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IMPACT OF LAND USE TYPES ON TOTAL SUSPENDED PARTICULATE (TSP) DISPERSION: A STUDY USING AERMOD MODEL

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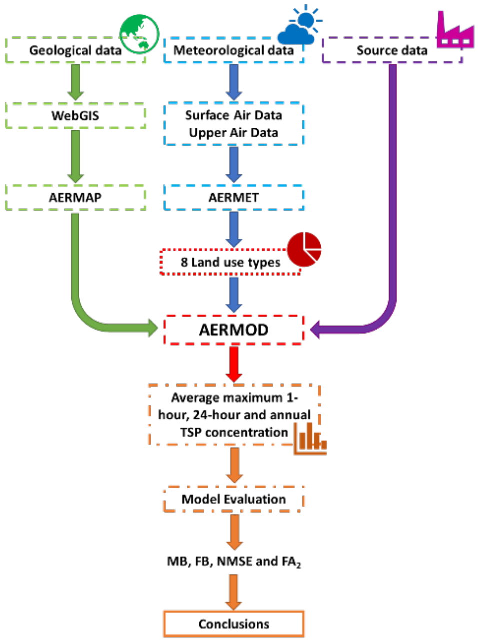
Graphical abstract



Abstract

This research investigated the influence of land use types on dispersion of total suspended particulate (TSP) using the AERMOD model. Eight land use types were analyzed: water (fresh and sea), deciduous forest, coniferous forest, swamp, cultivated land, grassland, urban and desert shrubland. The study area covered a 10-km radius within Patong Subdistrict Municipality, Hat Yai District, Songkhla Province, Thailand. Emission data from local wood processing factories and meteorological data from Kho Hong agricultural meteorological station (UTM x 661916.09 m: y 759424.31 m) were utilized. The results showed that variations in land use types influenced TSP dispersion due to changes in surface characteristics, such as albedo, Bowen ratio, and surface roughness length. The study of TSP dispersion characteristics across 8 land use types identified 3 distinct groups. Group 1 included urban, deciduous forest, and coniferous forest. Group 2 included water (fresh and sea) and swamp. Group 3 included cultivated forest, grassland, and desert shrubland in 1-hour, 24-hour and annual TSP dispersion. These groupings highlight the substantial variations in TSP concentrations driven by land use types. Additionally, the selection of different land use types resulted in substantial differences in the predicted TSP concentrations: 73.6% for 1-hour prediction, 30.31% for 24-hour prediction, and 28.1% for annual prediction. These findings highlight the complex interactions between land surface characteristics and TSP dispersion, highlighting the importance of accurately accounting for land use in air quality modeling.

Keywords: AERMOD, Land use types, TSP, Albedo, Bowen ratio, Surface roughness length

1.0 INTRODUCTION

Rapid economic development, coupled with significant social and environmental transformations and insufficient systematic oversight, has severely impacted the environment, ecosystems, and public health. The 2022 Thailand Environmental Pollution report identifies air pollution, particularly particulate matter in high-traffic areas and industrial zones, as a critical concern [1]. Industrial processes are major source of particulate matter emissions, posing direct risks to nearby communities [2]. Evidence indicates a strong association between particulate matter exposure and increased cardiovascular, respiratory and cerebrovascular mortality rates [3]. Given the challenges of continuous air quality monitoring across vast regions, employing mathematical models offers a more practical, cost-effective, and reliable approach to assess pollutant dispersion [4].

Air quality modeling plays a crucial role in understanding pollutant dispersion patterns and assessing potential health risks. AERMOD stands for American Meteorological Society/Environmental Protection Agency Regulatory Model. It is a Gaussian plume air dispersion model developed to assess air quality impacts from industrial emissions. AERMOD, developed by the American Meteorological Society and the U.S. Environmental Protection Agency (EPA), is a widely recognized. Gaussian plume model designed to simulate pollutant transport and dispersion in the atmosphere. It incorporates both surface and upper air meteorological data, terrain features, and source emissions to estimate pollutant concentrations at various distances from the source. AERMOD's robust framework and adaptability make it a preferred choice for regulatory applications and environmental impact assessments worldwide [5].

Land use types are essential inputs in AERMOD, as they influence key surface parameters such as albedo, Bowen ratio, and surface roughness length, all of which affect pollutant dispersion dynamics. Accurate land use classification is critical for generating reliable model predictions, as misclassification can lead to significant deviations in pollutant concentration estimates [6]. Research indicates that using a single land use type, such as urban, may underestimate pollution levels, while accounting for diverse land cover types yields more precise results [7-8].

The Gaussian plume model is a well-established mathematical tool widely used for air pollution forecasting and management. Studies have shown that this model can predict air quality impacts with an error margin of less than 7% [9]. AERMOD, a Gaussian plume model developed by the American Meteorological Society and the Environmental Protection Agency Regulatory Model Improvement Committee (AERMIC), is among the most widely utilized models for air quality prediction. The previous study demonstrates the superior performance of the AERMOD model in estimating pollutant concentrations, particularly in complex terrain, when compared to earlier models such as ISC3 and CALPUFF [10-12]. Nontheless, AERMOD exhibits certain limitations, including a more restricted estimatin range relative to the CALPUFF model [11,13], as well as reduced accuracy under conditions of incomplete meterological data [14]. The U.S. EPA has designated AERMOD as the primary model for evaluating pollutant concentrations within a 50-km radius of the emission source [5]. In Thailand, AERMOD is extensively used in Environmental Impact Assessment (EIA) reports and is officially recognized by the Office of Natural Resources and Environmental Policy and Planning [4].

The AERMOD model operates through the integration of two primary datasets: 1) topographic data and 2) meteorological data, processed via the AERMET and AERMOD subprograms, along with source emissions data. The AERMET subprogram utilizes three types of meteorological data: 1) surface data, 2) upper air data, and 3) surface characteristic data. Surface characteristics are defined by key parameters, including Albedo (reflectance of radiation), the Bowen ratio (ratio of sensible to latent heat flux), and Surface Roughness Length (height at which wind speed approaches zero). These parameters are determined based on land use types [6]. Accurately defining land use types is essential for reliable pollution dispersion modeling. Based on 8 land use types, the study area's land use types should closely reflect the actual conditions to ensure reliable predictions [15-16]. Studies have demonstrated that relying solely on an urban land use classification can result in underpredicted pollutant concentrations, while varying land use types yield distinct dispersion patterns [7-8].

