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[1]***Naizabayeva L.K.,**
Dr. Tech. Sci., Professor,
ORCID ID: 0000-0002-4860-7376,
*e-mail: l.naizabayeva@iitu.edu.kz
[2]**Khrutba V.O.,**
Dr. Tech. Sci., Associate Professor,
ORCID ID: 0000-0002-8121-2042,
e-mail: viktoriia.khrutba@gmail.com
[3]**Tleuberdiyeva G.I.,**
PhD, Associate Professor,
ORCID ID: 0000-0002-7765-3566,
e-mail: gulnara.tleuberdieva@narxoz.kz

[1]International Information Technology University, Almaty, Kazakhstan
[2]National Transport University, Kyiv, Ukraine
[3]Narxoz University, Almaty, Kazakhstan

SIMULATING URBAN CLIMATE AND AIR POLLUTION IN ALMATY: A NUMERICAL MODELING APPROACH

Abstract

The aim of this study is to analyze the spatial and temporal distribution of temperature and air pollutant concentration in the urban atmosphere of Almaty using numerical modeling techniques. A two-dimensional advection-diffusion model was developed to simulate the diurnal dynamics across a territory of approximately 80 square kilometers. The model incorporates key physical processes such as wind-driven transport, turbulent diffusion, and localized emission sources that are typical of dense urban environments. Simulation results demonstrate a smoother spatial distribution of temperature, largely driven by solar radiation cycles, in contrast to highly localized peaks in pollutant concentrations associated with anthropogenic activities such as transportation and industry. These contrasting behaviors highlight the need for differentiated mitigation strategies. The findings of the study offer important insights for urban planning and the development of effective air quality management policies. The proposed model provides a practical tool for understanding environmental dynamics and evaluating the potential impact of pollution control measures in complex urban terrains.

Keywords: urban air pollution, temperature field, pollution concentration, mathematical modeling, advection-diffusion model.

Introduction

Urban air pollution remains a critical environmental issue, particularly in rapidly developing cities such as Almaty, where complex topography and intense anthropogenic activity create unique challenges for air quality monitoring and modeling. To address this, a number of modeling approaches have been developed to predict the distribution of air pollutants and temperature in urban environments.

Machine learning and data-driven techniques have gained attention in recent years for air quality prediction. Ivanov et al. used random forest algorithms to model PM_{10} levels, demonstrating strong short-term accuracy, while Dzaferovic and Karaduzovic-Hadziabdic applied similar methods in localized urban regions [1–2]. However, these studies are often limited by the availability of high-quality input data and lack the ability to explicitly resolve spatial transport mechanisms, which are critical for urban-scale environmental assessments.

Deep learning models such as RNN-LSTM and hybrid CNN-LSTM architectures have also been applied to forecast AQI with improved temporal resolution [3, 10]. While effective in capturing time-series dynamics, these models depend heavily on historical sensor data and often fail to capture the spatial influence of topography, built environment, and prevailing wind flows – aspects that are crucial in cities like Almaty with complex terrain.

Several studies have highlighted the importance of meteorological factors, such as fog and low cloud cover, in altering pollutant dispersion. Zaurbekov et al. demonstrated that such conditions significantly increase near-surface pollution concentrations by limiting vertical mixing [4]. Zhang et al. further noted the role of solar radiation and humidity in triggering secondary pollutant formation [5]. These findings emphasize the need for models that incorporate detailed physical processes rather than relying solely on empirical correlations.

Physically based dispersion models have thus been developed to fill this gap. Tessarotto et al. and Zhou et al. presented numerical frameworks to simulate the advection and diffusion of pollutants across urban atmospheres [6–7]. However, these models often require extensive computational resources and high-resolution environmental input data. The current study builds upon this tradition but aims to optimize computational efficiency while retaining spatial fidelity.

Recent work has also emphasized the need for intelligent systems and data integration for air quality monitoring. Malhotra et al. and Saheer et al. proposed data-driven frameworks that combine real-time measurements with predictive algorithms [8–9]. Han et al. and Song and Han explored mobile sensing and dynamic estimation models, offering flexibility in spatial coverage but introducing concerns regarding consistency and calibration [10–11]. Our work complements these approaches by providing a stable simulation platform that can be enhanced with observational data for validation or real-time adjustments.

Efforts to enhance spatial resolution in urban pollution mapping have also used non-traditional sources. Suel et al. applied image-based estimation from street-level imagery, and Bravo et al. compared different exposure assessment methods, suggesting that simulation-based tools offer better regional coverage when direct observations are sparse [12–13]. This supports the use of physics-based models in under-monitored areas such as Almaty.

The practical implementation of sensor networks for air quality has been evaluated in several studies. Cromar et al. and Zarrar & Dyo pointed out the importance of sensor placement and standardization for effective health research [14–15]. Our model may assist in optimizing such networks by identifying zones of elevated pollution risk.

