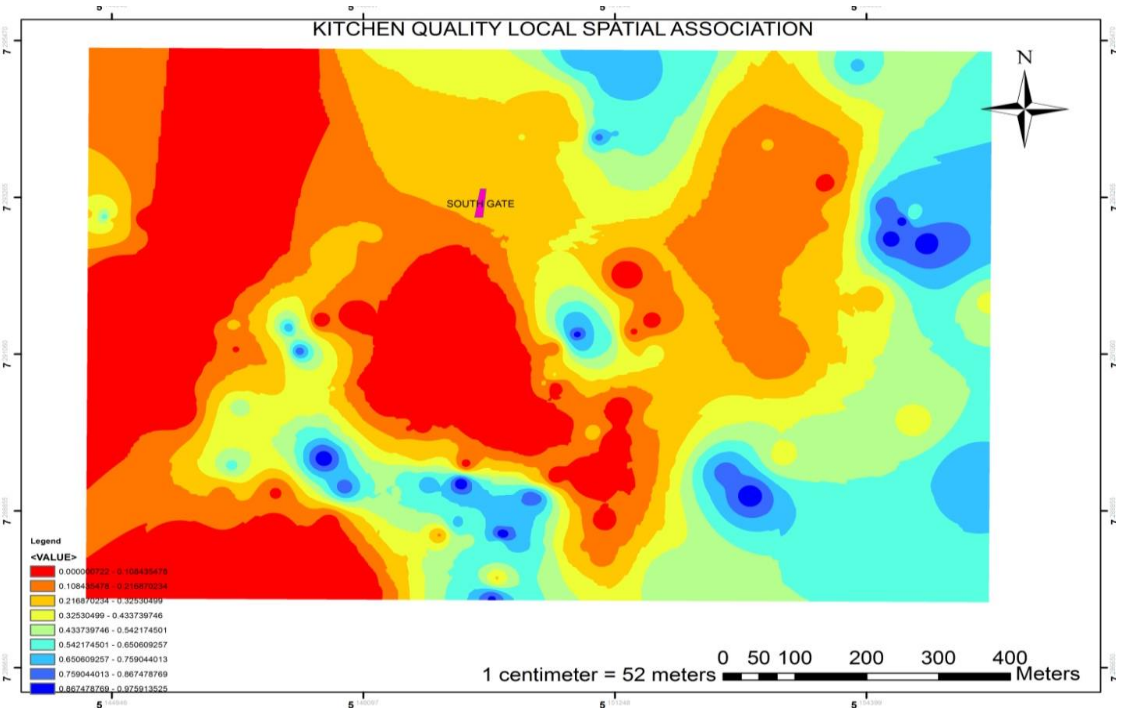

Figure 4. Map of the interpolated p-value of the kitchen quality

5.4. Window quality local spatial association

For the window quality, there are 66 spatial locations which represent 33.8% of the 195 points that have significance, where low window qualities are surrounded by other self-contained residential properties with low window quality as well. Similar to what was observed in the kitchen quality, the LL spatial association is followed by spatial points where high window-quality self-contained properties are surrounded by others with high window quality. From the desirability perspectives obtained in a reconnaissance survey, low window quality is those with louver blades and without antiburglary bars while those of high quality are windows of glazed aluminum with anti-burglary bars and adequate illumination and lightning. Similar to the kitchen quality, the map in Figure 5 shows that the statistically significant 66 spatial points that have spatial association are in the central and northwestern parts of the study area, where a similar explanation as regards the trends of development for the kitchen quality applies to the window quality which could be explained for door quality. However, a significant association does not exist for window/door quality in the southwestern part which suggests that there is no spatial association in the distribution of window/door quality in this axis of the study area.

