



Research Article

การประยุกต์ทฤษฎี Similarity ร่วมกับเทคนิค Eddy Covariance สำหรับการจำแนกความคงตัวของบรรยากาศในประเทศไทย

Application of similarity theory associate with eddy covariance technique for atmospheric stability classification in Thailand

รัสมุนต์ จาเรย์พันธุ์, สุรัตน์ บัวเลิศ*, ภาคภูมิ ชุมณี, ธัญภัลล์ ทองเย็น, กิตติชัย ดวงมาลย์

Rossumont Jaryabhand, Surat Bualert*, Parkpoom Choomanee, Thunyapat Thongyen,

Kittichai Duangmal

คณะสิ่งแวดล้อม มหาวิทยาลัยเกษตรศาสตร์

Faculty of Environment, Kasetsart University.

*Corresponding author, e-mail: surat.b@ku.ac.th

Received: 14 August 2024; Revised: 16 September 2024; Accepted: 19 September 2024

บทคัดย่อ

การจำแนกเสถียรภาพของอากาศเป็นวิธีการสำคัญในการประเมินแนวโน้มการสะสมพลังในบรรยากาศของพื้นที่ทางภูมิศาสตร์ แม้ว่าสถานีตรวจวัด KU Tower ของมหาวิทยาลัยเกษตรศาสตร์ กรุงเทพมหานคร จะสามารถจำแนกเสถียรภาพของอากาศได้หลากหลายวิธี แต่การจำแนกเหล่านี้ไม่สามารถนำไปประยุกต์ใช้กับสถานีอุตุนิยมวิทยาทั่วไปได้เนื่องจากต้องใช้อุปกรณ์เฉพาะทาง งานวิจัยนี้จึงนำเสนอทฤษฎี Monin-Obukhov Similarity Theory (MOST) เป็นทางเลือกที่ใช้เพียงข้อมูลอุตุนิยมวิทยาพื้นฐานในการตรวจสอบความถูกต้องของวิธีการดังกล่าว ขั้นแรกผู้วิจัยได้รวบรวมข้อมูลรายชั่วโมง จำนวน 44,814 ค่า ในช่วงปี พ.ศ. 2559-2566 จาก KU Tower เพื่อเปรียบเทียบผลการจำแนกจากสามวิธี ได้แก่ วิธี Temperature Gradient (Delta-T), Richardson Number (Ri) และ Monin-Obukhov (MO) โดยใช้อุปกรณ์ IRGASON ด้วยเทคนิค eddy covariance เปรียบเทียบกับวิธี Solar Radiation Delta-T (SRDT) ผลการศึกษาพบว่า วิธี MO มีความสอดคล้องกับ SRDT มากที่สุด ($NMSE = 0.301$) จากนั้นจึงนำ MOST มาประยุกต์ใช้กับข้อมูลอุตุนิยมวิทยาพื้นฐาน (ความเร็วลม อุณหภูมิ และปริมาณเมฆ) ร่วมกับข้อมูลพื้นผิวทางภูมิศาสตร์ (ความชุกรูระบะของผิว ค่าอัลบีโอด และอัตราส่วนโบเวน) จาก Google Earth Engine ผลการเปรียบเทียบระหว่าง MOST กับวิธี MO แสดงความสอดคล้องปานกลาง ($NMSE = 0.238$) ซึ่งยืนยันว่า MOST สามารถจำแนกเสถียรภาพของอากาศได้อย่างมีประสิทธิภาพโดยใช้เพียงข้อมูล

อุดมวิทยาที่มีอยู่ทั่วไป วิธีการนี้สามารถนำไปประยุกต์ใช้ในการจัดการคุณภาพอากาศของประเทศไทย ทั้งด้านการวางแผนการใช้ประโยชน์ที่ดิน การกำหนดเขตอุตสาหกรรม และการออกกฎหมายเบี่ยงการปล่อยมลพิษเฉพาะพื้นที่

คำสำคัญ: การจำแนกเสถียรภาพอากาศ; ทฤษฎี Monin-Obukhov Similarity (MOST); เทคนิค Eddy Covariance