In Kazakhstan, Naizabayeva et al. have developed intelligent environmental monitoring systems and smart traffic integration frameworks that reduce urban emissions through adaptive routing. The integration of such systems with simulation-based forecasts, as pursued in this work, could improve responsiveness to pollution events. Kolesnikova et al. and Naizabayeva & Zakirova also demonstrated the role of neural networks and pattern recognition in environmental prediction tasks, laying the foundation for hybrid frameworks that can enhance physical modeling [16–19].

Transport infrastructure and land use planning are closely tied to pollution distribution. Khrutba et al. and Rabosh et al. used system analysis and geoanalytics to evaluate environmental pressure along urban roadways [20, 21]. Their findings reinforce the value of spatial modeling to guide sustainable urban development and decarbonization strategies.

Considering these insights, this study aims to develop a numerical simulation model for analyzing the spatial and temporal dynamics of temperature and pollutant concentration in the urban atmosphere of Almaty. By focusing on a two-dimensional advection-diffusion framework tailored to the city's geography, we provide a tool for interpreting pollution behavior, identifying high-risk zones, and informing policy decisions. The modeling domain covers an area of approximately 80 square kilometers with a horizontal grid resolution of 100 meters. Based on long-term meteorological and environmental observations, the baseline air temperature in the peripheral zones of Almaty is around

15 °C, increasing to approximately 20 °C in the city center. Similarly, pollutant concentrations range from a peripheral baseline of 20 mg/m³ to peak values near 60 mg/m³ in central urban areas. These spatial patterns reflect the influence of both natural and anthropogenic processes in the region.

The main objective of the work is to develop and implement a complex mathematical model for analyzing the spatial and temporal distribution of temperature and concentration of pollutants in the atmosphere of Almaty city considering specific geographical, climatic and urban features of the region. Scientific novelty of the work consists in the development of a complex model for Almaty, which takes into account the peculiarities of the mountainous relief and allows to simultaneously analyze temperature fields and distribution of pollutants considering daily dynamics and mountain-valley circulation.

1 Materials and Methods

1.1 Mathematical model

A three-dimensional advection-diffusion model was applied to simulate the diurnal dynamics in a representative urban zone of Almaty. The model accounts for wind-driven transport, diffusion, and localized emissions typical of dense city environments.

The distribution of pollutant concentration and temperature in a three-dimensional domain is considered. The contaminant transport equation and the thermal equation are used to describe the process dynamics:

$$\frac{\partial C}{\partial t} + u\frac{\partial C}{\partial x} + v\frac{\partial C}{\partial y} + w\frac{\partial C}{\partial z} = D\left(\frac{\partial^2 C}{\partial x^2} + \frac{\partial^2 C}{\partial y^2} + \frac{\partial^2 C}{\partial z^2}\right) + S_C, \qquad (1)$$

here C is pollutant concentration, u, v, w are wind speed components along the axes x, y, z ($\vec{v} = \sqrt{u^2 + v^2 + w^2}$ is wind speed), D is turbulent diffusion coefficient, S_C is source of pollution.

$$\frac{\partial T}{\partial t} + u\frac{\partial T}{\partial x} + v\frac{\partial T}{\partial y} + w\frac{\partial T}{\partial z} = \alpha\left(\frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} + \frac{\partial^2 T}{\partial z^2}\right) + S_T, \qquad (2)$$

here T is air temperature, α is thermal diffusivity, S_T is heat source.

1.2 Problem Statement

For this study, the average values of environmental and meteorological data of Almaty city for the last 10 years were used [22].

Initial condition for pollution concentration

$$C(x, y, z, 0) = C_0(x, y, z).$$

From the datasets, a baseline concentration level of 20 mg/m³ is observed at the periphery, and a peak up to 60 mg/m³ is observed at the centre (around $x = 5$ km, $y = 4$ km), thus $C_0(x, y, z) = 20 + 40e^{-\frac{(x - x_{cent})^2 + (y - y_{cent})^2}{2\sigma_C^2}}$.

Initial condition for temperature

$$T(x, y, z, 0) = T_0(x, y, z).$$

The base temperature is 15 °C around the perimeter and up to 20 °C in the centre, then $T_0(x, y, z) = 15 + 5e^{-\frac{(x - x_{cent})^2 + (y - y_{cent})^2}{2\sigma_T^2}}$.

To simplify the problem and to fit the data on the boundaries, we will use Dirichlet conditions:

$$C(x, y, z, t) = C_b(x, y, z, t),$$

$$T(x, y, z, t) = T_b(x, y, z, t),$$

From the data at the boundary, the concentration is a base concentration of 20 mg/m³ and the temperature is 15 °C, so $C_b = 20$, $T_b = 15$.