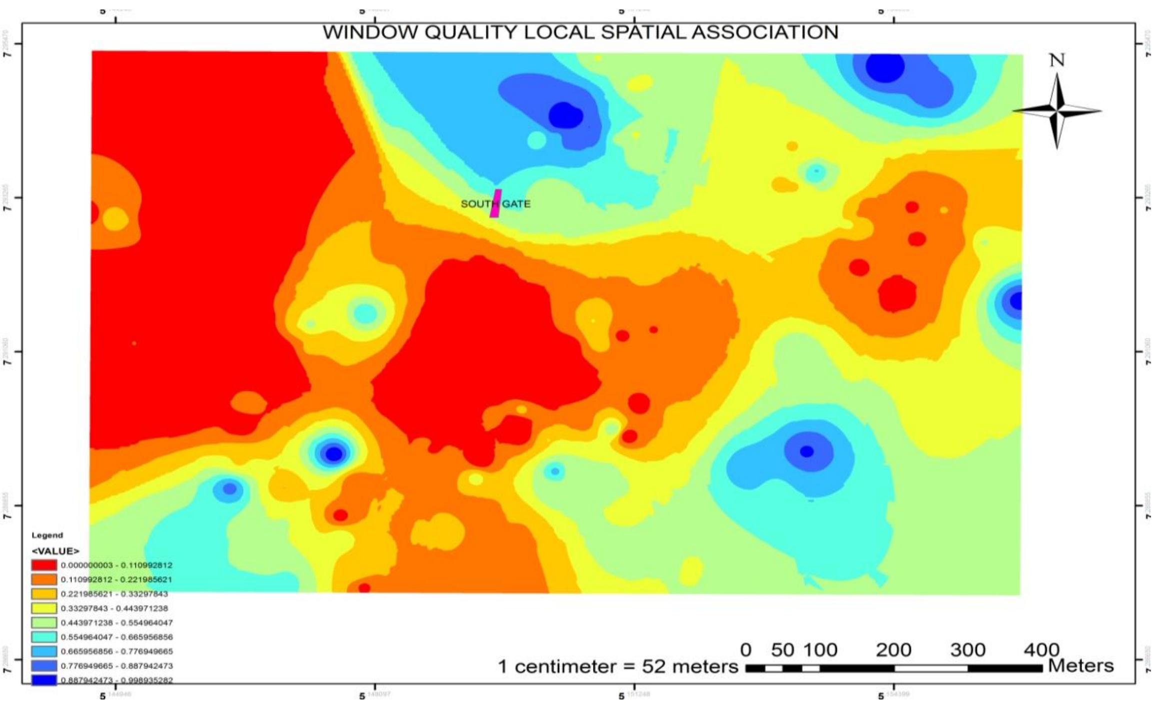

Figure 5. Map of the interpolated p-value of the window quality

5.5. Wall-quality local spatial association

Similar to the pattern of local spatial associations observed in both kitchen quality and window quality, wall quality has the highest spatial association in points where low wall quality is surrounded by other self-contained residential apartments with low wall quality. No spatial association was observed in the HL clustering/outlier but 22 locations exhibited significant local spatial association of high wall quality being surrounded by high wall quality self-contained residential apartments in the study area. In total, 27.2% of the 195 spatial locations showed significant spatial association in the wall quality. The visual display of significant association among wall quality of the self-contained apartment in the study area shows that the 27.2% spatial points that have the significant association are distributed across the central, western and southwestern parts of the study area. This means that there are low wall qualities that are surrounded by other properties with low wall qualities especially in the central parts of the study area while the farther western and southwestern parts where there are significant spatial associations are of spatial locations where high wall quality are surrounded by other high wall qualities self-contained residential properties.