Abstract

Atmospheric stability classification is essential for determining pollution accumulation tendencies in geographical areas. While the KU Tower monitoring station at Kasetsart University, Bangkok, can classify atmospheric stability via multiple methods, these classifications are impractical for general meteorological stations due to specialized equipment requirements. This study proposes before use of Monin-Obukhov Similarity Theory (MOST) as a solution, which requires only basic meteorological parameters. To validate this approach, we first compared three conventional methods at KU Tower from 2016-2023 (44,814 hourly measurements): The temperature Gradient (Delta-T), Richardson Number (Ri), and Monin-Obukhov (MO) using IRGASON equipment, against Solar Radiation Delta-T (SRDT) as reference. The MO Method showed the best agreement with SRDT (NMSE = 0.301). Building on this finding, we implemented MOST using basic meteorological data (wind speed, temperature and cloud cover) and geographical surface parameters (roughness length, albedo and Bowen ratio) from Google Earth Engine. A comparison between MOST and the validated MO Method reveals moderately similar (NMSE = 0.238), confirming the effectiveness of MOST for classifying atmospheric stability via widely available meteorological data. This method can support air quality management in Thailand through applications in land use planning, industrial zone designation, and area-specific emission regulations.

Keywords: Atmospheric Stability Classification; Monin Obukhov Similarity Theory (MOST); Eddy Covariance Technique

Introduction

Air pollution represents a significant health and environmental concern and originates from various sources including fossil fuel combustion, agricultural burning, dust, industrial emissions, waste burning, and natural disasters. [1, 2] The accumulation of pollutants is heavily influenced by atmospheric stability, particularly during conditions of high stability with air subsidence. [3] Therefore, atmospheric stability classification is important in air quality assessment, as air quality can differ even with the same emission levels.[4] For example, research on the Atmospheric Stability Pattern over Port Harcourt, Nigeria has used atmospheric stability classification to study the dispersion and subsidence of the atmosphere in port areas with pollution emissions, such as oil vapor gases and others. [5]

The development of stability classification methods has progressed from basic smoke plume observations to the Pasquill-Gifford method, which introduces the fundamental A-F stability classification system. [6, 7] While modern stability assessments typically require specialized equipment, as demonstrated in studies using atmospheric towers [8] or SODAR-RASS systems [9], most Thai meteorological stations lack such capabilities, having only single-level wind speed and temperature measurements.

This research presents two distinct investigations of atmospheric stability classification. First, utilizing the well-equipped KU tower at Kasetsart University, Bangkok, four established methods are compared; 1) Solar Radiation Delta-T (SRDT) as a comparison standard. 2) Temperature Gradient (Delta T) 3) Richardson number (Ri) 4) Monin-Obukhov (M-O) using IRGASON equipment with Eddy Covariance technique. [10-13] Second, and more critically, this research addresses the equipment limitations of Thai meteorological stations by exploring the application of Monin-Obukhov Similarity Theory (MOST). This approach requires only basic meteorological measurements while incorporating geographical and land use parameters through Google Earth Engine technology. The methodology integrates standard meteorological data from the KU Tower and Bang Khen Meteorological stations with Stull's equations for solar radiation calculations. [14]

The study aims to validate MOST's capability by comparing its results with those of M-O method via IRGASON measurements. Success would provide Thai meteorological stations with an accessible, equipment-minimal approach to stability classification, significantly advancing environmental and meteorological research across the country. This advancement is essential for understanding pollution dispersion dynamics and improving air quality assessment capabilities in regions with limited monitoring infrastructure. The conceptual framework of this research is summarized in Figure 1.

