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GIS-Based Spatial Risk Zoning of Ambient Air Pollution Using the Air Pollution Standard Index (ISPU) Around the Celukan Bawang Coal-Fired Power Plant

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Abstract: Air pollution emitted from coal-fired power plants may influence ambient air quality and its spatial distribution in surrounding residential areas. This study aimed to analyze the spatial distribution of ambient air pollutants using the Air Pollution Standard Index (ISPU) integrated with Geographic Information System (GIS) analysis around the Celukan Bawang Coal-Fired Power Plant, Bali, Indonesia. Ambient air quality measurements were conducted at 20 monitoring locations within a 1-km radius of the power plant for SO_2, NO_2, $PM_{2.5}$, and PM_{10}. ISPU values were calculated following the Indonesian Ministry of Environment and Forestry Regulation No. 14 of 2020 and spatially interpolated using the Co-Kriging method in ArcGIS. The resulting spatial distribution maps were interpreted together with wind direction, wind speed, topography, and land-use characteristics. All measured pollutant concentrations complied with the Indonesian ambient air quality standards, and the calculated ISPU values were predominantly classified as Good, with $PM_{2.5}$ showing the highest relative ISPU values. Spatial analysis revealed relatively higher pollutant concentrations near the industrial complex and along the dominant wind pathway while remaining within acceptable air quality conditions. The integration of GIS, ISPU, and Co-Kriging provides a practical framework for visualizing spatial variations in ambient air quality and supports environmental monitoring, land-use planning, and evidence-based environmental management in industrial areas.

Keywords: Air pollution; CFSPP; GIS; ISPU; Risk zoning

Introduction

Environmental pollution represents an important environmental concern because changes in environmental quality can affect both ecosystems and human activities (Sastrawijaya, 2009). Air pollution remains one of the most significant environmental challenges worldwide because of its adverse impacts on human health, ecosystem quality, and sustainable development. Coal-fired power plants are recognized as major stationary emission sources of sulfur dioxide (SO_2), nitrogen dioxide (NO_2), particulate matter less than 2.5 µm ($PM_{2.5}$), and particulate matter less than 10 µm (PM_{10}), all of which may influence ambient air quality and long-term environmental exposure in surrounding communities (WHO, 2014; Amster, 2019; Cummiskey et al., 2019; Myllyvirta, 2021; Farhan, 2023; Singh et al., 2025). Ambient air quality monitoring is commonly performed to evaluate compliance with regulatory standards. Air-quality monitoring technologies have also evolved through Internet of Things-based systems that enable continuous monitoring of environmental parameters, particularly in indoor environments (Rumampuk et al., 2021). However, concentration measurements alone cannot adequately explain the spatial variability of pollutant exposure. Pollutant dispersion is strongly influenced by meteorological and geographical conditions, including

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wind direction, wind speed, topography, land-use characteristics, and distance from emission sources, resulting in heterogeneous environmental risks even when measured concentrations satisfy ambient air quality standards (Li et al., 2020; Zhang & Wang, 2021). Consequently, environmental assessment should extend beyond concentration-based evaluation to include spatial characterization and integrated air quality management approaches (Gulia et al., 2020).

Residential areas surrounding industrial facilities represent priority locations for environmental assessment because local populations experience continuous exposure to ambient air pollutants during daily activities. The potential environmental impact is not solely determined by pollutant concentrations but also by spatial variations in pollutant transport and accumulation, which may create localized exposure hotspots within residential environments (Du, 2023). Therefore, identifying the spatial distribution of environmental risk is essential for supporting environmental monitoring, land-use planning, pollution mitigation, and evidence-based environmental management, particularly in communities located near large stationary emission sources such as coal-fired power plants. The integration of GIS with population and settlement information can further support spatial exposure assessment by identifying areas where pollutant distributions overlap with potentially exposed populations.

Geographic Information Systems (GIS) have been widely applied to integrate environmental measurements with spatial information for analyzing pollutant distribution and identifying environmentally vulnerable areas. Through geostatistical interpolation and spatial overlay analyses, GIS converts discrete monitoring observations into continuous spatial representations, providing a more comprehensive understanding of pollutant dispersion than conventional statistical approaches (Gupta et al., 2020). In Indonesia, ambient air quality is officially evaluated using the Air Pollution Standard Index (ISPU), which standardizes pollutant concentrations into air quality categories reflecting potential environmental and public health impacts (Ministry of Environment and Forestry Regulation No. 14 of 2020). Although ISPU effectively communicates air quality conditions, it is generally presented as numerical or categorical information without incorporating spatial environmental characteristics that influence pollutant dispersion. Consequently, ISPU alone provides limited support for identifying localized environmental risk patterns around industrial emission sources.

Previous studies have applied satellite observations, atmospheric dispersion models, Google Earth Engine, and GIS techniques to investigate the spatial distribution of air pollutants (Chairunnisa et al., 2025). Ambient monitoring studies have also demonstrated the importance of simultaneously evaluating multiple pollutants, including NO_2, SO_2, and PM_{10}, to characterize variations in air quality conditions (Hardiyan & Zulistyawan, 2023). Hartanto et al. (2024) analyzed regional SO_2 and NO_2 distributions using Sentinel-5P satellite imagery and Google Earth Engine, whereas Leko & Manullang (2024) employed AERMOD to simulate pollutant dispersion around a cement industry. Ramdhanu et al. (2024) estimated $PM_{2.5}$ contributions from coal-fired power plants using satellite-derived observations, Satellite-based indicators such as aerosol optical depth have also been investigated for their potential to estimate and characterize ambient $PM_{2.5}$ conditions (Rosidin & Dirgawati, 2023). While Gupta et al. (2020) demonstrated the capability of GIS to identify spatial pollution hotspots. Despite these important contributions, previous studies generally focus on pollutant concentration assessment, satellite observation, atmospheric dispersion modeling, or GIS visualization separately. Limited studies have integrated field-measured ambient air quality data, standardized ISPU assessment, geostatistical interpolation, and environmental controlling factors within a unified GIS framework to produce spatial environmental risk zoning capable of directly supporting environmental management and spatial planning in residential areas surrounding coal-fired power plants.

Previous studies have also demonstrated the usefulness of portable and optical particle sensing technologies for particulate monitoring, although sensor accuracy and measurement uncertainty require careful consideration (Hagan & Kroll, 2020). Previous ambient air quality research around the Celukan Bawang CFSPP has also evaluated $PM_{2.5}$ and PM_{10} concentrations using an air quality detector, providing preliminary information on particulate matter conditions surrounding the power plant (Colorado et al., 2025). The performance of particulate-matter sensors may be affected by measurement conditions and environmental factors such as relative humidity, highlighting the importance of calibration and measurement-quality assessment in air-quality monitoring (Hagan & Kroll, 2020; Wang et al., 2021; Le et al., 2025). Environmental assessment of the Celukan Bawang CFPP has also been discussed from the perspective of integrating climate-change considerations into environmental impact assessment, indicating the broader importance of environmental evaluation for power-generation activities in this area (Ismaya & Wafi, 2023) To address this research gap, this study proposes an integrated spatial environmental assessment framework that combines field-measured ambient air quality data, ISPU assessment based on the Indonesian Air Pollution Standard Index regulation, Co-Kriging spatial interpolation, and multiple environmental controlling variables, including wind direction, wind speed, topography, and land-use characteristics, within a Geographic Information System. Unlike previous studies that primarily evaluate pollutant concentrations or atmospheric dispersion independently, the proposed framework integrates standardized air quality assessment with spatial environmental characteristics to generate air pollution risk zoning representing the spatial variability of environmental exposure in residential areas. This integrated approach provides a more comprehensive basis for environmental monitoring, pollution mitigation, and evidence-based environmental decision-making than conventional concentration-based assessment alone.