The eight land use types recommended by the U.S. EPA are defined by a set of surface characteristic parameters. These parameters play a crucial role in determining the pollutant dispersion profile, primarily through three key factors: albedo, Bowen raio, and surface roughness length. Albedo refers to the propotion of solar radiation reflected from the Earth's surface back into the atmosphere. The Bowen ratio represents the ratio of sensible heat flux to latent heat flux at the surface. Surface roughness length characterizes the aerodynamic roughness of the terrain, influencing the dispersion of pollutants [17]. The input of land use types significantly influences the spatial distribution of air pollutant concentrations within the AERMOD [18]. These input parameters directly affect pollutant dispersion characteristics, making the land use specification a highly sensitive and impactful aspect of the modeling process. Therefore, this study systematically designs the input parameters for albedo, Bowen ratio, and surface roughness length by comparing eight distinct land use types: water (fresh and sea), deciduous forest, coniferous forest, swamp, cultivated land, grassland, urban, and desert shrubland. The objective is to investigate the influence of different land use characteristics on air quality assessments using the AERMOD model, with the goal of enhancing the accuracy of pollution impact predictions across diverse landscapes.

2.0 METHODOLOGY

2.1 AERMOD Model

The AERMOD model, developed in 1990 by American Meteorological Society (AMS) from the Industrial Source Complex Model (ISC3), applies the Planetary Boundary Layer theory to predict air pollutant concentrations. As a steady-state Gaussian plume model, AERMOD assumes a normal distribution of pollutant concentrations in both vertical and horizontal planes [6]. Comparative studies indicate that AERMOD provides more accurate predictions than ISC3 when validated against field measurements [19]. As a result, the U.S. EPA designates AERMOD as the preferred model for assessing pollutant concentrations within a 50-km radius of an emission source [5]. In this study, the AERMOD model (version 12.0.0) (License Type: AERMOD MPI Web License, Serial#: AER0012816) developed by Lake Environmental Software was employed to estimate Total Suspended Particulate (TSP) concentrations for 1-hour, 24-hour, and annual averaging periods.

AERMOD model operates through two key processors: AERMET, which processes meteorological data, and AERMAP, which processes topographical data, to prepare pollutant dispersion predictions, as illustrated in Figure 1.

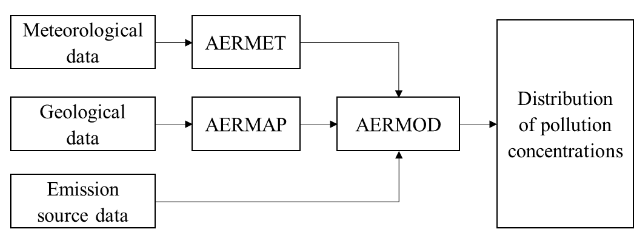


Figure 1 AERMOD process [20]

2.1.1 AERMET

AERMET requires two primary data inputs: surface air data and upper air data. Surface air data were collected from the Kho Hong Agricultural Meteorological Station (UTM x 661916.09 m: y 759424.31 m), while upper air data were obtained from the National Oceanic and Atmospheric Administration (NOAA) for the years 2022 and 2023. These data include station number, date, sampling hour, base height of meteorological phenomena, wind direction, wind speed, dry-bulb temperature, meteorite volume, and meteorite cover density. AERMET processes these meteorological parameters in conjunction with land use types to generate meteorological profiles for the study area.

2.1.2 Land Use Type In AERMOD

Land use classification is a critical component in AERMOD, as it defines parameters such as Albedo, Bowen ratio, and Surface Roughness Length, which influence pollutant dispersion. Albedo represents the surface reflectivity and ranges from 0 to 1, where a lower value indicates high reflectivity and a higher value corresponds to greater absorption of solar radiation. This parameter influences surface heating and subsequently affects atmospheric turbulence. The Bowen ratio is the ratio of sensible heat flux to latent heat flux and serves as an indicator of surface moisture content. A high Bowen ratio denotes a dry surface that heats rapidly, whereas a low ratio indicates a moist surface. Surface roughness length refers to the height at which horizontal wind speed theoretically becomes zero, directly influencing wind flow and turbulence near the ground. A low surface roughness implies a smooth surface with limited turbulence, while a high value indicated a rougher surface that promotes atmospheric turbulence and enhances pollutant dispersion [17].

These parameters, categorized by land use type, directly impact pollutant transport dynamics near the Earth's surface [6]. Table 1 through Table 3 outlines the seasonal variations of these parameters for different land use categories such as water (fresh and sea), deciduous forest, coniferous forest, swamp, cultivated land, grassland, urban, and desert shrubland.

Table 1 Albedo of ground covers by land use and season [21]

Land Use types	Spring	Summer	Autumn	Winter
Water	0.12	0.10	0.14	0.20
Deciduous Forest	0.12	0.12	0.12	0.50
Coniferous Forest	0.12	0.12	0.12	0.35
Swamp	0.12	0.14	0.16	0.30
Cultivated Land	0.14	0.20	0.18	0.60
Grassland	0.18	0.18	0.20	0.60
Urban	0.14	0.16	0.18	0.35
Desert Shrubland	0.30	0.28	0.28	0.45

Table 2 Bowen ratio of ground covers by land use and season, Average moisture [21]

Land Use types	Spring	Summer	Autumn	Winter
Water	0.10	0.10	0.10	1.50
Deciduous Forest	0.70	0.30	1.00	1.50
Coniferous Forest	0.70	0.30	0.80	1.50
Swamp	0.10	0.10	0.10	1.50
Cultivated Land	0.30	0.50	0.70	1.50
Grassland	0.40	0.80	1.00	1.50
Urban	1.00	2.00	2.00	1.50
Desert Shrubland	3.00	4.00	6.00	6.00

Table 3 Surface roughness length of ground covers by land use and season [21]

Land Use types	Spring	Summer	Autumn	Winter
Water	0.0001	0.0001	0.0001	0.0001
Deciduous Forest	1.00	1.30	0.80	0.50
Coniferous Forest	1.30	1.30	1.30	1.30
Swamp	0.20	0.20	0.20	0.05
Cultivated Land	0.03	0.20	0.05	0.01
Grassland	0.05	0.10	0.01	0.001
Urban	1.00	1.00	1.00	1.00
Desert Shrubland	0.30	0.30	0.30	0.15

2.1.3 AERMAP

AERMAP extracts digital elevation data from WebGIS to define terrain features. The study area, located in Patong Subdistrict Municipality, Hat Yai District, Songkhla Province, Thailand, hosts approximately 7,000 residents and various industrial facilities, including medical glove, finger cots, melamine-coated paper, and rubberwood furniture factories. Pollution emissions were analyzed using 16 receptors within 5- and 10-km radius, as shown in Figure 2 and detailed in Table 4.