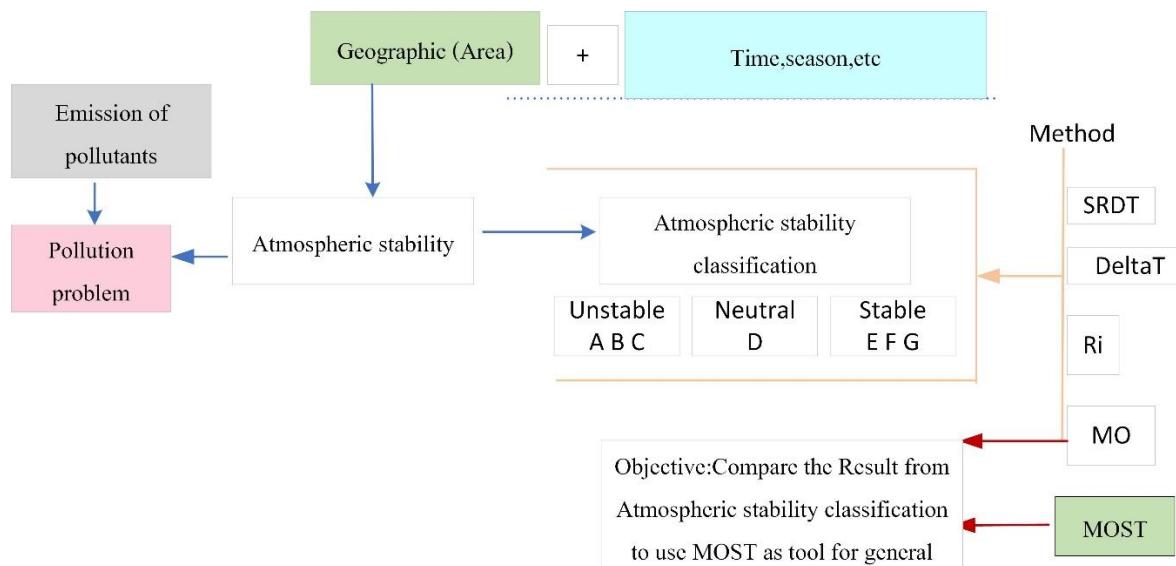


Figure 1 The Research Conceptual Framework.

Objectives

1. To examine multiple methods of atmospheric stability classification via available data from KU tower instrumentation, the temperature Gradient (Delta-T), Richardson Number (Ri), and Monin-Obukhov (M-O) methods are compared with the solar radiation delta temperature (SRDT) method.
2. The application of the Monin-Obukhov Similarity Theory (MOST) is implemented and assessed for atmospheric stability classification at standard meteorological stations lacking specialized equipment, and the Google Earth Engine is utilized for site-specific data acquisition.
3. The feasibility and accuracy of MOST-based calculations are validated through statistical comparison with data obtained from the Eddy covariance technique with IRGASON specialized equipment, to determine their acceptability for atmospheric stability classification.

Methods

The research methodology consists of two phases: First, utilizing comprehensive instrumentation of the KU tower capabilities for atmospheric stability classification, this study evaluates and compares various methods to demonstrate their physical consistency. In this phase, the tower's multi-level measurements enable comparison among the SRDT, Delta-T, Richardson number, and Monin-Obukhov methods, validating their theoretical physical relationships. Second, this study explores the application of Monin-Obukhov Similarity Theory (MOST) using general meteorological data to calculate the Obukhov length for stability classification. The MOST results are then validated through comparative analysis with Obukhov length measurements obtained directly from the Eddy covariance technique via IRGASON equipment, assessing the potential of MOST as a widely applicable tool for stability classification.

Site

The study was conducted at the KU Meteorological Tower, which located on the campus of Kasetsart University in Bangkok, Thailand (13°51'16.7"N, 100°34'11.9"E), within an urban environment. The flux tower is equipped with various meteorological instruments (Figure 2).



Figure 2 The measurement site, featuring a flux tower equipped with various meteorological instruments.

Instruments

The measurement system consisted of two main components from Campbell Scientific, Inc., USA. The first was an IRGASON (Model: ESAT300 (EC200)) mounted at a height of 30 m on the KU tower, which combines a three-dimensional sonic anemometer with an infrared gas analyzer. This system measures friction velocity, sensible heat flux, three-dimensional wind components (u , v , w), and sonic temperature at a 10 Hz sampling frequency via the Eddy Covariance technique [13]. The second system comprised temperature and wind speed sensors installed at different heights for vertical profile measurements.

Dataset Description and Filtering Methodology

The dataset comprises hourly meteorological measurements collected from January 2016 to December 2023, including wind speed and temperature readings at multiple heights (10, 30, 50, 75, and 110 meters), along with IRGASON measurements at 30 m using the eddy covariance method for sensible heat flux, friction velocity, and air density. To ensure data quality, the dataset was filtered to include only days with complete 24-hour measurements (both day and night periods), and outliers were removed on the basis of 2 criteria; temperature readings at 10 meters exceeding 50°C and wind speeds above 50 km/h (associated with depression storms). This filtering process reduced the dataset from 57,385 to 44,814 data points, which were used for subsequent analysis. The final dataset includes comprehensive wind speed and temperature measurements at 10 meters from 2016 to 2023, encompassing minimum, maximum, mean, and standard deviation values.