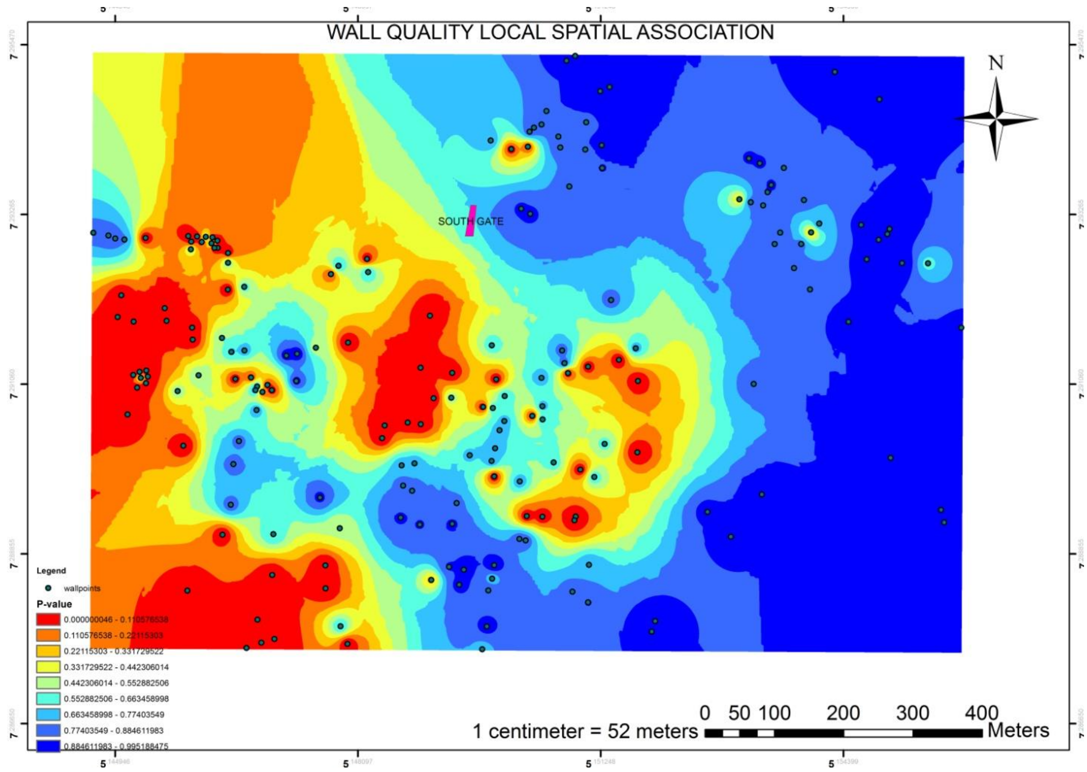

Figure 6. Map of the interpolated p-value of the wall quality

5.6. Bathroom Quality Local Spatial Association

Unlike the kitchen quality, window quality and wall quality, bathroom quality showed higher spatial associations in locations where higher bathroom quality is surrounded by other self-contained residential properties with high bathroom quality with 29 points out of the 50 significant locations in the bathroom quality. This was followed by 15 locations where low bathroom quality is surrounded by other self-contained residential properties that have low bathroom quality. The result further shows that out of the 25.5% of locations that have significant spatial locations, 58% are points where high bathroom qualities are surrounded by other self-contained apartments with high bathroom qualities. Most of the statistically significant spatial points of the bathroom quality are found in the central part, transcending the northwestern part. A similar trend of discussion along the line of stages of development could be responsible for the pattern of the spatial association where lower bathroom quality is closer to the south gate than the farther northwestern part where there are new developments of higher bathroom quality with spatial clustering.

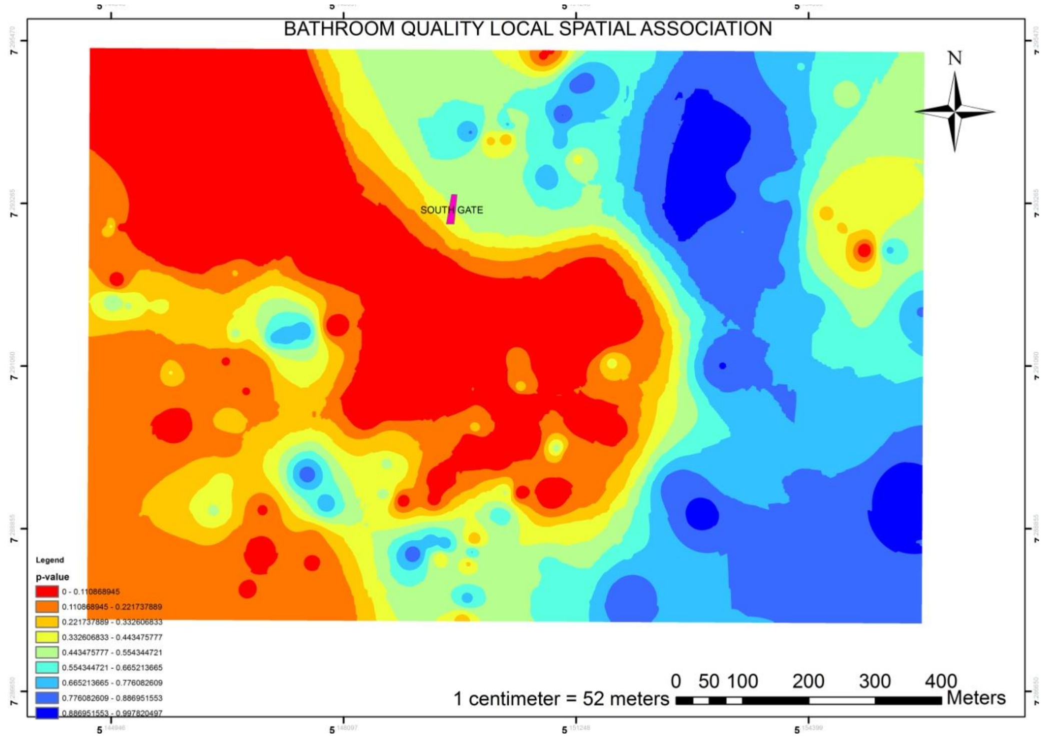

Figure 7. Map of the interpolated p-value of the bathroom quality

5.7. Toilet quality Local Spatial Association

The condition of the toilet qualities in the self-contained properties showed the least spatial association where only 24.1% of the 195 spatial locations exhibited spatial association. Most of these significant spatial associations (61.7%) are observed in points where low-quality toilet facilities are surrounded by other self-contained residential properties that have similar low toilet quality toilet facilities. This was followed by locations that have high-quality toilet facilities surrounded by low-quality toilet facilities. From the map in Figure 8, significant spatial associations in toilet quality are majorly concentrated in the northwestern part of the study area where the number of spatial associations shows that there are significant self-contained properties with low toilet quality surrounded by other self-contained properties that have low toilet quality and this might be connected to the quality of toilet facilities used by property owners and developers, which is the basic and old designs of water closest (WC) installation, with a significant association in the western and northwestern parts of the study area.