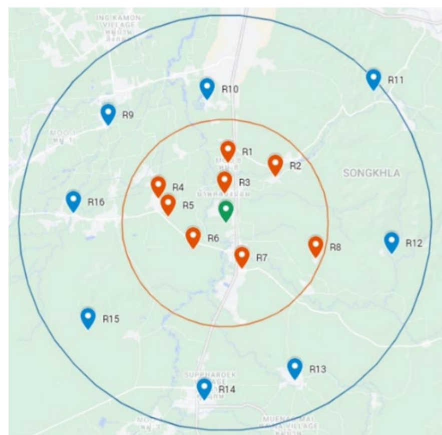


Figure 2 Study area and 16 receptors

Table 4 Study areas and receptor coordinates

	Receptor	Receptor type	Latitude	Longitude	Zone
5 km	R1	Village 1	6.89398	100.46624	47N
	R2	Mosque 1	6.88777	100.48718	47N
	R3	Village 2	6.88087	100.46465	47N
	R4	Local government 1	6.87865	100.43550	47N
	R5	Farm	6.87104	100.44013	47N
	R6	Park 1	6.85660	100.45099	47N
	R7	School 1	6.84792	100.47234	47N
	R8	Park 2	6.85246	100.50462	47N
10 km	R9	Temple 1	6.91021	100.41376	47N
	R10	Temple 2	6.92115	100.45720	47N
	R11	Recreational area **1**	6.92528	100.53016	47N
	R12	Temple 3	6.85451	100.53803	47N
	R13	School 2	6.79956	100.49571	47N
	R14	Market	6.79086	100.45577	47N
	R15	Temple 4	6.82134	100.40493	47N
	R16	Temple 5	6.87237	100.39839	47N

2.2 Study case

The case study incorporated eight land use scenarios: urban, desert shrubland, grassland, cultivated land, swamp, coniferous forest, deciduous forest, and water (fresh and sea). Meteorological data from year 2023 were sourced from the Kho Hong Agricultural Meteorological station, while emission data were scaled to 50 times the emission reduction from medium-density fiberboard factory, with a stack height of 50 meters within the AERMOD model incorporates 8 scenarios based on the land use types defined by AERMOD: Urban, Desert Shrubland, Grasslands, Cultivated Land, Swamp, Coniferous Forests, Deciduous Forests, and Water (fresh and sea). Meteorological data from the Kho Hong Agricultural Meteorological Station for 2023 were used. Emission data were based 50 times on the emission reduction from the medium-density fiberboard factory, with a stack height of 50 m and a stack diameter of 3 m.

2.3 Validation

2.3.1 Model Evaluation

Model performance was evaluated using statistical performance measures recommended [22]. These included Model Bias (MB), Fractional Bias (FB), Normalized Mean Square Error (NMSE), and Factor of Two (FA_2) [7]. The equations are presented below:

(1) Model bias (MB): Measures whether predictions are consistently higher or lower than observations. Model bias is calculated using equation (1) [7].

$$\text{Model Bias (MB)} = (\bar{C}_p - \bar{C}_o) \tag{1}$$

When C_p = the predicted values
C_o = the observed values

(2) Fractional Bias (FB): Normalized bias, ranging from -2 to +2. Fractional Bias is calculated using equation (2) [7].

$$\text{Fractional Bias (FB)} = 2\,[(\bar{C}_o - \bar{C}_p) / (\bar{C}_o + \bar{C}_p)] \tag{2}$$

(3) Normalized Mean Square Error (NMSE): Emphasizes the scatter in the entire set and is an estimator of the overall deviations between the observed and predicted values. Smaller values of NMSE indicate better performance and it is not biased toward models that over predict or underpredict. Normalized Mean Square Error is calculated using equation (3) [7].

$$\text{NMSE} = [(\bar{C}_o - \bar{C}_p)^2 / (C_o + C_p)] \tag{3}$$

(4) Factor of Two (FA_2): Defined as the percentage of prediction within a factor of 2 of the observed values. Factor of two is calculated using equation (4) [7].

$$\text{Factor of Two } (FA_2) = (C_p / C_o) \tag{4}$$

A perfect model would yield MB, FB and NMSE = 0; and FA_2 = 1 [23]. In this study, the observed values (C_o) in this research is obtained from measurements conducted at a medium-density fiberboard (MDF) factory using the High-Volume Air Sample method, in accordance with U.S. EPA 40 CFR Part 50, Appendix B.

2.3.2 Percentage Difference

The study compared maximum 1-hour, 24-hour, and annual concentrations across land use types. If the difference between model results for two land use types was within 2%, they were considered equivalent [24]. The percentage difference is calculated using equation (5) [25]:

$$\text{Percentage difference} = \{(C_1-C_2)/[(C_1-C_2)/2]\} \times 100 \tag{5}$$

When C_1 = Maximum intensity values of comparable land use types
C_2 = Maximum concentration values of reference land use characteristics

3.0 RESULTS AND DISCUSSION

3.1 Meteorological Observations

The wind speed at Kho Hong Agricultural Meteorological Station in 2023 range from 0.0-8.8 m/s, with an annual average characterized by calm conditions (57%). Wind speeds between 0.5-2.1 m/s at 25.9%, 2.1-3.6 m/s at 9.4%, 3.6-5.7 m/s at 7.7%, and 5.7-8.8 m/s at 0.1%, as illustrated in Figure 3.

Figure 4 shows the wind direction and wind rose for 2023, indicating that the predominant wind direction was northeast (NE). The secondary wind direction was southwest (SW), aligning with previous studies on wind resources in southern Thailand, which reported dominant wind directions from the northeast and southwest [26]. This pattern corresponds to Thailand's monsoon system, where the southwest monsoon originates from the southern hemisphere over the Indian Ocean, while the northeast monsoon flows from the northern hemisphere, particularly from Mongolia and China, toward Thailand. Given that the study area and meteorological station are in the eastern part of southern Thailand, near the Gulf of Thailand, they are more influenced by the northeast monsoon.