Step 1: Evaluate and compare the various atmospheric stability classification methods

Four established methods are compared: 1) Solar Radiation Delta-T (SRDT) as a comparison standard. 2. Temperature Gradient (Delta T) 3. Richardson number (Ri) 4. Monin-Obukhov (M-O) using IRGASON equipment with the Eddy Covariance Technique. Key features of the atmospheric stability classification methods from Table 1.

Table 1 Key features of atmospheric stability classification methods.

Method	Day/Night	Parameters Used
SRDT	Separated	Daytime: 10 m wind speed, Solar Radiation. Nighttime: Temperature gradient
Delta T	Not separated	Temperature profile
Richardson (Ri)	Not separated	Wind speed and temperature at multiple levels
MoninObukhov (M-O)	Not separated	Friction velocity, sensible heat flux

The Solar Radiation/Delta-Temperature (SRDT) method classifies atmospheric stability into seven classes (A-F, from extremely unstable to very stable) using the Pasquill-Gifford criteria. The classification

combines daytime parameters (wind speed and solar radiation) and nighttime conditions (wind speed and vertical temperature gradient). Solar radiation is calculated using the equation $R = E \cdot \sin(\Psi)$, where E is the solar constant (1361 W/m^2), and Ψ is the local solar elevation angle, which is determined using latitude, longitude, and solar geometry equations. The sunrise and sunset times are determined using the latitude, longitude, and UTC time. The daytime period is defined as starting one hour after sunrise and ending one hour before sunset, when these parameters are used for the stability classification.

Table 2 Key to Solar Radiation Delta-T (SRDT) method for estimating Pasquill-Gifford (P-G) stability categories. [15]

Wind speed (m/s)	Daytime				Nighttime	
	Solar Radiation (W/m^2)				Vertical Temperature Gradient	
	≥ 925	925 - 675	675-175	≤ 175	< 0	≥ 0
0-2	A	A	B	C	E	F
2-2.5	A	B	C	D	D	E
2.5-3	A	B	C	D	D	D
3-5	B	B	C	D	D	D
5-6	C	C	D	D	D	D
> 6	C	D	D	D	D	D

Delta T or Gradient Method

The temperature gradient method uses measurements from two heights: 10 m (T10) and 110 m (T110). These specific heights were selected because using all available height measurements would reduce the filtered dataset by 40%. The temperature gradient is calculated as:

$$\Delta T / \Delta z = (T_{110} - T_{10}) / 100 \quad (\text{per } 100 \text{ m}) \quad (1)$$

This temperature gradient method solely relies on vertical temperature differences to classify atmospheric stability, without considering other meteorological parameters, e.g.; wind speed or solar radiation, as specified in Table 3.

Richardson Number (Ri method)

The Richardson number (Ri) is a dimensionless parameter that quantified the relative of buoyancy and shear during turbulence generation. [16] It is calculated using vertical temperature and wind speed profiles:

$$Ri = \frac{g \left(\frac{T_1 - T_2}{z_1 - z_2} \right)}{T(z_1) \left(\frac{u_{z1} - u_{z2}}{z_1 - z_2} \right)^2} \quad (2)$$

Where: g is the acceleration due to gravity = 9.81 m.s^{-2} and T is the mean temperature

From Table 2. presents the Businger version [17, 18] of the atmospheric stability classification based on Ri values, as designated by Sedefian and Bennett (1980). [19]

Table 3 Atmospheric Stability Class with a temperature gradient. [17-19]

Pasquil Stability Class	$\Delta T / \Delta Z$ (Degree K/100 m)	Ri
A	$\Delta T / \Delta Z < -1.9$	$Ri < -0.86$
B	$-1.9 \leq \Delta T / \Delta Z < -1.7$	$-0.86 \leq Ri < -0.37$
C	$-1.7 \leq \Delta T / \Delta Z < -1.5$	$-0.37 \leq Ri < -0.1$
D	$-1.5 \leq \Delta T / \Delta Z < -0.8$	$-0.1 \leq Ri < 0.053$
E	$-0.5 \leq \Delta T / \Delta Z < 1.5$	$0.053 \leq Ri < 0.134$
F	$1.5 \leq \Delta T / \Delta Z < 4.0$	$0.134 \leq Ri < 0.25$
G	$4. \leq \Delta T / \Delta Z$	$0.25 \leq Ri$

Monin-Obukhov method (M-O Method)