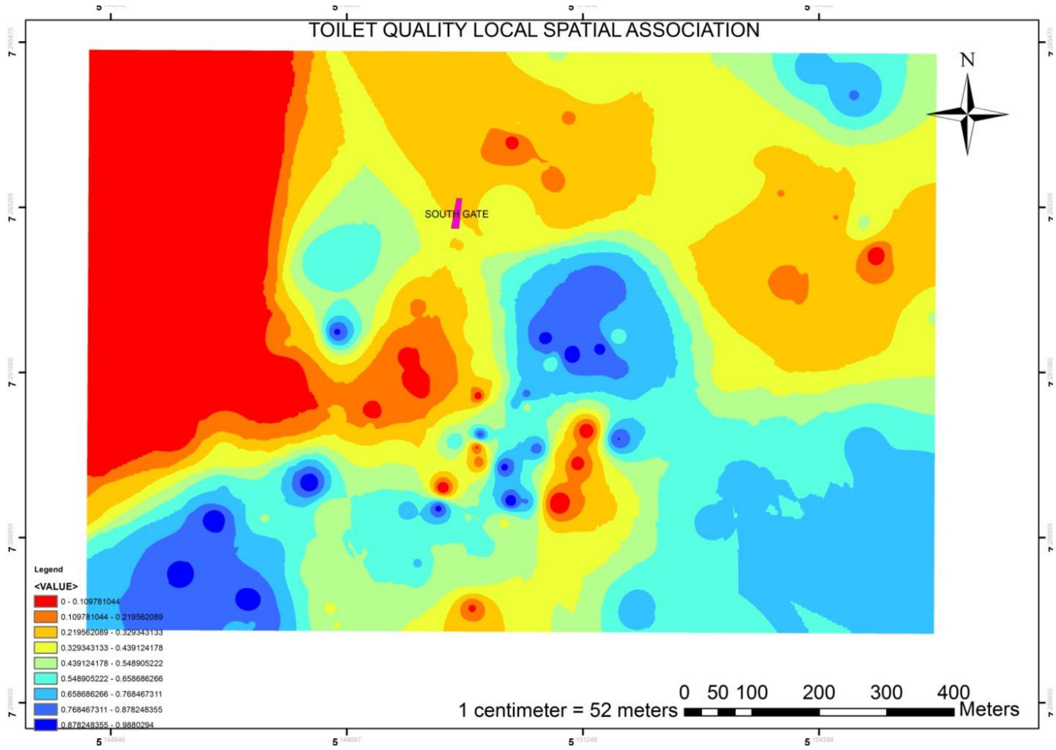

Figure 8. Map of the interpolated p-value of the toilet quality

6. Conclusion

Considering the preference of students for off-campus accommodation, there are basic attributes that attract accommodation interests and influence the price paid for residential apartments by the students who seek the accommodation. For the Federal University of Technology, Akure (FUTA), the most prominent factor that influences rental prices of off-campus accommodation is the distance from the University as discovered in the study of Adebisi & Bello (2017) and Bello & Binuyo (2020). The influence of this factor on the values with distance of the accommodation from the University was further reinforced with the result of this study where it was discovered that the rental prices paid by the students decrease with distance from the university as observed from the statistically significant negative relationship that exists between the two variables. There are other factors that attract students to the self-contained apartments which are the physical attributes of the property. In line with the studies of Anthony (2012) and Okorie (2015), the results of the analysis show that the physical attributes of the property that influence rental prices paid by the students include qualities of the kitchen, toilet, bathroom, wall, floor, window and door.

There are multicollinearities among some of the physical attributes which indicates that respondents gave similar responses to such attributes, and it was not possible to compute regression analysis with them to avoid overinflation of results. This suggests that in computing relationships between dependent and independent variables for property values or prices, it is necessary to examine if there are some variables that exhibit collinearity.

However, due to the spatial reference of property value, it is imperative to examine the possibility of spatial relationship among the attributes, to confirm the findings of Can (1990), and Li et al. (2020) that property attributes often have spatial association. The use of the Local Indicator of Spatial Association (LISA) of Anselin (1995) provided an opportunity for examining the clustering and by implication, outliers of each of the property characteristics which are better appreciated through the visual display of ArcGIS-analyzed maps. The result of this analysis on each of the property attributes shows that there are significant clustering and outliers in some parts of the study area. From the maps of the results, the central part, northwestern part and southwestern part of the Southgate axis reveal spatial associations where there are high-quality attributes clustering around high-quality attributes and other areas where there is low-quality clustering for each of the attributes. These results are linkable to evidence from the development trends of self-contained properties in the study area, where there is low-quality clustering in areas where development started and high-quality clustering in newer areas. This confirms that there is a need to examine the spatial distribution of attributes and characteristics when modeling property prices as the specific locations where the spatial association or autocorrelation exist might be different.