Method

This study employed a quantitative spatial research design to analyze the spatial distribution of ambient air pollutants and develop air pollution risk zoning in residential areas surrounding the Celukan Bawang Coal-Fired Power Plant (CFPP), Bali, Indonesia. The study focused on residential settlements located within a 1-km radius of the power plant, encompassing Tinga-Tinga Village, Tukadsumaga Village, Pungkukan Hamlet, and Brombong Hamlet. These residential areas were selected because they represent the communities most likely to experience continuous exposure to ambient air pollutants emitted from the power plant. Moreover, the study area reflects varying environmental characteristics, including topography, land-use patterns, and prevailing meteorological conditions, which may influence pollutant dispersion and spatial exposure patterns (Li et al., 2020; Zhang & Wang, 2021).

The unit of analysis comprised ambient air quality conditions measured at representative monitoring locations within the study area. A purposive sampling strategy was adopted to ensure that sampling locations adequately represented differences in residential distribution, distance from the emission source, dominant wind direction, land-use characteristics, and topographic conditions. Rather than applying equal spatial intervals, sampling density was adjusted according to the distribution of residential settlements to better represent potential human exposure. The distribution of monitoring locations was designed to represent potential residential exposure rather than maintaining equal spatial intervals from the emission source. Residential settlements within the 0–250 m buffer is relatively limited because much of the area is occupied by industrial facilities and supporting infrastructure. Consequently, fewer sampling locations were assigned to this zone, whereas additional monitoring points were allocated to outer buffer zones where residential density and potential human exposure are substantially higher. Consequently, a total of 20 monitoring locations were established within four buffer zones surrounding the power plant: 0–250 m (2 points), 250–500 m (4 points), 500–750 m (6 points), and 750–1,000 m (8 points). The distribution of monitoring locations is presented in. The spatial distribution of the sampling locations is presented in Table 1 and Figure 1.

Table 1. Sampling distribution

Distance from CFPP (m)	Number of sampling points
0–250	2
250–500	4
500–750	6
750–1,000	8
Total	20

Source: author's research results

Field measurements were conducted directly at the selected monitoring locations following the sampling design presented in Figure 2. Ambient air sampling, meteorological observations, and GPS positioning were performed simultaneously to ensure the representativeness and spatial accuracy of the collected data. Representative photographs of field sampling activities are presented in Figure 2.

Primary data consisted of ambient air quality measurements of sulfur dioxide (SO_2), nitrogen dioxide (NO_2), particulate matter less than 2.5 µm ($PM_{2.5}$), and particulate matter less than 10 µm (PM_{10}), representing the principal atmospheric pollutants associated with coal-fired power generation. Ambient air sampling and laboratory analyses were conducted in accordance with the applicable Indonesian National Standards (SNI) and Government Regulation No. 22 of 2021. To minimize temporal variation during field measurements, ambient air monitoring was performed using five sampling units operated simultaneously at five monitoring locations over a continuous 24-hour sampling period. This procedure was repeated over four consecutive sampling campaigns until measurements were completed at all 20 monitoring locations. Conducting simultaneous measurements within each campaign reduced temporal bias among sampling sites while maintaining compliance with the standard 24-hour ambient air sampling protocol. Although the ambient NO_2 concentration was obtained from the field monitoring campaign, conversion into ISPU followed the breakpoint concentrations and calculation procedure stipulated in Minister of Environment and Forestry Regulation No. 14 of 2020.

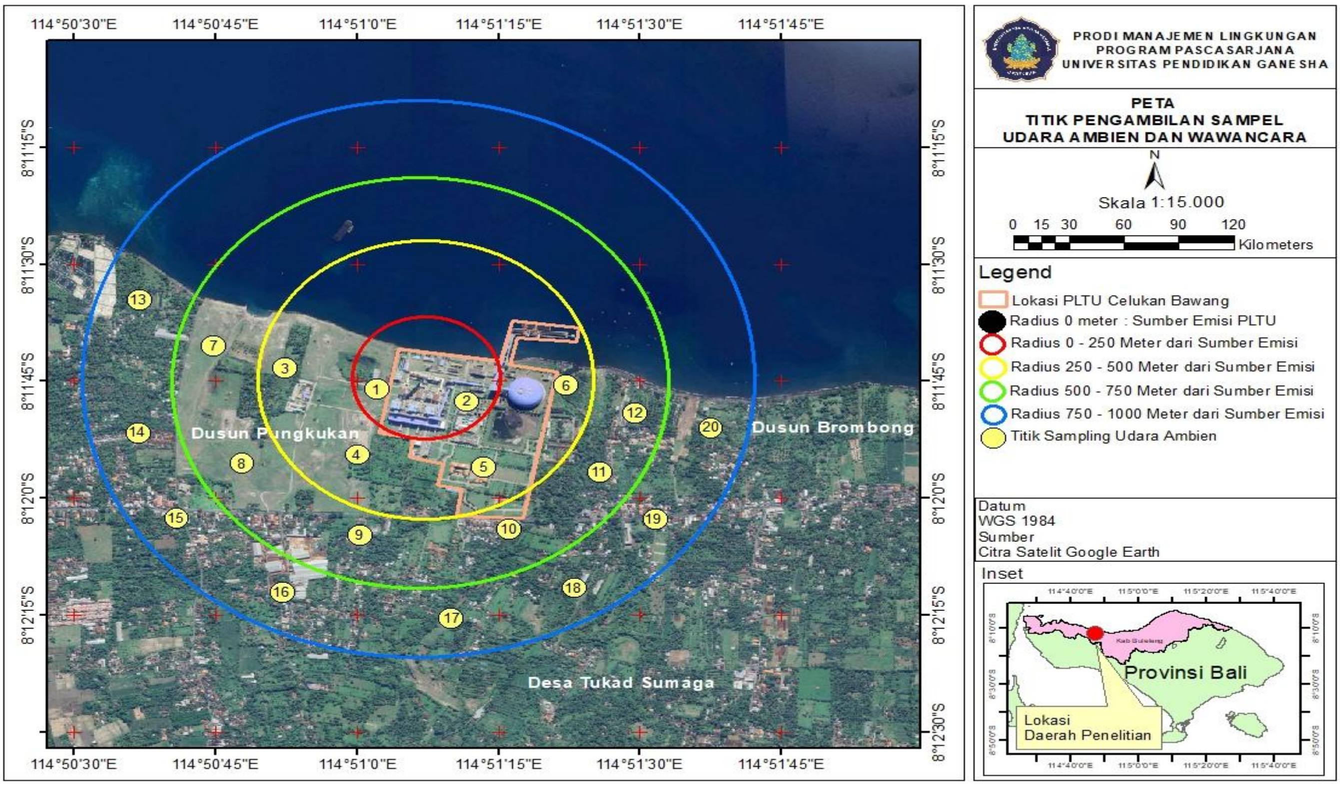

Figure 1. Sampling point map of research locations air quality

Figure 2. Field sampling activities for Ambien air quality

Table 2. Ambient air quality parameters and national standards

Parameter	Unit	Averaging Time	Standard (µg/m³)
SO_2	µg/m³	24 hours	75
NO_2	µg/m³	1 hour	200
$PM_{2.5}$	µg/m³	24 hours	55
PM_{10}	µg/m³	24 hours	75

Source: Government Regulation of the Republic of Indonesia No. 22 of 2021.

Secondary datasets consisted of administrative boundaries, digital elevation models (DEM), land-use maps, and meteorological data, including wind direction and wind speed. These datasets were incorporated because pollutant transport and dispersion are strongly affected by atmospheric circulation, terrain characteristics, and land-surface conditions (Mikkelsen, 2003; Li et al., 2020; Xie et al., 2020).

The geographic coordinates of all monitoring locations were recorded using a Global Positioning

System (GPS) receiver to ensure accurate spatial positioning. All primary and secondary datasets were subsequently integrated into a Geographic Information System (GIS) environment for spatial database development and analysis. GIS provides an effective platform for integrating environmental measurements with geographically referenced information to support environmental mapping and spatial decision-making (Prahasta, 2002; Gupta et al., 2020). Spatial data processing and visualization were performed using ArcGIS software. Digital mapping technologies can further facilitate the presentation and communication of geographically referenced information through map-based visualization (Rohim et al., 2015).