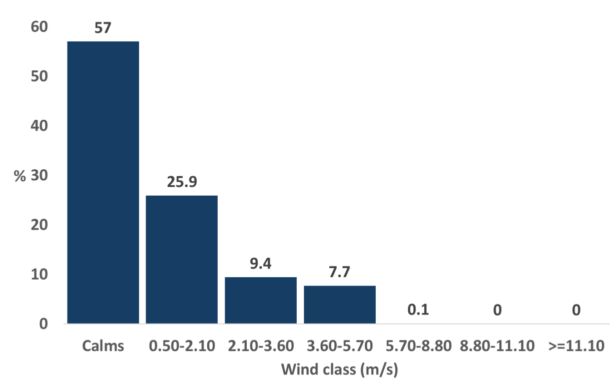


Figure 3 Wind class frequency distribution

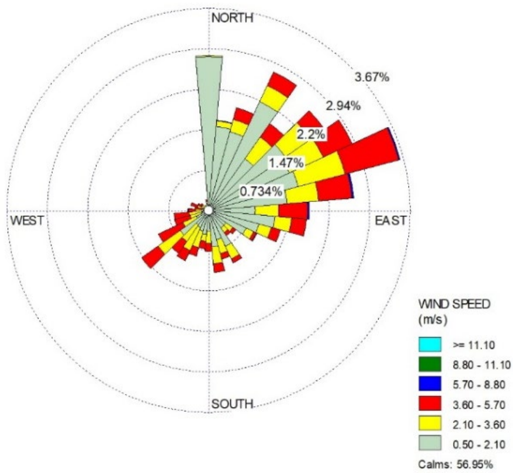


Figure 4 Wind rose for Kho Hong agricultural meteorological station 2023, Songkhla, Thailand

3.2 AERMOD Results

The AERMOD model predictions for eight land use types provided TSP concentrations for 1-hour, 24-hour, and annual averages, along with the locations and directions of the affected receptors, as summarized in Table 5 and figure 5. The highest average 1-hour TSP concentration was 367.483 μg/m^3, observed in Case 2 (Water) at receptor R6 (Park 1). In contrast, the lowest average 1-hour TSP concentration was 169.773 μg/m^3, found in both Case 1 (Urban) and Case 3 (Deciduous forest) at receptor R3 (Village 2). The TSP distribution characteristics, illustrated in Figure 6, can be classified into three groups:

- Group 1: Case 1 (Urban), Case 3 (Deciduous forest) and Case 4 (Coniferous forest)
- Group 2: Case 5 (Swamp) and Case 6 (Cultivated land)
- Group 3: Case 7 (Grassland) and Case 8 (Desert shrubland)

The grouping of TSP distribution characteristics revealed that each group exhibited similar values for surface characteristic factors. For instance, in Group 1, comparable albedo values were observed during the spring season: Case 1 (Urban) = 0.14, Case 3 (Deciduous forest) = 0.12, and Case 4 (Coniferous forest) = 0.12. In contrast, Case 2 (Water) demonstrated a distinct dispersion pattern, attributed to its very low surface roughness length, which enhances atmospheric turbulence and facilitates effective TSP dispersion.

The highest average 24-hour TSP concentration was 39.338 μg/m³, recorded in Case 4 (Coniferous forest) at receptor R3 (Village 2), while the lowest concentration was 28.983 μg/m³ in Case 8 (Desert shrubland) at the same receptor. As shown in Figure 7, the dispersion patterns remained consistent with the 1-hour results, forming three groups with elevated concentrations in the southwest area across all cases. The characteristics of TSP dispersion can be classified into three groups: (1) Case 1 (Urban), Case 3 (Deciduous forest), and Case 4 (Coniferous forest); (2) Case 2 (Water), Case 5 (Swamp), and Case 6 (Cultivated land); and (3) Case 7 (Grassland) and Case 8 (Desert shrubland).

The highest annual average TSP concentration was 10.739 μg/m³ in Case 8 (Desert Shrubland) at receptor R3 (Village 2), while the lowest concentration was 8.093 μg/m³ in Case 5 (Swamp) at receptor R6 (Park 1). The annual TSP distribution, shown in Figure 8, also followed the three-group classification, with consistently elevated concentrations in the southwest region across all cases. The characteristics of TSP distribution can be categorized into three groups: (1) Case 1 (Urban), Case 3 (Deciduous forest), and Case 4 (Coniferous forest); (2) Case 2 (Water), Case 5 (Swamp), and Case 6 (Cultivated land); and (3) Case 7 (Grassland) and Case 8 (Desert shrubland).

Across all scenarios, elevated 1-hour, 24-hour, and annual TSP concentrations were consistently observed in the southwestern region. Notably, TSP accumulation at the center of the study area accounted for approximately 57% of the 24-hour and annual TSP concentrations associated with calm wind conditions, as recorded by meteorological stations in 2023.

AERMOD-predicted TSP concentrations for land use types with very low surface roughness length (Water) demonstrated efficient dispersion and resulted in elevated 1-hour TSP concentrations at the downwind receptor (R6). In contrast, TSP concentrations at the same receptor decreased with increasing surface roughness length for land uses such as cultivated land and grassland [16]. However, for the 24-hour and annual averaging periods, low surface roughness length did not correspond to the highest concentrations at R6. Instead, the highest concentrations were observed at receptors located closer to the study center. Notably, for annual concentrations, land use characterized by a high Bowen ratio and low albedo (Desert shrubland) yielded the highest TSP concentration [15-27].