7. Recommendations

From the results of the analysis of this study, it is necessary for real estate property value/price researchers to examine the possibility of multicollinearity among the property characteristics used in modeling to avoid over-bloated results. Meanwhile, in an extension of the existing knowledge on spatial autocorrelation where large study areas are often considered, the results of this study show that there is a possibility of spatial clustering even within a small geographic space. The identification of this spatial clustering would reveal parts of the study area that have significant spatial clustering and where such does not exist. Having this knowledge would help developers with the specific property characteristics (attributes) that need to be improved to positively influence property values with reference to specific locations in the study area. It is also recommended that university off-campus real estate investment analysts conduct their analysis beyond the scope of profitability to specific details of the properties that need to be put in place to enhance the values depending on the location of the investment.

Author Contributions

The contributions of the authors to the article are equal.

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

Research and publication ethics were complied with in the study.

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A Review: Detection types and systems in remote sensing

Ceren Tabakoglu*[1]

[1]*Mersin University, Faculty of Architecture, Department of Architecture, Mersin, Turkey*

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Abstract

Remote sensing (RS) is the process of capturing, measuring, and digitally storing the reflection, radiation, and scattering values emitted by an object in one or more different band ranges of the broad electromagnetic spectrum and using this data to identify tools. RS is a method used by many professional disciplines and is frequently preferred today. Therefore, it has been the subject of this study. This study aims to conduct in-depth literature research on RS and present the results of related studies. For this goal, studies in the literature were reviewed. In addition, studies connected to RS or types were scanned in the Vosviewer application, and maps were constructed based on the locations, years, and keywords of the studies done. By developing remote sensing methods, researchers have achieved successful results in environmental analysis, increasing the productivity of agricultural areas, natural disaster management and many other fields. The rapid development of RS technology, improvement of data analysis algorithms and advances in satellite technologies show that this field will gain even more importance in the future. As the application areas of this method expand, it becomes important to use and interpret the data provided by RS more effectively.

1. Introduction

Remote sensing (RS) is the science of gathering information about objects without making direct physical contact, using various sensing methods. In greater detail, RS involves the detection, measurement, and digital storing of emission and scattering values that can be isolated from the object in one or more discrete band intervals across a large range of the spectrum (Lillesand & Kiefer, 2004). RS systems are classified into two types: active and passive. These are active systems in which objects or particles are artificially delivered to be analyzed and their energy changes as a result of reflection and analysis. It is included in this class Radio Detection and Range (Radar). Passive systems, on the other hand, differ from active remote sensing in that they interact with particles and surfaces to offer the needed information about the physical and chemical properties of naturally emitted radiation, such as solar radiation. (Kavak, 1998).

RS technique is based on perception, which is the process of determining correlations between electromagnetic radiation reflected or emitted by objects and their qualities. Passive systems detect naturally occurring electromagnetic radiation. Cameras that take aerial photos for photogrammetric evaluations are an example of passive systems. Active systems detect artificial radiation, while passive systems detect natural radiation emitted by objects and the atmosphere (Olgun, 2012). Active systems examples are radar and LiDAR.

RS system is made up of an energy source, energy/matter interaction, atmosphere, sensor, and data-gathering system components. RS is utilized in a variety of applications, including determining land cover and distribution, agriculture and forestry, urban planning, coastal area management, drinking water supply and irrigation, formation detection, and biodiversity. (Karthikeyan et al., 2020; Adjovu et al., 2023). The use of Geographic Information Systems (GIS) and RS in modeling land use and land cover (LLC) is also a suitable approach to understand the future pattern (Shafiq & Mahmood, 2022). This study focused on RS, which is a method utilized by many professional areas and is widely preferred nowadays (Çelik & Yakar, M., 2023; Çelik et al., 2024a, Çelik et al., 2024b). Because of its importance, it was determined that extensive literature research on RS was required, and the study concentrated on this topic. In this study, detailed literature research was conducted and the results of relevant studies were presented.

2. Literature review

Previous articles on RS and RS systems, which form the study's major axis, were reviewed, together with their features, methodologies, data, and so on. Table 1 shows the details of the researchers analyzed.