Two key scaling parameters characterize the atmospheric surface layer: friction velocity u^* (measuring mechanical turbulence from wind shear) and Monin-Obukhov length L (representing the depth where shear effects are significant). The parameters are defined as

$$L = - \frac{\rho C_P T_{u^*}^3}{kgH_s} \quad (3)$$

Where k is the Von Karman constant (≈ 0.4), H_s is the sensible heat flux, ρ is the air density, and C_P is the specific heat capacity at constant pressure. Turbulent flux measurements allow the classification of atmospheric stability regimes on basis of the Monin-Obukhov length (L) as shown in Table 4. [20, 21]

Table 4 Atmospheric Stability Classification based on the Monin-Obukhov Length. [20, 21]

	Class	MO length
D	Neutral conditions	$L < -100000$
C	Slightly unstable conditions	$-100000 < L < -500$
B	Moderately unstable conditions	$-500 < L < -100$
A	Extremely unstable conditions	$-100 < L < 0$
G	Extremely Stable	$0 < L < 100$
F	Moderately stable conditions	$100 < L < 500$
E	Slightly stable conditions	$500 < L < 100000$
D	Neutral conditions	$100000 < L$

Using the IRGASON, Equation (3) is applied with the friction velocity and sensible heat flux to calculate the Obukhov length. The class G classification range of the Monin Obukov (M-O) method reflects the potential for pollutant accumulation under stable atmospheric conditions. [22] The class A classification range, which spans from certain values to near-zero values, indicates extremely unstable conditions leading to pollutant dispersion.

Step 2: Monin Obukhov Similarity theory

Monin-Obukhov Similarity theory: Equations (4)-(11) use various constants that are derived from land use characteristics and geographical parameters. These constants include albedo, Bowen ratio, and surface roughness. All of these parameters, except for the ground heat constant, are obtained from Google Earth Engine.

According to Monin-Obukhov Similarity Theory (MOST), the equations differ for daytime conditions ($H_s > 0$) and nighttime conditions ($H_s < 0$) This is based on the function of the dimensionless length parameter $\zeta = z/L$, derived from the Buckingham Pi theorem of dimensional analysis. The equations to be used are specific to daytime and nighttime conditions.

Unstable condition or Daytime or $H_s > 0$:

Friction velocity

$$u = \frac{u_*}{k} \left\{ In \frac{z}{z_0} + In \left[\frac{(n_0^2 + 1)(n_0 + 1)^2}{(n^2 + 1)(n + 1)^2} \right] + 2[arctan(n) - arctan(n_0)] \right\}$$

$$n_0 = \left(1 - 16 \frac{z_0}{L} \right)^{1/4} \quad n = \left(1 - 16 \frac{z}{L} \right)^{1/4} \quad (4)$$

Sensible heat flux from equation (2), derived from Net radiation. The total radiation energy at a specific location and time on the Earth's surface can be calculated from the incident radiation. As stated in Holtslag and van Ulden. [23]

$$R_N = \frac{R(1-r) + 60n - 5.67x10^{-8}T^{-4} + 5.31x10^{-13}T^{-6}}{1.12} \quad (5)$$

R : Insolation Rn : Net radiation on the Earth's surface a: albedo T: temperature n: cloud cover

$$\text{Sensible heat flux } Hs = \frac{(1-C_G)R_N}{1+1/B} \quad (6)$$

C_G is ground heat constant. The ground heat flux depends on the ground heat constant (C_G), which varies according to soil type.

$$G = C_G R_n$$

Stable condition, Nighttime condition or $Hs < 0$:

$$L = \frac{u_*^2 T_0}{kg\theta_*} \quad (7)$$

$$\text{Potential temperature } \theta_* = 0.09(1 - 0.5N^2) \quad N - \text{CloudCover} \quad (8)$$

$$\text{Friction velocity: } u_* = \frac{C_D u}{2} \left[1 + \sqrt{1 - \left(\frac{2u_0}{\sqrt{C_D u}} \right)} \right] \quad (9)$$

$$C_D = \frac{k}{In(z/z_0)} \quad (10)$$

$$u_0^2 = \frac{5g\theta_*(Z-Z_0)}{T_0} \quad (11)$$

Equations (4)-(6) are written in Python to calculate the Obukhov length for unstable conditions, and from equations (7)-(11) for stable conditions. When calculating the Obukhov length, the program may fail to produce output under certain conditions:

1. At zero wind speed, applying the limit as the wind speed approaches 0 yields a small negative Obukhov length in the extremely unstable range or small positive Obukhov length in the extremely unstable range.