Table 5 Dispersion model results for peak receptors average maximum 1-hour, 24-hour and annual TSP

Land Use types	Peak Receptor		
	1-hour	24-hour	Annual
Urban	R3	R3	R3
Water	R6	R6	R6
Deciduous Forest	R3	R3	R3
Coniferous Forest	R3	R3	R3
Swamp	R4	R6	R6
Cultivated Land	R6	R3	R6
Grassland	R6	R3	R3
Desert Shrubland	R6	R3	R3

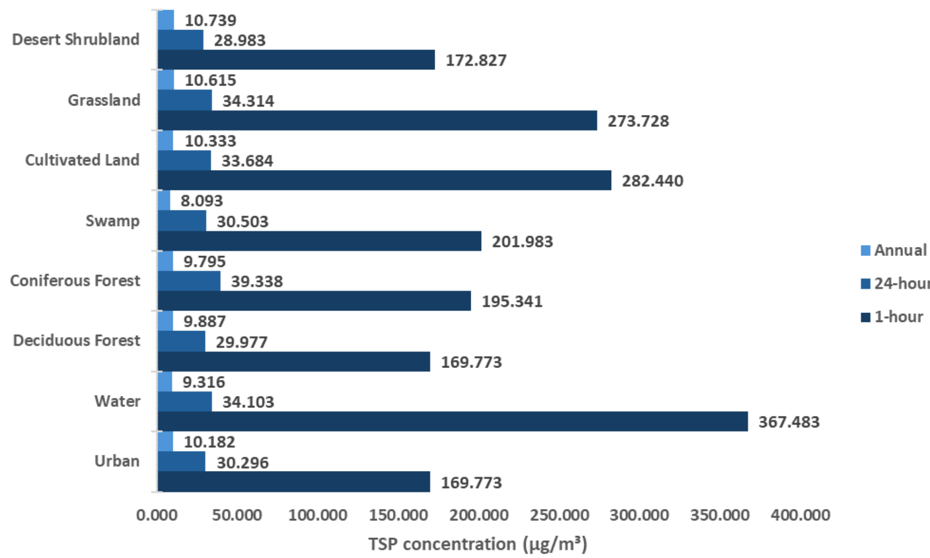
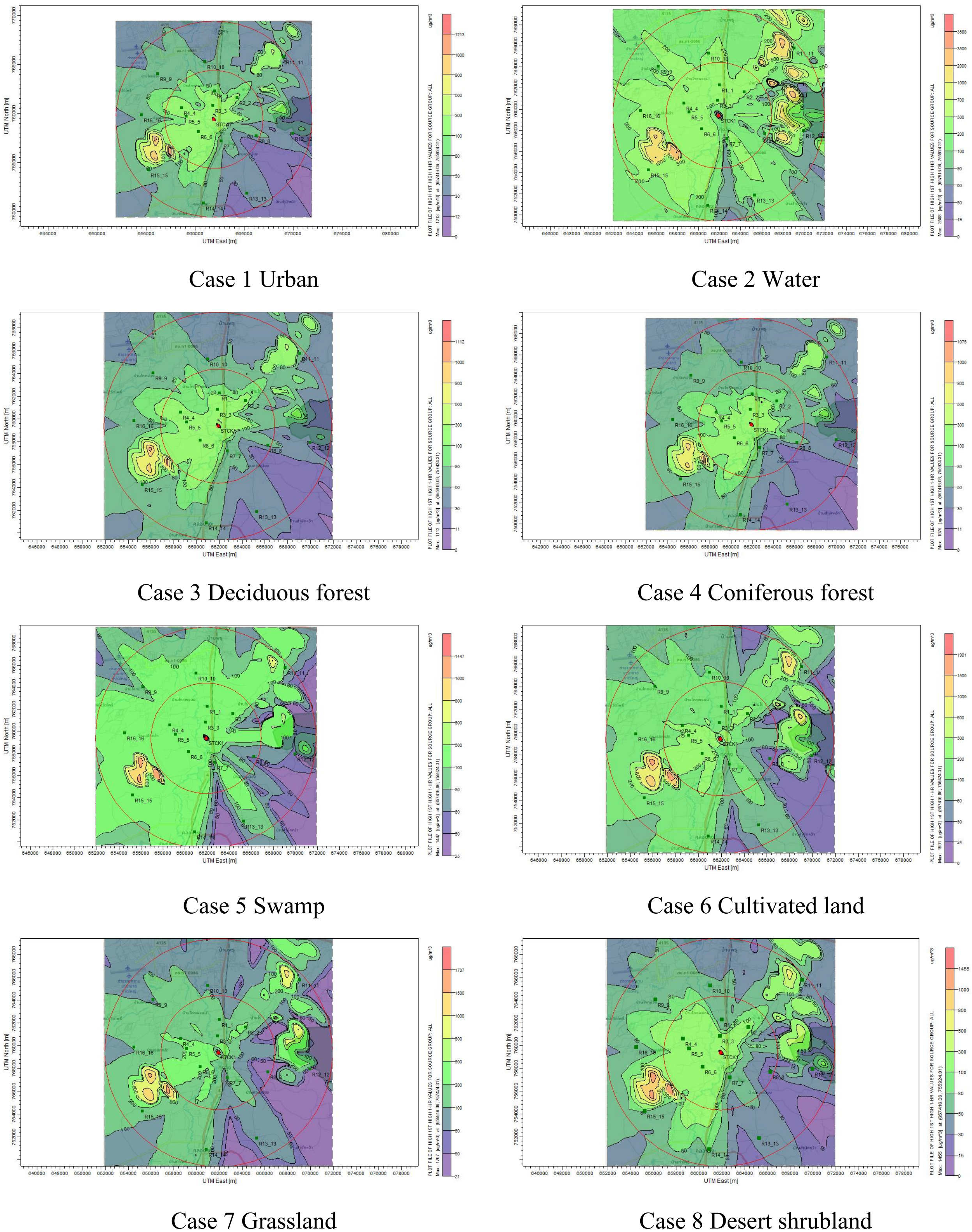


Figure 5 Dispersion model results for average maximum concertation 1-hour, 24-hour and annual TSP