***Corresponding Author**
*(23023410001@mersin.edu.tr) ORCID 0009-0002-0468-625X

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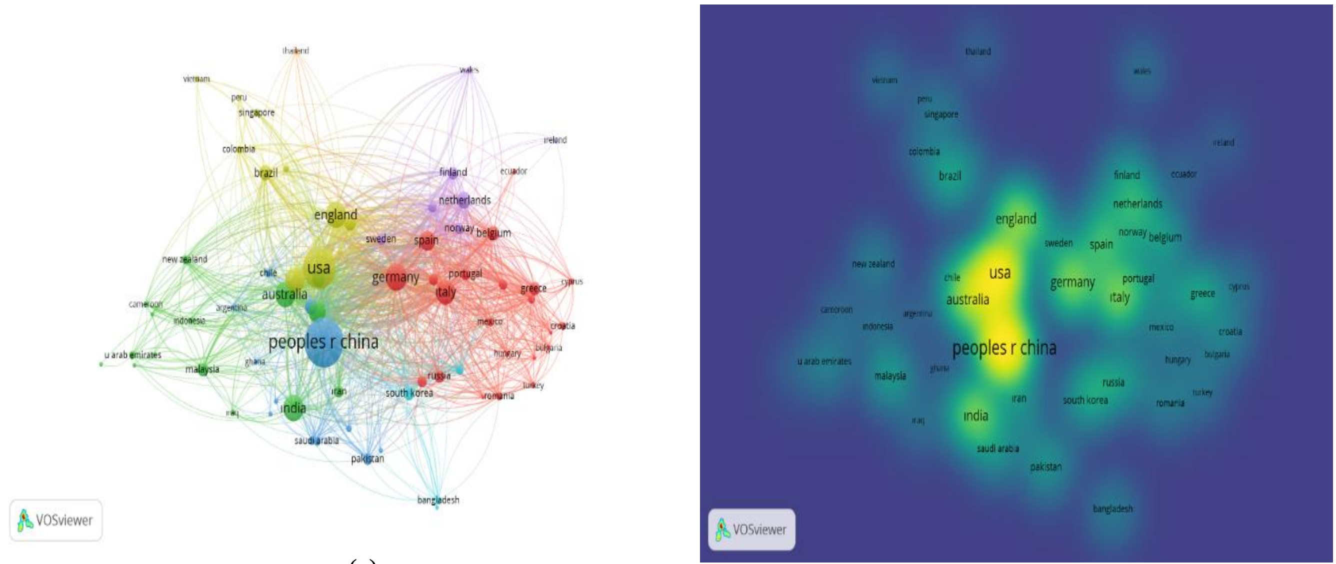
Table 1. Summary of literature

Reference	Type of study	Aim of study
Jia & Ye (2023)	Review	Deep learning approaches were used to investigate data connected to seismic events and the things they affected.
Cuca et al., (2023)	Review	RS and earth observation methods were utilized to assess damage to European cultural heritage.
Zhou et al. (2023)		A general evaluation of existing techniques and methods for obtaining coastlines from RS data was made. A general evaluation of existing techniques and methods for obtaining coastlines from RS data was made.
Wang & Zhang (2023)	Review	Desert movement was assessed utilizing RS techniques.
Kurbanov et. al. (2022)	Review	The effects of forest fires were evaluated using RS methods.
Lan et. al. ((2022)	Review	The precursors of major landslides were researched via RS approaches.
Yu & Fang (2023)	Review	The role of remote sensing and large-scale spatial data has been examined in urban studies in recent years.
Tanniru, & Ramsankaran (2023)	Review	The microwave approach was used to determine snow thickness in the study.
Neyns & Canters (2022)	Review	The mapping of vegetation in urban areas using high-resolution satellite imagery was investigated.
Ma et. al. (2023)	Review	Remote sensing techniques were applied to investigate marine pollution on a worldwide scale.
Janga et. al. (2023)	Review	Existing literature on remote sensing and artificial intelligence methodologies was examined.
Anand & Deb (2023)	Review	The potential of RS and GIS techniques for urban building energy modeling tools was extensively evaluated in the study.
Xu et. al. (2023)	Review	Platforms for SAR, optical remote sensing, and laser technologies used in China were summarized.
Louw et. al. (2022)	Review	Variety of pandemic-related topics were handled through RS.
Zheng et. al. (2023)	Review	This study investigated the usage of NTL (Nighttime Light) data in basic urban applications.

When the research on RS listed in Table 1 was analyzed, it was clear that this issue was significant. At this point, it would be incredibly beneficial to review other research in the literature on RS, which is employed by many professional fields and today maintains a very important position. In this regard, research on RS and RS types was scanned in the Vosviewer tool, and maps were constructed based on the places, years, and keywords where the studies were conducted.