Ambient air quality was evaluated using the Air Pollution Standard Index (Indeks Standar Pencemaran Udara- ISPU), the official air quality assessment system adopted in Indonesia. ISPU converts measured pollutant concentrations into standardized index values representing potential environmental and public health impacts based on pollutant-specific breakpoint concentrations established by the Ministry of Environment and Forestry Regulation No. 14 of 2020. Air-quality classification provides a practical approach for transforming pollutant measurements into categories that facilitate the interpretation and communication of environmental air-quality conditions (Nugroho et al., 2023). The ISPU values for SO_2, NO_2, $PM_{2.5}$, and PM_{10} were calculated using the official interpolation equation prescribed in the regulation. For NO_2, ISPU calculation followed the pollutant averaging time specified by the applicable national regulation to ensure consistency with Indonesian ambient air quality standards.

Various spatial interpolation techniques, including inverse distance weighted, natural neighbor, and spline methods, have been applied to estimate spatial values between observation points (Pasaribu & Harjoko, 2012). Spatial interpolation was performed using the Co-Kriging geostatistical interpolation method within the ArcGIS environment to estimate pollutant distribution at unsampled locations and generate continuous spatial surfaces of ISPU values. Recent developments in air-quality mapping have also demonstrated the application of spatio-temporal kriging combined with machine-learning approaches for air-quality estimation (Jeong & Koo, 2025). GIS-based spatial interpolation can support the estimation of atmospheric pollutant distributions when monitoring observations are spatially limited (Batterman et al., 2025). Recent developments in air-quality mapping have also demonstrated the application of spatio-temporal kriging combined with machine-learning approaches for air-quality estimation (Jeong & Koo, 2025). The reliability of geostatistical interpolation depends on the spatial and temporal structure of the monitoring data, emphasizing the importance of evaluating spatial dependence before generating continuous prediction surfaces (Hernández-Gress & Conchouso González, 2026). Spatial interpolation methods are widely used to estimate values at unsampled locations based on measurements obtained from surrounding sampling points (Azpurua & Ramos, 2010). Compared with deterministic interpolation methods, Co-Kriging incorporates spatial autocorrelation between the primary variable and correlated secondary variables, thereby improving prediction accuracy where environmental variables influence spatial variability (Goovaerts, 1997; Webster & Oliver, 2007).

In this study, ambient air quality measurements (ISPU values) were treated as the primary variable, while digital elevation (topography) served as the secondary variable in the Co-Kriging interpolation process because terrain characteristics influence atmospheric circulation and pollutant accumulation. Model performance was evaluated through semivariogram modelling prior to interpolation to ensure that the spatial dependence of the measured data was adequately represented.

Following the Co-Kriging interpolation, the resulting spatial distribution maps of ISPU were spatially compared with land-use, wind direction, wind speed, and topographic datasets to interpret the influence of environmental characteristics on pollutant distribution patterns. Wind direction and wind speed were used to explain dominant pollutant transport pathways, whereas topography and land-use characteristics were employed to interpret potential pollutant accumulation and exposure conditions within residential environments. These environmental variables were incorporated for spatial interpretation rather than as weighted criteria in a multi-criteria decision analysis, thereby allowing the observed spatial patterns to be explained based on environmental characteristics without introducing subjective weighting factors. Although weighted overlay is commonly available in GIS for combining multiple spatial criteria (ESRI, 2023), the environmental variables in this study were used only for spatial interpretation and were not assigned subjective weights.

Finally, air pollution risk zones were classified into low, medium, and high categories based on the spatial distribution of ISPU values. Descriptive spatial analysis was subsequently employed to evaluate pollutant distribution patterns and identify residential areas potentially experiencing relatively higher environmental exposure. The integration of GIS, ISPU assessment, Co-Kriging interpolation, and environmental interpretation provides a comprehensive framework for supporting environmental monitoring, spatial planning, and evidence-based environmental management in residential areas surrounding coal-fired power plants.

Result and Discussion

Environmental Characteristics Influencing Air Pollution Distribution

The spatial distribution of air pollutants in the study area is influenced by several environmental factors, including wind characteristics, topography, and land use. These environmental variables play an important role in controlling pollutant dispersion patterns and determining the spatial variation of ambient air quality around the Celukan Bawang Coal-Fired Power Plant (CFPP).

The study area is characterized by dominant wind movement from the coastal area toward inland settlements with wind speeds ranging from 2–5 m/s. This pattern reflects the typical sea breeze circulation occurring in coastal environments, where air masses move from the sea toward warmer land surfaces. Such wind conditions contribute significantly to pollutant transport and dispersion processes from the power plant toward surrounding residential areas. Atmospheric transport is particularly relevant in power-plant assessments because pollutant movement can influence the spatial relationship between emission sources and potentially exposed populations (Zigler et al., 2020). Figure 3 illustrates the spatial distribution of wind direction and wind speed within the study area.

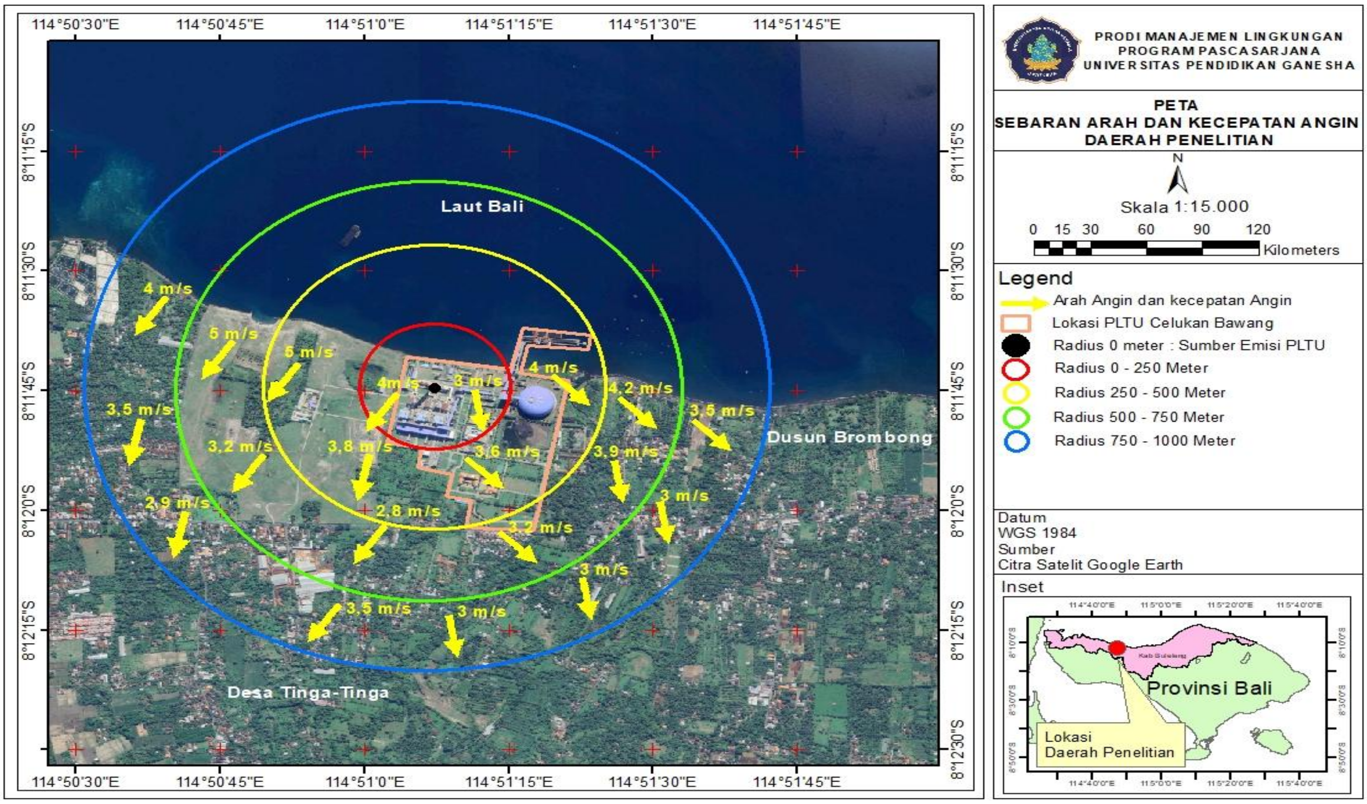

Figure 3. Wind direction and wind speed distribution map

The topographic condition of the study area consists primarily of coastal alluvial plains with elevations ranging from 0–25 m above sea level and slopes between 0° and 4°. The relatively flat terrain facilitates horizontal movement of air masses and pollutant transport. Consequently, pollutant accumulation is influenced more strongly by meteorological conditions than by terrain barriers.