Case 1 Urban

Case 2 Water

Case 3 Deciduous forest

Case 4 Coniferous forest

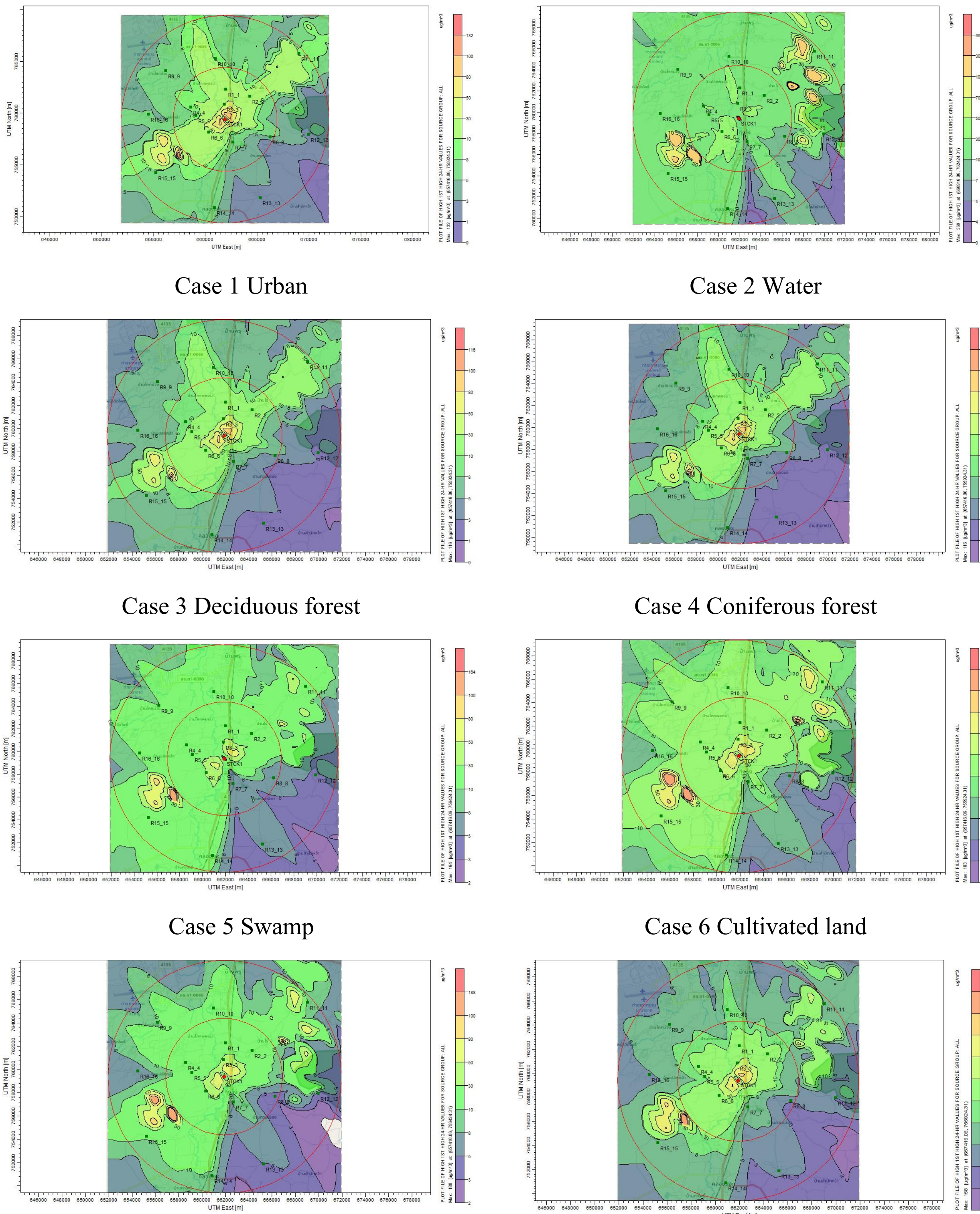
Case 5 Swamp

Case 6 Cultivated land

Case 7 Grassland

Case 8 Desert shrubland

Figure 6 Characteristics of the TSP dispersion over a 1-hour period



Case 1 Urban

Case 2 Water

Case 3 Deciduous forest

Case 4 Coniferous forest

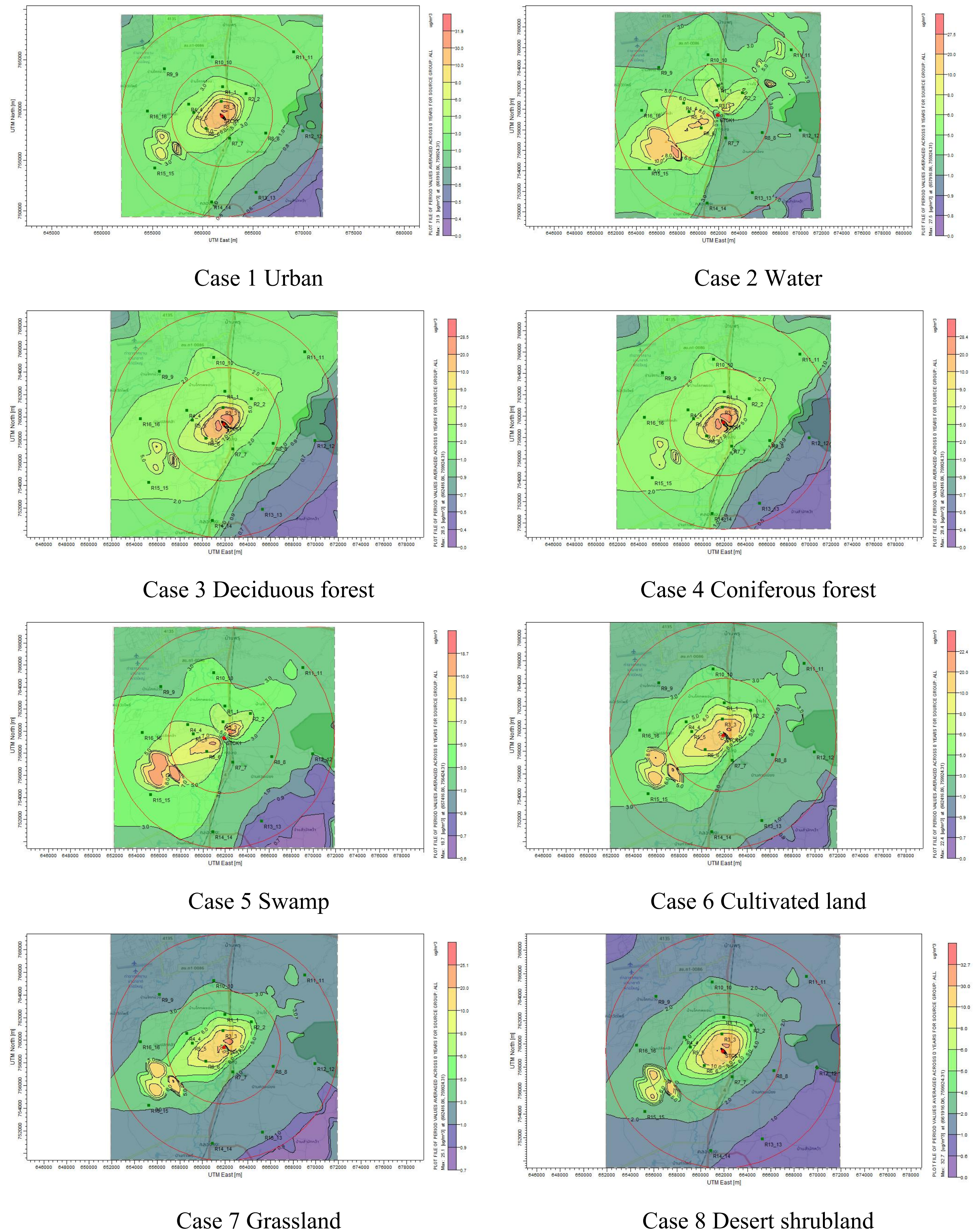
Case 5 Swamp

Case 6 Cultivated land

Case 7 Grassland

Case 8 Desert shrubland

Figure 7 Characteristics of the TSP dispersion over a 24-hour period



Case 1 Urban

Case 2 Water

Case 3 Deciduous forest

Case 4 Coniferous forest

Case 5 Swamp

Case 6 Cultivated land

Case 7 Grassland

Case 8 Desert shrubland

Figure 8 Characteristics of the TSP dispersion over an annual period

3.3 Model Evaluation

The predicted values from the AERMOD model were compared with the National Ambient Air Quality Standards (NAAQS) threshold, which are 150 µg/m³ for 24-hour concentrations and 75 µg/m³ for annual concentrations [21]. The highest predicted 24-hour average TSP concentration was 39.338 µg/m³ in Case 4 (Coniferous forest), and the highest annual average TSP concentration was 10.333 µg/m³ in Case 8 (Desert shrubland). Notably, all predicted values were below the regulatory limits.

Table 6 presents the evaluation of the model against actual measurements from Station R3 in May 2023. The model performance was assessed using four statistical metrics: Model Bias (MB), Fractional Bias (FB), Normalized Mean Square Error (NMSE), and Factor of Two (FA_2).

- Model Bias (MB) measures whether the model overpredicts or underpredicts compared to observed values (C_o). Case 6 (Cultivated land) and Case 7 (Grassland) had the smallest bias values, -0.316 and 0.314, respectively, indicating the highest accuracy.
- Fractional Bias (FB) quantifies bias on a scale of -2 to +2, where 0 represents a perfectly unbiased model. Case 6 and Case 7 had the FB values closest to zero (0.09 and -0.09, respectively).
- Normalized Mean Square Error (NMSE) assesses the average squared difference between predicted (C_p) and observed values (C_o). Lower NMSE values indicate better performance. Both Case 6 and Case 7 had an NMSE of 0, reflecting an ideal model fit.
- Factor of Two (FA_2) represents the proportion of predictions within a FA_2 of observed values, with the ideal value being 1. Case 6 and Case 7 achieved near-perfect FA_2 values of 0.991 and 1.009, respectively.

These results suggest that Cultivated land and Grassland land use types yielded the most accurate predictions, aligning closely with real-world measurements. One possible explanation is that surface roughness and boundary layer characteristics can be more accurately represented in areas with minimal obstructions, thereby improving the agreement between simulations and observational data, especially for land use types such as grassland and cultivated land.

Table 6 Model evaluation of 24-hour TSP concentrations