2.1. Analysis based on the place where the studies were conducted

Review articles on RS and its types, made within 3 years covering the years 2021-2023, were examined. With this analysis, it was revealed in which countries RS and its varieties are the subject of more scientific studies (Figure 1). Therefore, the subject of the study was addressed by researchers in 113 different countries as a whole. The country with the most studies was China with 580, followed by the USA with 85. The countries where the least amount of work has been done vary from Nigeria to Wales, from Senegal to Qatar. The number of articles on the subject of the study in these countries was determined to be only 1.



(a) (b)

Figure 1. Analysis of the countries studied

2.2. Analysis according to the year the studies were made

Review articles published in 2021, 2022, and 2023 regarding RS and RS types subject to the study were examined with this analysis (Figure 2). According to the analysis results, 168 studies were published in 2021, 182 in 2022, and 230 in 2023. It is observed that there is an increase in the number of studies conducted over the years. At this point, it is possible to say that the subject of study is becoming increasingly popular around the world and is oftentimes occurring in scientific publications.

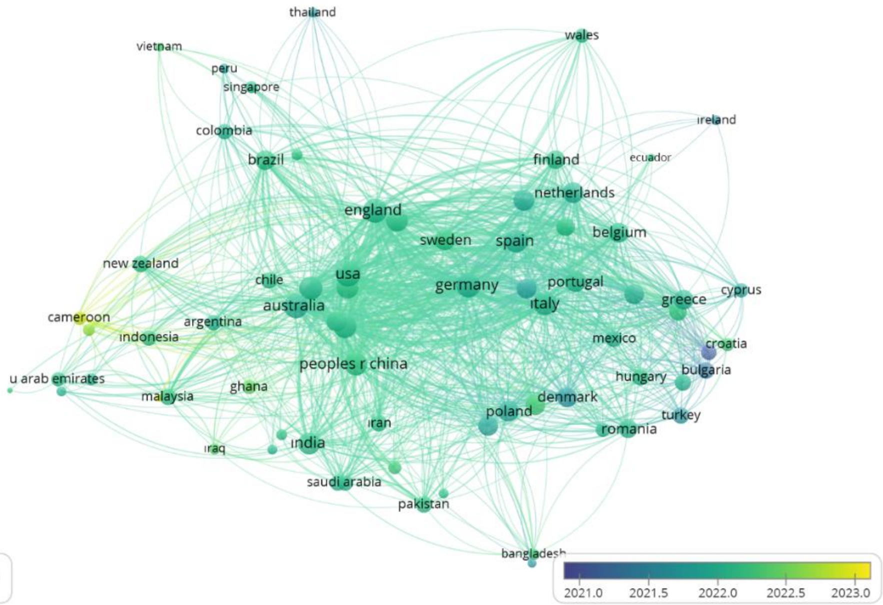
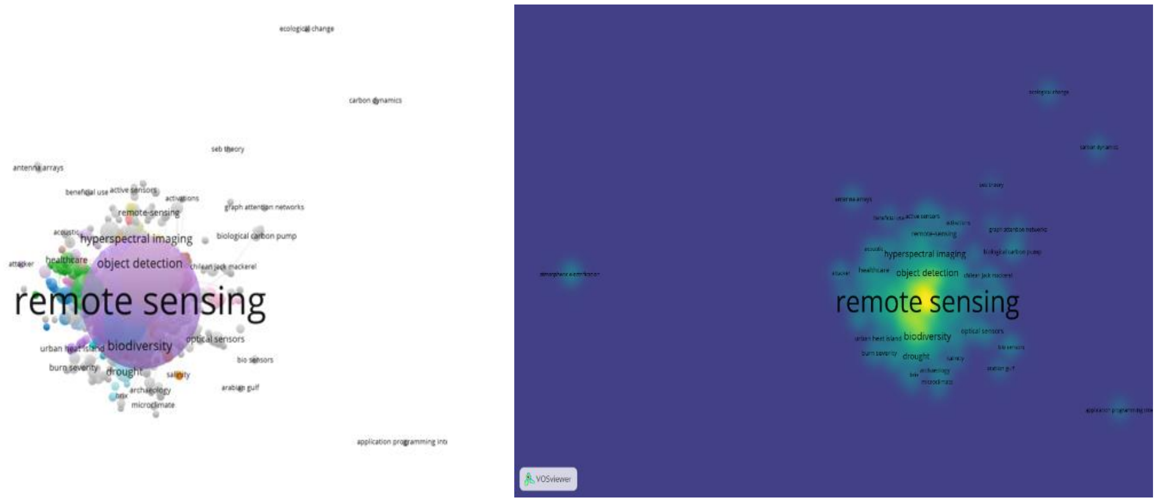


Figure 2. This is the example of figure formatting

2.3. Keyword Analysis

Keyword analysis is an analysis method employed to apprehend, classify, or summarize a text or document. With this analysis, other keywords related to the words "RS and RS types", which are the topic of the study, were found. It was determined which field UA was most frequently discussed (Figure 3). In light of the findings obtained from the analysis, it was determined that the keywords "object detection", "biodiversity" and "hyperspectral images" were frequently used together with RS.