In addition, land use patterns vary across the study area. Residential settlements and industrial facilities dominate the coastal zones of Dusun Pungkukan and Dusun Brombong, whereas agriculturaland, plantations, and rain-fed rice fields dominate Desa Tinga-Tinga and Desa Tukad Sumaga. From an environmental management perspective, the development and maintenance of green open spaces can also support environmentally sustainable management in coastal and industrial areas (Husna et al., 2024). These differences in land use influence population exposure levels and environmental vulnerability to air pollution Vegetation and green-space management are also relevant to environmental quality, as greening initiatives can support improvements in local environmental conditions (Jupri, 2022) (Figure 4).

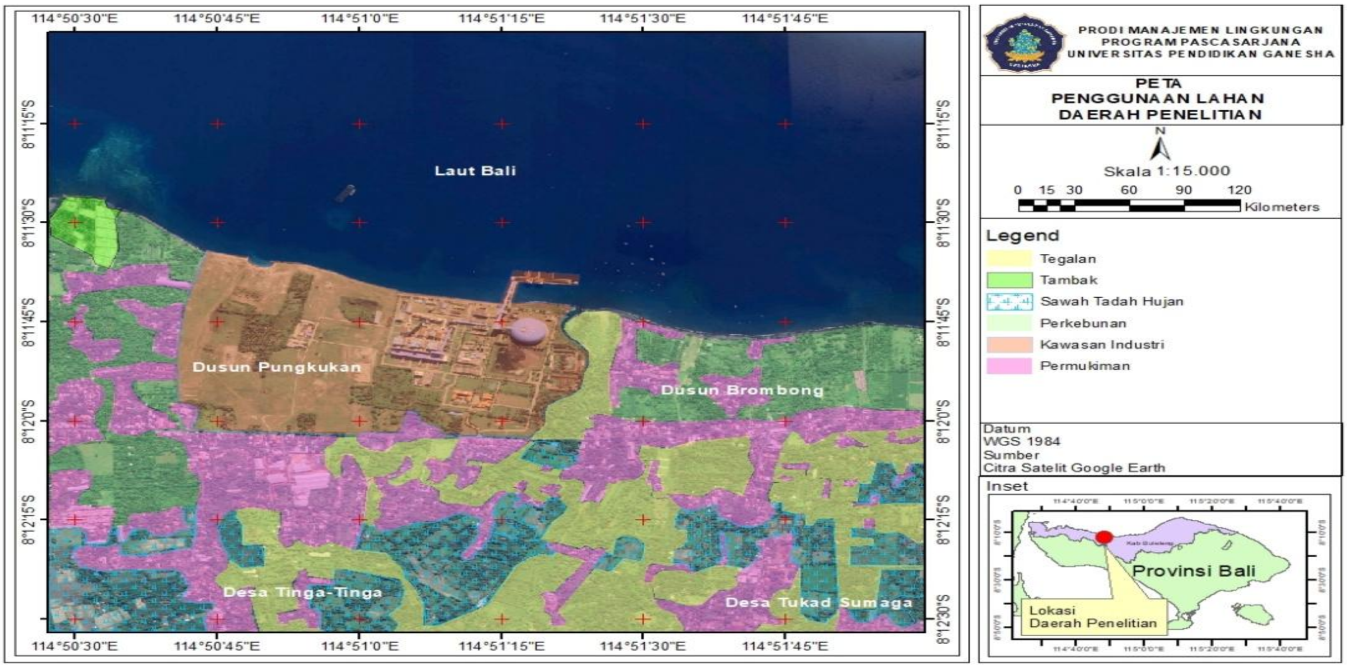

Figure 4. Topography and land use map

Ambient Air Pollutants Quality

Ambient air-quality assessment represents an important component of environmental monitoring in energy-related facilities and provides information regarding environmental conditions surrounding operational activities (Naimah et al., 2024). Twenty ambient air quality samples were taken. These samples were taken to verify that the air was free from pollution from the Celukan Bawang PLTU operation. The ambient air quality samples tested included SO2, NO2, and particulate matter (PM2.5 and PM10). These parameters were adjusted to comply with Government Regulation of the Republic of Indonesia Number 22 of 2021 concerning the Implementation of Environmental Protection and Management, in Appendix VII concerning Ambient Air Quality Standards. Detailed laboratory analysis results are presented in (Table 3).

Table 3. Descriptive statistics of ambient air quality parameters

Sample point	Parameters				Unit
	SO_2	NO_2	$PM_{2,5}$	PM_{10}	
1	28.93	13.75	18.70	27.75	µg/m³
2	28.43	13.45	18.95	27.50	µg/m³
3	27.43	13.11	17.41	26.13	µg/m³
4	27.40	13.12	17.46	25.11	µg/m³
5	26.99	12.86	14.26	23.43	µg/m³
6	26.21	11.41	13.58	21.01	µg/m³
7	24.35	10.17	11.97	20.88	µg/m³
8	24.17	10.15	11.62	20.74	µg/m³
9	22.17	9.67	11.21	20.42	µg/m³
10	22.01	9.53	11.18	20.23	µg/m³
11	22.01	9.31	11.07	20.12	µg/m³
12	22.01	9.21	11.02	20.10	µg/m³
13	20.87	8.79	10.84	19.92	µg/m³
14	20.75	8.69	10.79	19.80	µg/m³
15	20.68	8.61	10.73	19.79	µg/m³
16	20.51	8.47	10.43	19.74	µg/m³
17	20.44	8.41	10.44	19.78	µg/m³
18	20.10	8.21	10.27	19.44	µg/m³
19	20.23	8.38	10.31	19.51	µg/m³
20	20.28	8.37	10.39	19.57	µg/m³

Source: Author's research results

Ambient air quality measurements were conducted at 20 sample points with SO_2, NO_2, $PM_{2.5}$, and PM_{10} parameters. All measured concentrations complied with the Indonesian ambient air quality standards established in Government Regulation No. 22 of 2021. Therefore, the observed spatial variations represent relative differences in pollutant distribution rather than exceedances of national ambient air quality standards. All measurement results were below the national ambient air quality standards (SO_2 150 µg/m³; NO_2 200 µg/m³; $PM_{2.5}$ 55 µg/m³; PM_{10} 75 µg/m³). In general, the highest concentrations of all parameters were observed at the initial measurement points (points 1–5), then showed a decreasing trend until the final points (points 15–20). A comparison graph of the values of each parameter is presented in Figure 5.