Land use types	Concentrations (µg/m^3)	MB	FB	NMSE	FA_2
Urban	30.296	-3.704	0.115	0.013	0.891
Water	23.140	-10.860	0.380	0.150	0.681
Deciduous forest	29.977	-4.023	0.126	0.016	0.882
Coniferous forest	39.338	5.338	-0.146	0.021	1.157
Swamp	27.725	-6.275	0.203	0.042	0.815
Cultivated land	33.684	-0.316	0.009	0.000	0.991
Grassland	34.314	0.314	-0.009	0.000	1.009
Desert shrubland	28.983	-5.017	0.159	0.026	0.852

3.4 Percentage Difference

The results of the analysis of percentage differences in the maximum concentration values for 1-hour, 24-hour, and annual TSP concentrations, calculated from the assessment of the AERMOD air quality model using surface characteristics of the 8 land use types, revealed that:

For the average maximum 1-hour TSP concentration, with percentage differences not exceeding 2%, four pairs of land use types showed this level of similarity:

- The urban and deciduous forest pair, with a percentage difference of 0%.
- The urban and desert shrubland pair, with a percentage difference of 1.783%.
- The deciduous forest and desert shrubland pair, with a percentage difference of 1.783%.
- The cultivated land and grassland pair, with a percentage difference of 0%.

These results, displayed in Table 7, highlight that the TSP concentrations for the 1-hour period are remarkably similar between certain land use pairs, particularly the urban and deciduous forest pair, and the cultivated land and grassland pair. This suggests that the distribution and behavior of particulate matter in these land use types are closely aligned, despite differences in the underlying surface characteristics.

Table 7 Percentage difference of land use types of average maximum 1-hour TSP concentrations

Pair	Land use types		1-Hour
1	Urban	Water	-73.600
2	Urban	Deciduous Forest	0.000
3	Urban	Coniferous Forest	-14.006
4	Urban	Swamp	-17.329
5	Urban	Cultivated Land	-49.829
6	Urban	Grassland	-49.829
7	Urban	Desert Shrubland	-1.783
8	Water	Deciduous Forest	73.600
9	Water	Coniferous Forest	61.171
10	Water	Swamp	58.125
11	Water	Cultivated Land	26.170
12	Water	Grassland	26.170
13	Water	Desert Shrubland	72.053
14	Deciduous Forest	Coniferous Forest	-14.006
15	Deciduous Forest	Swamp	-17.329
16	Deciduous Forest	Cultivated Land	-49.829
17	Deciduous Forest	Grassland	-49.829
18	Deciduous Forest	Desert Shrubland	-1.783
19	Coniferous Forest	Swamp	-3.343
20	Coniferous Forest	Cultivated Land	-36.460
21	Coniferous Forest	Grassland	-36.460
22	Coniferous Forest	Desert Shrubland	12.230
23	Swamp	Cultivated Land	-33.218
24	Swamp	Grassland	-33.218
25	Swamp	Desert Shrubland	15.557
26	Cultivated Land	Grassland	0.000
27	Cultivated Land	Desert Shrubland	48.153
28	Grassland	Desert Shrubland	48.153

For the average maximum 24-hour TSP concentration, with percentage differences not exceeding 2%, five pairs of land use types showed this level of similarity:

- The urban and deciduous forest pair, with a percentage difference of 1.059%.
- The urban and swamp pair, with a percentage difference of 0.681%.