(a) (b)

Figure 3. Analysis of the keywords used

3. Discussion

In the study, studies conducted with RS and RS types and published in the literature were examined. In these studies, applications were carried out using mainly RS methods.

Cuca et al. (2023) integrated RS techniques and terrestrial measurement methods to detect deformations occurring in cultural heritage in Europe. Kurbanov et al. (2022) examined fires occurring around the world with RS methods in the study. Both studies are review articles and research the topics they focus on in depth. In this study, the issue of RS and RS types was discussed, and

Cuca et al. (2023) and Kurbanov et al. (2022) detailed research was carried out, as in the work of. As a result, a review article was created.

Cuca et al. (2023) investigated studies between 2000 and 2022, while Kurbanov et al. (2022) examined publications within 20 years covering the years 2000-2020. In this study, we wanted to analyze more current and newly conducted studies, and in this direction, publications from 2021, 2022, and 2023 were examined and the study was carried out. In this regard, it differs from the other two studies mentioned. Sutherland et al. (2023), Hu & Minner (2023) and Zheng et al. (2023). Cuca et al. (2023) differentiated RS systems were used to divide the architectural space in the upper and lower dimensions. In the research conducted by Cuca et al. (2023) and Sutherland et al. (2023), RS methods were used on issues related to cultural architectural heritage.

In the studies carried out by Jia & Ye (2023), Kurbanov et al. (2022), Lan et al. (2022) and Xu et al. (2023) data about disasters, the objects they affected, and the areas where disasters occurred were investigated with RS methods.

Other articles utilized techniques in coastline extraction, desert mobility assessment and desertification review, urban studies, marine pollution monitoring, urban building energy modeling, and research on unmanned aerial vehicles for search and rescue. In this study, RS and RS types were the subjects, and research was carried out in this direction. In addition, in the mentioned articles, articles related to the study subject in the literature were examined. In this study carried out by the authors of the article, studies in the literature were examined, as in the articles mentioned above. In this respect, it is possible to express that they are similar. Nevertheless, the popular Vosviewer Bibliometric (VB) analysis method, which is frequently used in review articles today, was not used in the studies examined. In this review article, to analyze the studies in the literature in depth and to make the study academically stronger, Sutherland et al. (2023) as in the study conducted by, the VB analysis method was preferred. In this context, it differs from other studies.

4. Conclusion

The primary focus of the research is RS and RS types. The authors of the article intend to create a review article to explore and determine the importance of this topic. In this regard, prior compilation studies on RS published in the literature were reviewed, and Table 1 was developed. This style of table is commonly used in review articles. However, research was undertaken using the Vosviewer program to further investigate the subject of the study and establish its trend in recent years. In this context, the VB Bibliometric analysis method was utilized, and several analyses were conducted on the study's topic (Figure 1-3).

In light of the experiences obtained during the research and writing process for this study, a few recommendations might be provided to researchers who will publish review articles on this or other topics.

- It is critical to thoroughly review the research in the literature on the topic of the study.
- Although learning the whole literature is extremely challenging, reviewing current studies, particularly those published in recent years, will help you gain a better knowledge of the topic.
- Finally, besides traditional scanning methods, the VB Bibliometric analysis method will be very useful in determining where, when, and in what types of publications the subject of the study is most commonly covered. The results of the analysis will allow for in-depth inferences about the subject. It is suggested that researchers focus on these topics.

The general purpose of this product is to compile and analyze the research on RS and RS types and to present the current knowledge and content of this subject. Based on the findings of the VB Bibliometric analysis conducted in this study, it is evident that RS and its various types have been gaining significant attention in recent years. Researchers venturing into the realm of review articles on this subject are advised to delve deep into the current literature, particularly recent publications, to grasp the latest advancements and trends in RS research. By employing advanced analysis tools like Vosviewer and the VB Bibliometric method, comprehensive insights into the coverage and prominence of the topic in academic publications can be acquired, paving the way for more informed and impactful scholarly contributions on this subject.

Evaluating the strengths and weaknesses of this study is important to better understand the scope and findings of the study. The study compiles and presents the current knowledge in this field by conducting a comprehensive literature review on RS (Recommender Systems) and RS types. In the study, comprehensive and detailed analyses were conducted among the publications in the literature using the Vosviewer program and the VB Bibliometric analysis method. Despite the wide scope of the literature review, there is always a risk that some important studies may be overlooked. The results of the study are based on the existing literature and it is possible that new research that emerged after the publication date was not taken into account.

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