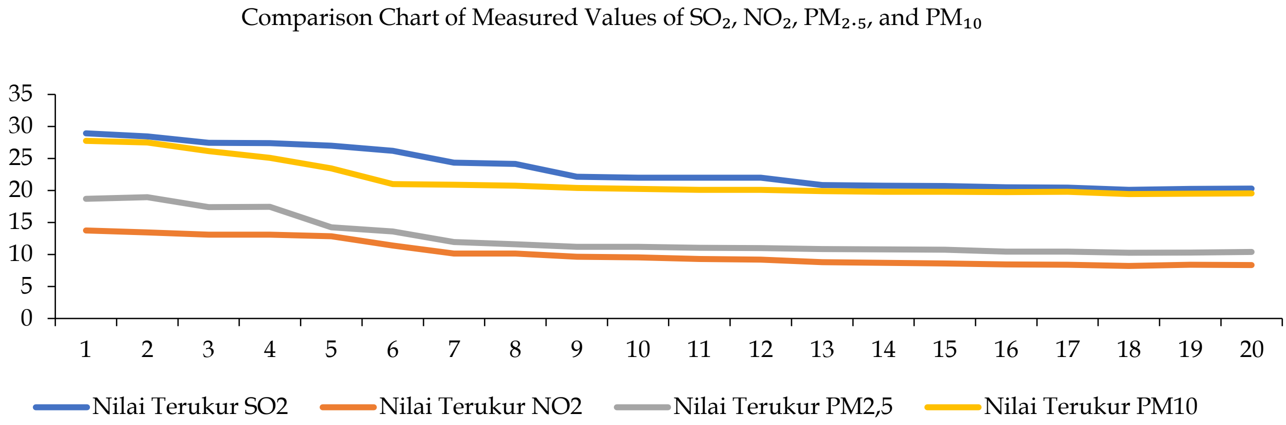

Figure 5. Comparison chart of measured values of SO_2, NO_2, $PM_{2.5}$, and PM_{10}

Spatial Distribution of Air Pollution Standard Index (ISPU)

To evaluate overall air quality conditions, pollutant concentrations were converted into Air Pollution Standard Index (ISPU) values based on the procedures established by the Ministry of Environment and Forestry Regulation No. 14 of 2020. The calculated ISPU values for SO_2, NO_2, $PM_{2.5}$, and PM_{10} at each of the 20 sampling locations are presented in (Table 4), while their spatial variation across the study area is illustrated in (Figure 6).

Table 4. Air pollution standard index (ISPU) values in residential areas around the Celukan Bawang CFSPP

Sample Point	SO_2 ISPU calculated	NO_2 ISPU calculated	$PM_{2,5}$ ISPU calculated	PM_{10} ISPU calculated
1	27.82	8.59	54.01	27.75
2	27.34	8.41	54.32	27.50
3	26.38	8.19	51.72	26.13
4	26.35	8.20	52.46	25.11
5	25.95	8.04	46.00	18.74
6	25.20	7.13	43.81	21.01
7	23.41	6.36	38.61	20.88
8	23.24	6.34	37.48	20.74
9	21.32	6.04	36.16	20.42
10	21.16	5.96	36.06	20.23
11	21.16	5.82	35.71	20.12
12	21.16	5.76	35.55	20.10
13	20.07	5.49	34.97	19.92
14	19.95	5.43	34.81	19.80
15	19.88	5.38	34.61	19.79
16	19,72	5.29	33.65	19.74
17	19.65	5.26	33.68	19.78
18	19.33	5.13	33.13	19.44
19	19.45	5.24	33.26	19.51
20	19.50	5.23	33.52	19.57
Category	Good (0-50)	Good (0-50)	Good (0-50)	Good (0-50)
Color	Green	Green	Green	Green

Source: author's research results

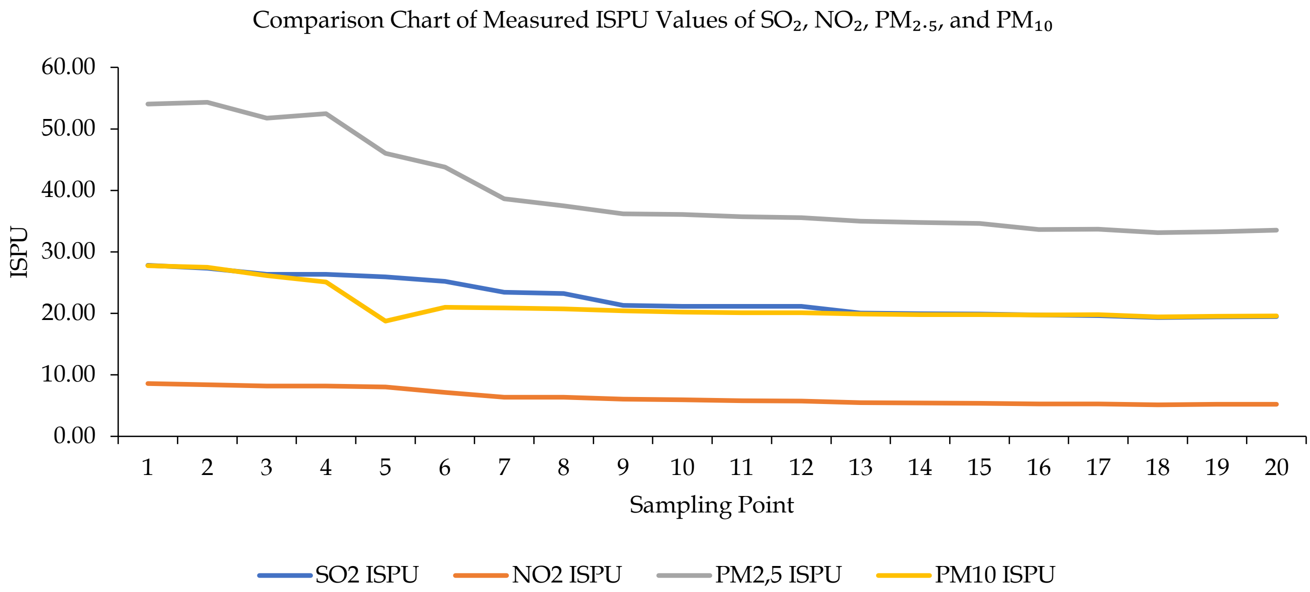

Figure 6. Comparison Chart of Measured ISPU Values of SO_2, NO_2, $PM_{2.5}$, and PM_{10}

Based on the comparison graph of ISPU values at 20 sampling points, it can be seen that all parameters (SO_2, NO_2, $PM_{2,5}$, and PM_{10}) are within a relatively low range and tend to be stable. $PM_{2,5}$ showed the highest ISPU value compared to other parameters at almost all sampling points, with a decreasing fluctuation pattern from the initial point to the final point. This indicates that fine particles are a major contributor to the formation of the air pollution index, although their values remain in the Good (green) category, indicating air-quality conditions with minimal adverse effects according to the ISPU classification (Mirawati et al., 2016).

Meanwhile, SO_2 and PM_{10} showed a gradual decreasing trend with relatively small variations between points, reflecting a fairly homogeneous concentration distribution at the monitoring location. The NO_2 parameter had the lowest and most stable ISPU value compared to the other parameters, with very small fluctuations between sampling points. This condition indicates that NO_2's contribution to air quality degradation is relatively minimal in the study area. Descriptive statistics show that differences between parameters are more pronounced than variations between sampling points, Overall, the observed spatial variation indicates that pollutant distribution was influenced by the combined effects of emission-source characteristics and environmental factors, including prevailing wind conditions, terrain, and land-use characteristics. The relatively smooth spatial transitions among monitoring locations also indicate the presence of spatial dependence, supporting the application of Co-Kriging interpolation for representing pollutant distribution across the study area.

GIS-Based Spatial Distribution of Ambient Air Pollutants

To obtain a more comprehensive understanding of air pollution risk, a GIS-based overlay analysis was conducted by integrating Air Pollution Standard Index (ISPU) values with environmental variables, including wind direction and speed, topographic characteristics, and land-use patterns. This approach enables the identification of areas with varying levels of environmental vulnerability by considering both ambient air quality conditions and factors influencing pollutant dispersion and exposure. The analysis was performed separately for each pollutant parameter (SO_2, NO_2, $PM_{2.5}$, and PM_{10}) to evaluate their respective spatial risk patterns and determine the relative contribution of each pollutant to environmental risk within the study area.