- The water and cultivated land pair, with a percentage difference of 1.235%.
- The water and grassland pair, with a percentage difference of 0.616%.
- The deciduous forest and swamp pair, with a percentage difference of 1.741%.
- The cultivated land and grassland pair, with a percentage difference of 1.852%.

These results are shown in Table 8, which illustrates the comparison of TSP concentrations over a 24-hour period. It is evident that the differences between certain land use types are relatively small, indicating a similarity in their air quality characteristics. For instance, the water and cultivated land pair, as well as the deciduous forest and swamp pair, exhibit almost identical particulate concentrations, suggesting that these land use types share similar atmospheric behaviors over a 24-hour period.

Table 8 Percentage difference of land use types of average maximum 24-hour TSP concentrations

Pair	Land use types		24-hour
1	Urban	Water	-11.824
2	Urban	Deciduous Forest	1.059
3	Urban	Coniferous Forest	-25.971
4	Urban	Swamp	-0.681
5	Urban	Cultivated Land	-10.592
6	Urban	Grassland	-12.438
7	Urban	Desert Shrubland	4.429
8	Water	Deciduous Forest	12.879
9	Water	Coniferous Forest	-14.256
10	Water	Swamp	11.144
11	Water	Cultivated Land	1.235
12	Water	Grassland	-0.616
13	Water	Desert Shrubland	16.232
14	Deciduous Forest	Coniferous Forest	-27.011
15	Deciduous Forest	Swamp	-1.741
16	Deciduous Forest	Cultivated Land	-11.648
17	Deciduous Forest	Grassland	-13.492
18	Deciduous Forest	Desert Shrubland	3.370
19	Coniferous Forest	Swamp	25.300
20	Coniferous Forest	Cultivated Land	15.485
21	Coniferous Forest	Grassland	13.643
22	Coniferous Forest	Desert Shrubland	30.313
23	Swamp	Cultivated Land	-9.912
24	Swamp	Grassland	-11.759
25	Swamp	Desert Shrubland	5.110
26	Cultivated Land	Grassland	-1.852
27	Cultivated Land	Desert Shrubland	15.004
28	Grassland	Desert Shrubland	16.844

For the average maximum annual TSP concentration, with percentage differences not exceeding 2%, three pairs of land use types exhibited this level of similarity:

- The urban and cultivated land pair, with a percentage difference of 0.752%.
- The deciduous forest and coniferous forest pair, with a percentage difference of 0.926%.
- The grassland and desert shrubland pair, with a percentage difference of 1.161%.

These results are presented in Table 9, which shows the comparison of TSP concentrations over an annual period. While the percentage differences between the pairs are generally small, it is noteworthy that the urban and cultivated land pair, and the grassland and desert shrubland pair, share similar concentration trends across the year. These observations indicate that certain land use types may exhibit comparable TSP levels annually, regardless of their distinct surface characteristics.

In summary, the analysis highlights the relationships between various land use types, demonstrating that certain pairs exhibit closely matched TSP concentration values across different time periods (1-hour, 24-hour, and annual). This suggests that land use characteristics significantly influence particulate matter distribution, and these findings can help inform air quality management strategies tailored to specific land use types in the study area.

Table 9 Percentage difference of land use types of average maximum annual TSP concentrations

Pair	Land use types		Annual
1	Urban	Water	8.879
2	Urban	Deciduous Forest	2.940
3	Urban	Coniferous Forest	3.866
4	Urban	Swamp	22.857
5	Urban	Cultivated Land	0.752
6	Urban	Grassland	-4.167
7	Urban	Desert Shrubland	-5.328
8	Water	Deciduous Forest	-5.942
9	Water	Coniferous Forest	-5.017
10	Water	Swamp	14.050
11	Water	Cultivated Land	-8.127
12	Water	Grassland	-13.034
13	Water	Desert Shrubland	-14.190
14	Deciduous Forest	Coniferous Forest	0.926
15	Deciduous Forest	Swamp	19.950
16	Deciduous Forest	Cultivated Land	-2.188
17	Deciduous Forest	Grassland	-7.106
18	Deciduous Forest	Desert Shrubland	-8.265
19	Coniferous Forest	Swamp	19.034
20	Coniferous Forest	Cultivated Land	-3.114
21	Coniferous Forest	Grassland	-8.030
22	Coniferous Forest	Desert Shrubland	-9.189
23	Swamp	Cultivated Land	-22.115
24	Swamp	Grassland	-26.961
25	Swamp	Desert Shrubland	-28.100
26	Cultivated Land	Grassland	-4.919
27	Cultivated Land	Desert Shrubland	-6.080
28	Grassland	Desert Shrubland	-1.161

When comparing the results with previous studies that examined percentage differences in land use characteristics using the AERMOD model to predict sulfur dioxide concentrations, it was noted that the differences in land use characteristics typically exceeded 2%. Only in the case of Swamp and Cultivated land did the percentage difference fall below 2% for both 1-hour and 24-hour concentration values [18]. This discrepancy with the current study's findings may be attributed to the difference in the pollutants being studied, as the current analysis focuses on TSP concentrations rather than sulfur dioxide.

4.0 CONCLUSION

The AERMOD model requires input on land use types, which determine surface area factors such as albedo, Bowen ratio, and surface roughness length to estimate TSP concentration. This study showed that the influence of 8 land use types: urban, water (fresh and sea), deciduous forest, coniferous forest, swamp, cultivated land, grassland, and desert shrubland, revealing significant differences in TSP concentrations across land use categories. The results indicated that the water (fresh and sea) type exhibited the highest TSP concentration at both the 1-hour and 24-hour, whereas the coniferous forest type showed the lowest TSP concentrations for both time periods. In contrast, for annual TSP concentration predictions, desert shrubland showed the highest concentration, whereas swamp recorded the lowest concentration. Furthermore, based on the dispersion of TSP concentrations, the land use types were classified into 3 distinct groups: Group 1 included urban, deciduous forest, and coniferous forest; Group 2 included water (fresh and sea) and swamp; and Group 3 included cultivated forest, grassland, and desert shrubland. These groupings highlight the substantial variations in TSP concentrations driven by land use types, with the difference in predicted 1-hour TSP concentration between water and grassland reaching 41.41%. The AERMOD model's predictive accuracy for different time periods-1 hour, 24 hours, and annual-is highly sensitive to the surface factor values associated with each land use type.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper

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