2. The program may become stuck in an excessive loop without output when the Obukhov Length value is extremely high. During day-night or night-day transitions, the program fails to run due to very small sensible heat fluxes, resulting in extremely high Obukhov length values.

These considerations are important when interpreting the results and comparing them with other data sources.

Albedo, Bowen ratio, and surface roughness. All of these parameters, except for the ground heat constant, are obtained from the Google Earth Engine can be used to analyze the physical properties of

geographical areas, including the Bowen ratio, albedo, and meteorological roughness. GEE is a cloud-based platform for geospatial data analysis and remote sensing developed by Google. It allows users to access, process, and analyze large datasets of satellite imagery and geospatial information through a web browser using JavaScript.

Table 5 The GEE datasets used to analyze each physical property:

Physical Property	GEE Dataset
Albedo	MODIS Albedo collection
Bowen ratio	ECMWF/ERA5-Land
Surface roughness	USGS/SRTMGL1_003

NMSE

To compare the results, the percentage of data points in each stability class per method will be calculated. The Normalized Mean Square Error (NMSE) will then be used for pairwise method comparison,

$$\text{via the following equation: } \text{NMSE} = \frac{1}{N} \frac{\sum (Xm1 - Xm2)^2}{\overline{Xm1} \cdot \overline{Xm2}} \quad \overline{Xm1} = \frac{\sum Xm1}{N}, \quad \overline{Xm2} = \frac{\sum Xm2}{N}$$

X where Xm1 and Xm2 are datasets or results from the two methods being compared

$\overline{Xm1}$ and $\overline{Xm2}$ are the mean values of datasets Xm1 and Xm2 respectively

If NMSE = 0	Results are identical
$0 < \text{NMSE} \leq 0.1$	Results are very similar
$0.1 < \text{NMSE} \leq 0.5$	Results are moderately similar
$0.5 < \text{NMSE} \leq 1.0$	Results are very different, low correlation
$\text{NMSE} > 1.0$	Results are very different and have almost no correlation

Results

Atmospheric stability classification methods

The atmospheric stability classification methods compared are Delta T, Richardson Number (Ri), and Monin-Obukhov (MO) methods against the Solar Radiation Delta-T(SRDT) method. The classification results are shown in Table 6.

Table 6 Classification scheme from the methods.

	A	B	C	D	E	F	G	Total
SRDT Method	11846	6252	617	5304	16386	4409		44814
	26.43%	13.95%	1.38%	11.84%	36.56%	9.84%		100.00%
DeltaT Method	315	781	2173	25249	14888	330	1078	44814
	0.70%	1.74%	4.85%	56.34%	33.22%	0.74%	2.41%	100.00%
Ri method	15974	7522	11201	3245	720	753	5399	44814
	35.65%	16.78%	24.99%	7.24%	1.61%	1.68%	12.05%	100.00%
M-O method	12963	9702	5129	64	3971	5788	7197	44814
	28.93%	21.65%	11.45%	0.14%	8.86%	12.92%	16.06%	100.00%

The atmospheric stability classifications show varying distributions of classes A to G across different methods:

The choice of classification method significantly influences the stability class distribution. SRDT favors E, Delta T heavily favors D, Ri emphasizes A and C, while M-O shows a more balanced distribution. These differences stem from varying input parameters and calculation methods used in each approach.

This study compared various atmospheric stability classification methods, including the SRDT, Delta T, Richardson number (Ri), and Monin-Obukhov (M-O) methods, using the Normalized Mean Square Error (NMSE) as a metric for evaluation. The results are shown in table 7.

Table 7 Normalized Mean Square Error (NMSE) values for various atmospheric stability classification methods.

	SRDT	DeltaT	Ri	M_O
SRDT		0.441	0.385	0.301
DeltaT	0.441		0.553	0.553
Ri	0.385	0.553		0.040
M_O	0.301	0.553	0.040	

Table 7 compares the atmospheric stability classification methods (SRDT, Delta T, Ri, and M-O) using Normalized Mean Square Error (NMSE) for evaluation. M-O method had the lowest NMSE (0.301) compared with the SRDT baseline, indicating high accuracy, compared with Ri, M-O had the lowest NMSE (0.040), likely due to similar physical principles. The Delta T method consistently showed higher NMSE values (0.553), struggling with temperature inversions and leading to less accurate classifications. Advantages of the M-O method include the following: 1) Comprehensive representation of the mechanical turbulence

and buoyancy effects 2) On the basis of well-established similarity theory 3) Detailed classification of stable conditions (classes E, F, and G).