Figure 7 illustrates the spatial distribution of SO_2 based on Co-Kriging interpolation and GIS analysis. The calculated ISPU-SO_2 values ranged from 19.50 to 27.34, indicating that ambient SO_2 concentrations remained within the Good category of the Indonesian Air Pollution Standard Index (ISPU) at all monitoring locations. Although relatively higher ISPU values were observed around the industrial complex, these differences represent relative spatial variations rather than hazardous pollution conditions. The spatial pattern indicates that areas with relatively higher SO_2 concentrations generally occurred near the industrial complex and along the prevailing wind pathway. However, these spatial variations should not be interpreted exclusively as the result of stack emissions. Local emission sources, including coal handling activities, vehicle movement, and fugitive dust generated within the industrial area, may also contribute to ambient SO_2 concentrations at nearby monitoring locations. Therefore, the observed distribution reflects the combined influence of industrial activities and local environmental conditions.

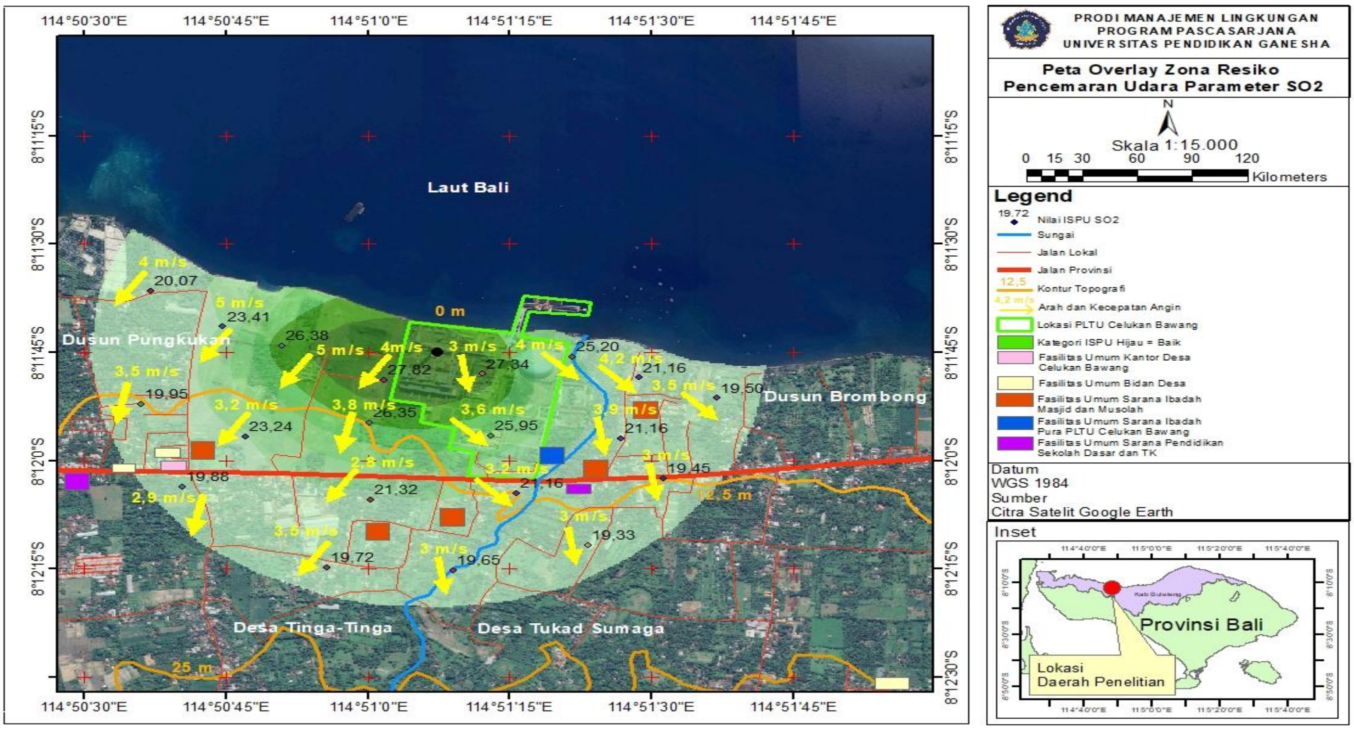

Figure 7. Spatial distribution of SO_2 based on GIS analysis

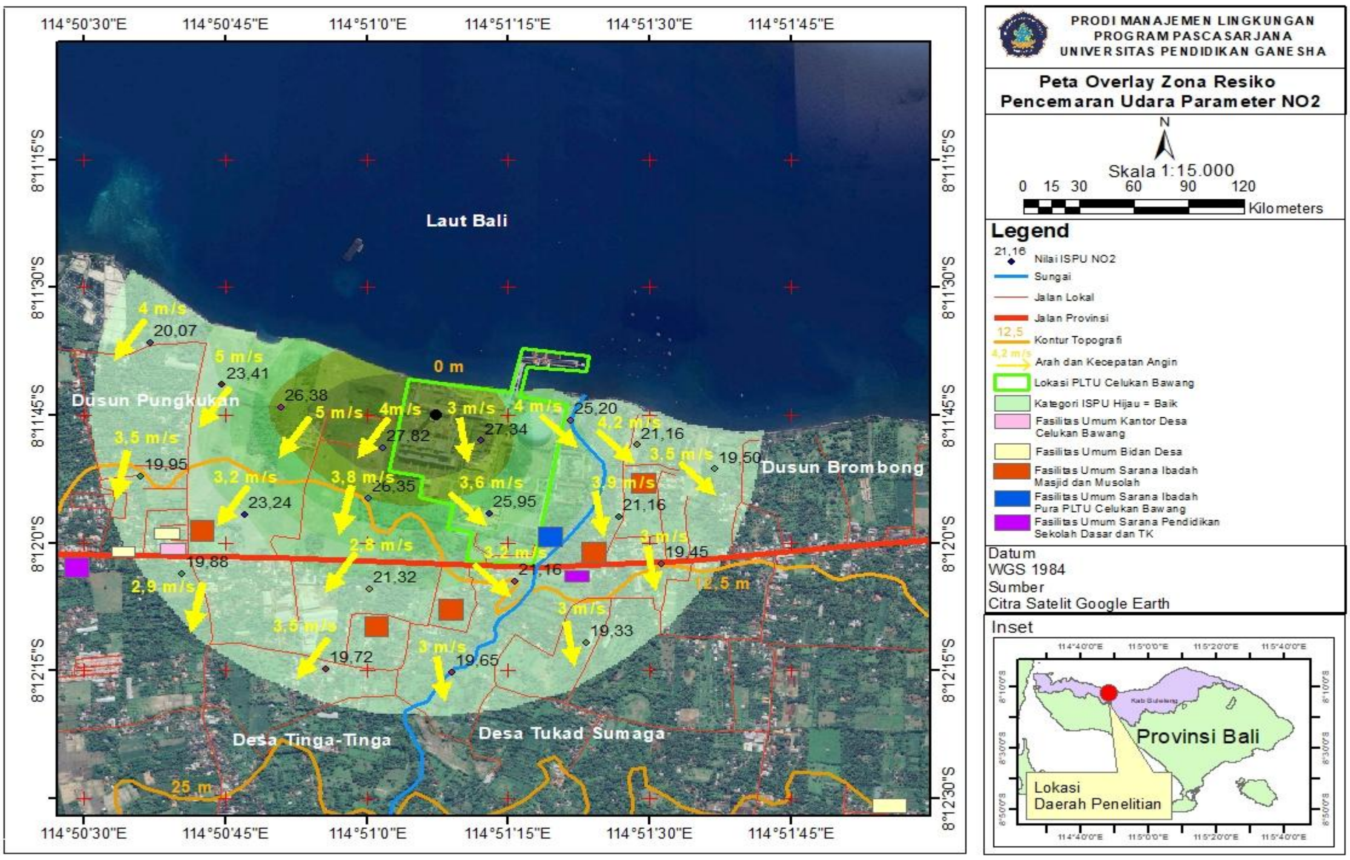

Figure 8. Spatial distribution of NO_2 based on GIS analysis

Figure 8 illustrates the spatial distribution of NO_2 based on GIS analysis. The calculated ISPU-NO_2 values ranged from 5.13 to 8.59, indicating consistently low NO_2 concentrations throughout the study area. Spatial variation was relatively limited compared with the other pollutants, suggesting a more homogeneous distribution pattern among monitoring locations. All monitoring points remained within the Good ISPU category, indicating that ambient NO_2 concentrations complied with national air quality standards. Slightly higher NO_2 values were observed in locations adjacent to the industrial complex.

Besides emissions originating from combustion processes, localized activities such as vehicle movement, transportation infrastructure, and operational activities may also influence ambient NO_2 concentrations. Consequently, the observed spatial pattern represents the combined effects of multiple local emission sources and prevailing environmental conditions rather than stack emissions alone.

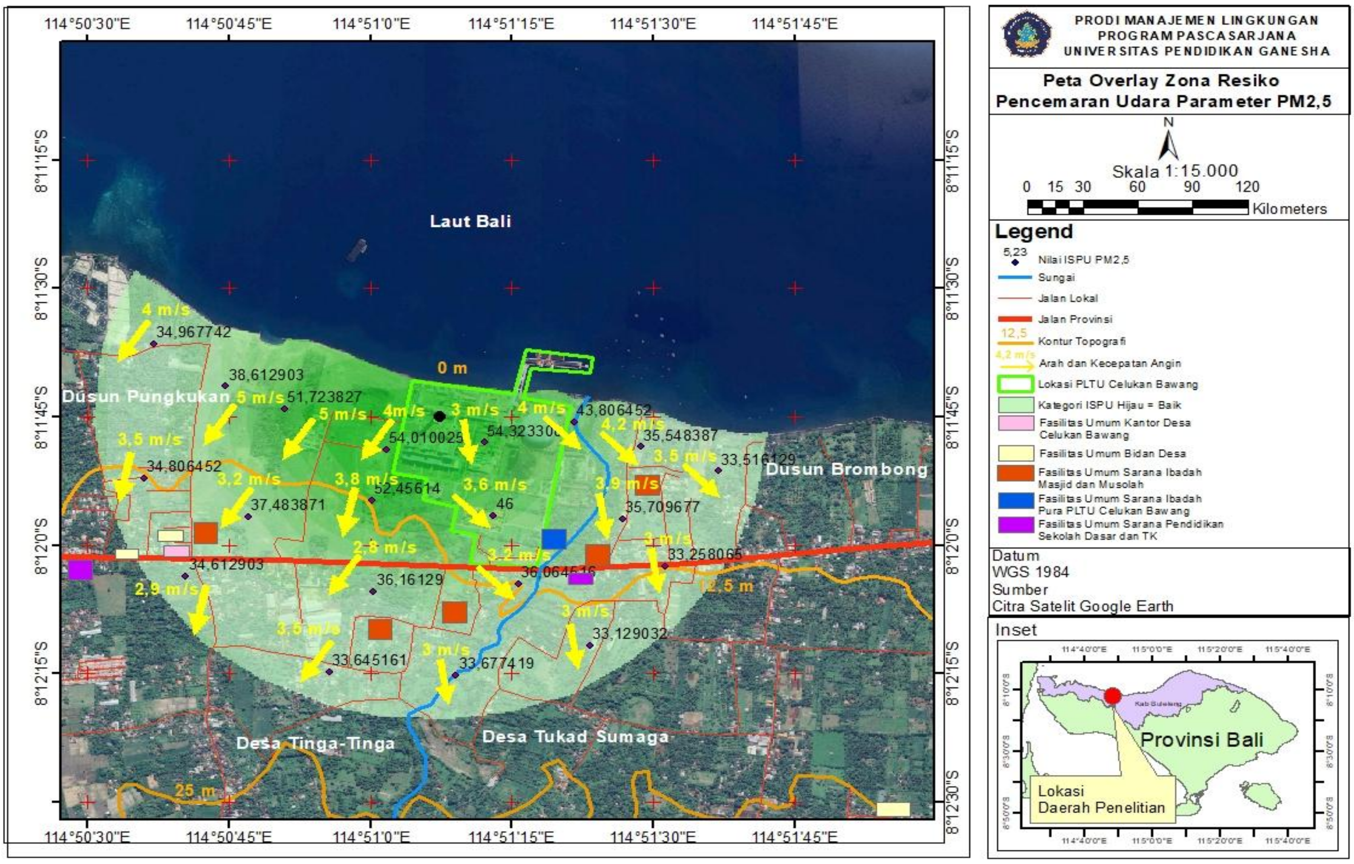

Figure 9. Spatial distribution of PM2,5 based on GIS analysis

Among the evaluated pollutants, $PM_{2.5}$ exhibited the highest ISPU values, ranging from 33.13 to 54.32. Although several monitoring locations approached the Moderate ISPU category, the majority remained within the Good category according to the Indonesian Air Pollution Standard Index. Consequently, the observed spatial pattern should be interpreted as representing relatively higher $PM_{2.5}$ concentrations rather than hazardous pollution conditions. The higher $PM_{2.5}$ values observed near the industrial complex may reflect the combined influence of stationary emissions, coal handling activities, vehicle movement, and the longer atmospheric residence time characteristic of fine particulate matter.

The highest zones were concentrated within residential settlements located directly along the dominant wind pathway extending southward from the power plant. This pattern suggests that fine particulate matter was transported more efficiently than gaseous pollutants due to its longer atmospheric residence time and greater dispersion potential. The overlay analysis also revealed that residential areas, educational facilities, and public facilities located near the dominant dispersion corridor were exposed to relatively higher $PM_{2.5}$-related environmental risks. Although the resulting ISPU category remained within the "Good" classification, $PM_{2.5}$ demonstrated the greatest potential influence on environmental quality and human exposure compared with other pollutants. Previous studies have also reported associations between $PM_{2.5}$ and PM_{10} exposure and respiratory health outcomes, including acute respiratory infections in urban populations (Adilasari et al., 2025).

These findings are consistent with previous studies identifying $PM_{2.5}$ as one of the most significant pollutants affecting environmental health due to its ability to penetrate deep into the respiratory system and remain suspended in the atmosphere for extended periods (Anjelicha et al., 2022). Previous studies have demonstrated the importance of $PM_{2.5}$ and PM_{10} exposure from a respiratory-health perspective, including associations with respiratory morbidity and other adverse health outcomes (Liu et al., 2019; Anjelicha et al., 2022; Wulan et al., 2024; Pertiwi et al., 2024; Wellid et al., 2024).