Monin Obukov Similarity theory

The Obukhov length is derived from thermal and mechanical effects in the atmosphere. It's determined using IRGASON measurements and calculated via using Python. Insolation and day/night periods were calculated on the basis of location and IRGASON measurement times. Geographical and environmental parameters from the Google Earth Engine (Table 7) were input into a computational code implementing MOST or related atmospheric stability calculations to generate results.

Table 8 From KU Tower via the google earth engine : make buffer 500 m.

Station	Latitude	Longitude	Bowen Ratio	Albedo	Surface Roughness
KU Tower Bangkok	13.85466	100.570047	0.312978772	0.125379	3.512422

Additionally, from the IRGASON instrument, friction velocity and sensible heat flux measurements were obtained. The outcomes of these calculations and measurements are summarized and presented in Table 9, which shows the percentage distributions of the atmospheric stability conditions.

Table 9 Percentage of Atmospheric Stability Conditions from MOST and Eddy Covariant technique (IRGASON).

	A	B	C	D	E	F	G
MOST	18.344	19.183	12.472	0.000	7.829	23.31	18.861
IRGASON	27.368	20.132	2.491	0.119	12.566	16.87	20.446

Table 9 compares atmospheric stability conditions derived from MOST calculations with those measured directly by the IRGASON, with stability classes ranging from A (very unstable) to G (very stable). The Normalized Mean Square Error (NMSE) between MOST and IRGASON is 0.238, indicating moderately similar between the methods and fair agreement between MOST predictions and IRGASON measurements using the Eddy covariance method. An average error of approximately 23.8% of the squared mean observation value, implies that MOST provides a reliable approximation of atmospheric stability conditions when compared to direct IRGASON. Table 9 shows that the frequency of stability class D (Neutral) is 0. Since the KU tower is in a tropical urban area characterized by the urban heat island effect, this observation can be explained by thermal dynamics: The urban heat island effect causes ground-level air heating and initial upward air movement. However, when the upper air is relatively warm, downward air movement occurs and creates temperature inversion conditions, which reduces the likelihood of neutral (class D) stability.

Conclusions and Discussion

This research compared various atmospheric stability classification methods (SRDT, Delta T, Richardson number, and Monin-Obukhov), and reveals that the M-O method performed best. This study demonstrated that atmospheric stability analysis can be conducted using standard meteorological tower data by applying Monin-Obukhov Similarity Theory (MOST) and incorporating parameters from the Google Earth Engine. This approach allows for stability characterization in areas lacking advanced instrumentation such as IRGASON, which uses the Eddy covariance method for direct measurements.

MOST offers several advantages: standardization across different studies and regions in Thailand, accessibility using basic meteorological data (wind speed, temperature and cloud cover), enhanced accuracy through insolation data integration, and broader applications to various geographical areas. This methodology bridges the gap between limited on-site measurements and comprehensive atmospheric stability data needs, particularly in equatorial regions where atmospheric dynamics may differ from those in mid-latitude areas.

By incorporating MOST into future research, Thai scientists could improve understanding of atmospheric processes, enhance air quality predictions, and develop more effective environmental management strategies.

air quality management strategies and research recommendations.

1. Area-Specific Air Quality Management:

Development early warning systems for areas with high atmospheric stability

Design stricter pollution control measures during high stability periods

Creating risk maps to identify areas requiring special monitoring

Implement targeted air quality management strategies specific to local conditions

2. Enhanced Monitoring:

Install additional air quality monitoring stations at strategic locations

Development of real-time data collection systems

Utilize cost-effective IoT technology and sensors for broader coverage

Establishing comprehensive monitoring networks in areas frequently experiencing high atmospheric stability

3. Urban Planning:

Analysis of the wind patterns and air circulation in the area.

Establishing buffer zones between pollution sources and communities

Design roads and buildings that facilitate air ventilation

Incorporating atmospheric stability considerations into urban planning, especially in cities with complex terrain

This approach could lead to more robust and comparable results across different studies and regions in Thailand, ultimately contributing to improved air quality management and public health

outcomes. The research results are expected to enhance the understanding of complex interactions between atmospheric stability in different environments, leading to the development of effective control measures and improved air quality management strategies.