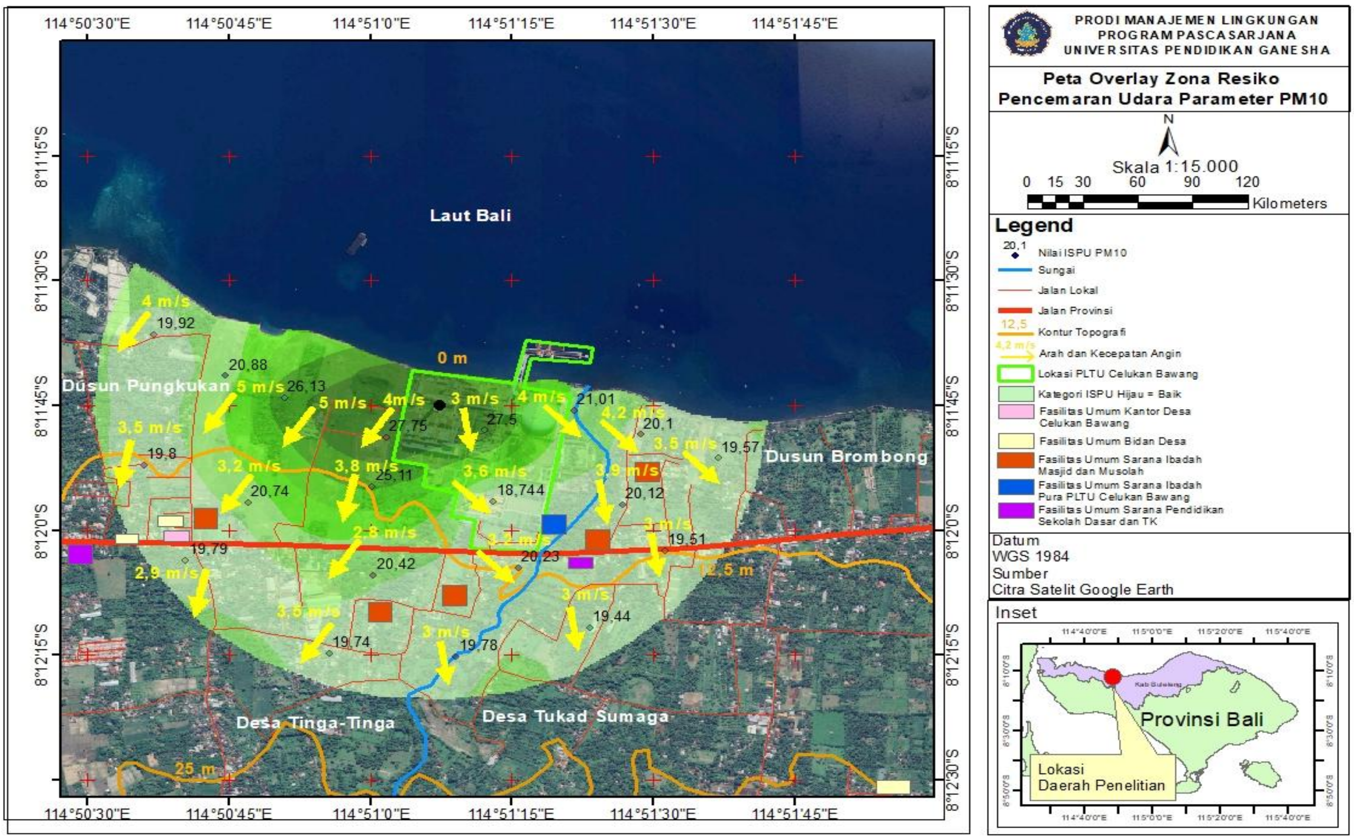

Figure 10. Spatial distribution of PM10 based on GIS analysis

Figure 10 illustrates the spatial distribution of PM_{10} based on Co-Kriging interpolation and GIS analysis. GIS-based spatial analysis provides an effective approach for visualizing and evaluating variations in PM_{10} distribution across monitoring locations (Pratama et al., 2021). The calculated ISPU-PM_{10} values ranged from 19.57 to 27.75, indicating that ambient PM_{10} concentrations remained within the *Good* category according to the Indonesian Air Pollution Standard Index (ISPU). Compared with $PM_{2.5}$, PM_{10} exhibited lower ISPU values and a relatively narrower spatial variation among monitoring locations. Consequently, the mapped distribution represents relative spatial differences in PM_{10} concentrations rather than hazardous pollution conditions.

The findings of this study indicate that ambient air quality surrounding the Celukan Bawang Coal-Fired Power Plant remained within the national ambient air quality standards established by Government Regulation No. 22 of 2021. Ambient air-quality evaluation around power-generation facilities is important for assessing environmental conditions and verifying compliance with applicable air-quality standards (Mukaddas, 2025). The calculated ISPU values for all monitoring locations were classified within the Good category, indicating that air quality conditions in the study area were generally favorable. Studies conducted around other coal-fired power plants have similarly emphasized the importance of evaluating ambient air quality to understand the potential influence of power-generation activities on surrounding environments (Ngamlana et al., 2025). These findings are consistent with previous studies conducted in industrial and energy-production areas that reported pollutant concentrations below regulatory thresholds while still exhibiting measurable spatial variations influenced by local environmental conditions (Hartanto et al., 2024; Ramdhanu et al., 2024).

Although all monitoring locations showed acceptable air quality conditions, GIS analysis revealed differences in the spatial distribution of pollutant concentrations and ISPU values. Locations situated closer to the power plant and within the dominant wind pathway generally exhibited relatively higher index values than locations farther away. However, these differences remained within the same air quality classification category. This finding suggests that meteorological factors influence the spatial distribution of pollutants without necessarily causing deterioration of ambient air quality. Similar observations were reported by Li et al. (2020) and Zhang & Wang (2021), who found that wind direction and wind speed are important determinants of pollutant transport and dispersion patterns around emission sources.

Among the evaluated pollutants, $PM_{2.5}$ contributed the largest proportion to the calculated ISPU values. This result is consistent with previous studies identifying fine particulate matter as a dominant contributor to air quality indices because of its longer atmospheric residence time and wider dispersion potential compared with larger particles and gaseous pollutants (Achakulwisut et al., 2019; Chen et al., 2020). Nevertheless, the $PM_{2.5}$ concentrations measured in this study remained substantially below the applicable ambient air quality standard, indicating that air quality conditions were still within acceptable environmental limits.

The spatial overlay analysis demonstrated the usefulness of integrating ISPU values with environmental variables such as wind characteristics, topography, and land use. Rather than identifying areas of pollution concern, the resulting maps provide a representation of relative environmental conditions across the study area. This approach enables the identification of locations that may require greater attention in future monitoring activities while maintaining an overall understanding that air quality conditions remain within acceptable standards. Similar benefits of GIS-based environmental assessments have been reported by Prihandito & Nuraeni (2020) and Dheekwal et al. (2025), who emphasized the ability of spatial analysis to support environmental planning and monitoring programs.

The influence of land-use characteristics observed in this study is also consistent with previous findings indicating that spatial patterns of settlements, agricultural land, and open spaces affect the distribution of environmental exposure (Xie et al., 2020). In the present study, differences in ISPU values among villages were relatively small, suggesting that the combined effects of pollutant dispersion, topography, and land-use characteristics resulted in generally comparable air quality conditions throughout the study area.

From a practical perspective, the developed GIS-based mapping approach provides valuable support for environmental management and monitoring activities. The integration of ambient air quality data with environmental variables allows stakeholders to visualize spatial patterns of air quality conditions more effectively than conventional tabular data alone. In addition, the resulting maps may serve as supporting information for environmental monitoring programs, spatial planning, and sustainable environmental management around industrial facilities.

Overall, this study demonstrates that GIS-based integration of ISPU values, meteorological conditions, topographic characteristics, and land-use patterns can effectively describe spatial variations in ambient air quality. Although all monitoring locations were classified within the Good air quality category, the spatial analysis provides additional insight into environmental distribution patterns and supports more informed environmental management and decision-making processes.

Conclusion

This study successfully characterized the spatial distribution of ambient air pollutants surrounding the Celukan Bawang Coal-Fired Power Plant using an integrated Geographic Information System (GIS), Air Pollution Standard Index (ISPU), and Co-Kriging approach. Ambient concentrations of SO_2, NO_2, $PM_{2.5}$, and PM_{10} at all monitoring locations complied with the Indonesian ambient air quality standards, while the calculated ISPU values were predominantly classified within the *Good* category. Among the evaluated pollutants, $PM_{2.5}$ exhibited the highest relative ISPU values and the widest spatial distribution, whereas NO_2 showed the lowest spatial variability across the study area. The GIS-based spatial analysis demonstrated that integrating ISPU with environmental variables, including wind characteristics, topography, and land use, effectively visualized relative spatial variations in ambient air quality across residential areas surrounding the industrial complex. The resulting spatial information provides practical support for environmental monitoring, land-use planning, and evidence-based environmental management while demonstrating the applicability of GIS as a decision-support tool for ambient air quality assessment. Future research is recommended to expand the monitoring network by increasing the number of sampling locations and extending the spatial coverage beyond the current study area. The incorporation of longer-term meteorological observations, additional environmental variables, and complementary atmospheric dispersion models may further improve the representation of pollutant distribution patterns. Furthermore, integrating GIS-based spatial analysis with population exposure assessment would provide broader information for supporting sustainable environmental management and future environmental planning.

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Conceptualization, formal analysis, investigation, resources, writing original draft, project administration, L.I.C.; methodology, writing review and editing, I.G.A.W.; funding acquisition, L.I.C. and I.G.A.W.; visualization, supervision, I.M.G. All authors have read and approved the published version of the manuscript.

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Authors declare that no conflict of interest in this publication.

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