References

- [1] Manisalidis, I., Stavropoulou, E., Stavropoulos, A., and Bezirtzoglou, E. (2020). Environmental and health impacts of air pollution: A review. *Frontiers In Public Health*, 8, 14.
- [2] Amaral, S. S., de Carvalho, J. A., Costa, M. A. M., and Pinheiro, C. (2015). An overview of particulate matter measurement instruments. *Atmosphere*, 6(9), 1327-1345.
- [3] Pelliccioni, A., Monti, P., Gariazzo, C., and Leuzzi, G. (2012). Some characteristics of the urban boundary layer above Rome, Italy, and applicability of Monin-Obukhov similarity. *Environmental Fluid Mechanics*, 12, 405-428.
- [4] Gifford, F. (1961). Use of routine meteorological observations for estimating atmospheric dispersion. *Nuclear Safety*, 2(4), 44-57.
- [5] Edokpa, D., and Nwagbara, M. (2017). Atmospheric stability pattern over port harcourt, Nigeria. *Journal of Atmospheric Pollution*, 5(1), 9-17.
- [6] Hunt, G. R., and Van Den Bremer, T. S. (2010). Classical plume theory: 1937–2010 and beyond. *IMA Journal of Applied Mathematics*, 76(3), 424-448.
- [7] Pasquill, F. (1961). The estimation of the dispersion of windborne material. *Meteorological Magazine*, 90(1063), 33-49.
- [8] DeMarrais, G. A. (1978). Atmospheric stability class determinations on a 481-meter tower in Oklahoma. *Atmospheric Environment*, 12(10), 1957-1962.
- [9] Pérez, I. A., García, M., Sánchez, M. L., and de Torre, B. (2004). Autocorrelation analysis of meteorological data from a RASS sodar. *Journal of Applied Meteorology*, 43(8), 1213-1223.
- [10] Bowen, B. M., Dewart, J. M., and Chen, A. I. (1983). *Stability-class determination: A comparison for one site*. Los Alamos National Laboratory.
- [11] Golder, D. H. (1972). Relations among stability parameters in the surface layer. *Boundary-Layer Meteorology*, 3, 47-58.
- [12] Oard, M. J. (1974). Application of a diagnostic Richardson number tendency to a case study of clear air turbulence. *Journal of Applied Meteorology*, 13(7), 771-777.
- [13] Aubinet, M. Vesala, T., and Papale, D. (2012). *Eddy covariance: A practical guide to measurement and data analysis*. Springer Science and Business Media.
- [14] Stull, R. B. (2012). *An introduction to boundary layer meteorology* (Vol. 13). Springer Science & Business Media.

[15] Bailey, D. T. (2000). *Meteorological monitoring guidance for regulatory modeling applications*. EPA-454/R-99-005. U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards.

[16] Miles, J. W. (1961). On the stability of heterogeneous shear flows. *Journal of Fluid Mechanics*, 10(4), 496-508.

[17] Businger, J. A., Wyngaard, J. C., Izumi, Y., and Bradley, E. F. (1971). Flux-profile relationships in the atmospheric surface layer. *Journal of The Atmospheric Sciences*, 28(2), 181-189.

[18] Businger, J. A. (1973). *Turbulence transfer in the atmospheric surface layer*. In Workshop on Micrometeorology (pp. 67-100). American Meteorological Society, Boston, MA.

[19] Sedefian, L., and Bennett, E. (1980). A comparison of turbulence classification schemes. *Atmospheric Environment*, 14(7), 741-750.

[20] Kaimal, J. C., and Finnigan, J. J. (1994). *Atmospheric boundary layer flows: Their structure and measurement*. Oxford University Press.

[21] Seinfeld, J. H., and Pandis, S. N. (2016). *Atmospheric chemistry and physics: From air pollution to climate change* (3rd ed.). John Wiley & Sons.

[22] Arya, S. P. (1999). *Air pollution meteorology and dispersion* (Vol. 310). Oxford University Press New York.

[23] Holtslag, A., and Van Ulden, A. (1983). A simple scheme for daytime estimates of the surface fluxes from routine weather data. *Journal of Applied Meteorology and Climatology*, 22(4), 517-529.