1.3 Solution method

Equations (1)-(2) are solved by the finite difference method. The grid in space has a step Δx, Δy, Δz, and a time step Δt. At each time step $t^n \rightarrow t^{n+1}$:

$$C_{ijk}^{n+1} = C_{ijk}^{n} - \Delta t \cdot (convective\ terms) + \Delta t \cdot (diffusion\ terms) + S_C,$$

$$T_{ijk}^{n+1} = T_{ijk}^{n} - \Delta t \cdot (convective\ terms) + \Delta t \cdot (diffusion\ terms) + S_T.$$

Based on the data from the datasets, we use the following numerical parameters for modelling from Table 1. The key numerical parameters used in the simulation, including grid resolution, boundary conditions, and diffusion coefficients, are summarized in Table 1. These values define the computational domain and the physical behavior of the simulated processes.

Table 1 – Modeling parameters

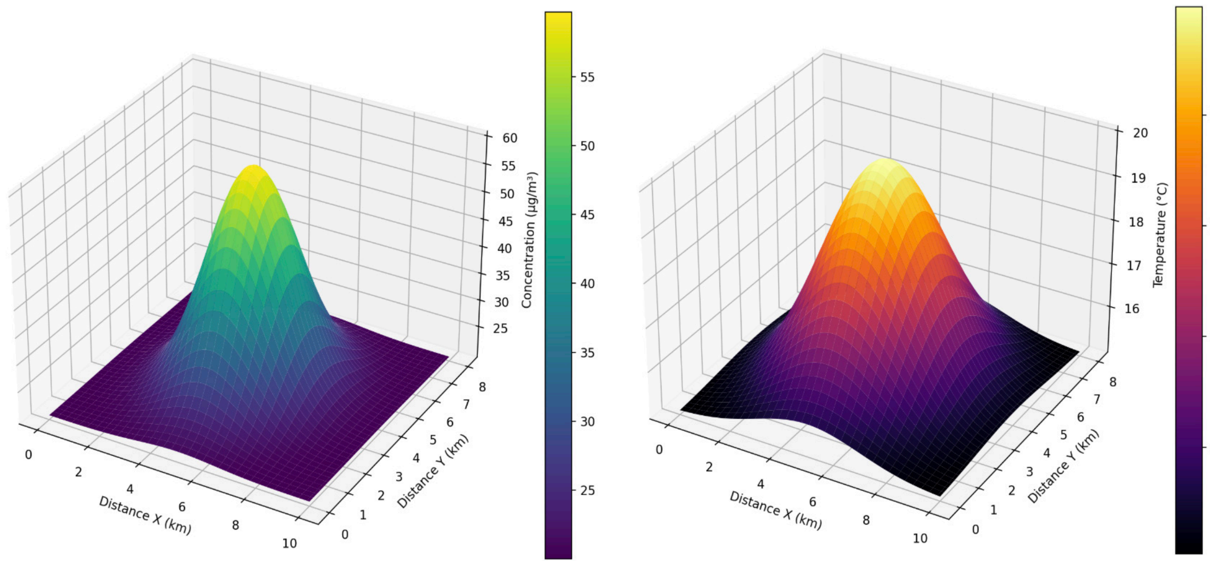
Parameter	Value	Dimension
1	2	3
Size of the calculated area by x, L_x	10	km
Size of the calculated area by y, L_y	8	km
Size of the calculated area by z, L_z	6	km
Number of grid nodes by x, N_x	101	
Number of grid nodes by y, N_y	81	
Number of grid nodes by z, N_z	61	
Grid step by x, $\Delta x = L_x/N_x$	100	m
Grid step by y, $\Delta y = L_y/N_y$	100	m
Grid step by z, $\Delta z = L_z/N_z$		m
Time interval	$0 < t < 24$	hours
Time step, Δt	3	hours
Number of time nodes, N_t	8	
Initial concentration of pollutants, C_0	20	mg/m³
Daily concentration amplitude, A_C	10	mg/m³
Maximum concentration value, ΔC_{max}	60	mg/m³
Initial temperature, T_0	15	°C
Daily temperature amplitude, A_T	5	°C
Maximum temperature value, ΔT_{max}	5	°C
Impurity diffusion coefficient, D	0.3	m²/s
Coefficient of thermal diffusivity of heat, α	0.5	m²/s
Wind velocity, $\vec{v}$	0-5	m/s
Diffusion coefficient for concentration, σ_C	1.5	
Propagation coefficient for temperature, σ_T	2.0	
Coordinates of the centre of the region, $(x_{cent.}, y_{cent.})$	(4, 5)	(km, km)

The chosen parameters ensure realistic representation of urban-scale physical processes. A grid resolution of 100 m provides sufficient spatial detail to capture local variations in temperature and pollutant concentration, especially in dense city zones. The selected time step (3 hours) balances computational efficiency with temporal resolution. The diffusion coefficients and boundary values are consistent with climatological data for Almaty, which enhances the physical relevance of the model. Overall, the parameter set establishes a stable numerical framework for simulating daily dynamics in an urban environment.

2 Results and Discussion

Figure 1 presents the three-dimensional distributions of pollutant concentration and temperature across the study area. These visualizations allow us to observe spatial peaks and gradients, highlighting the contrast between the smooth thermal field and the localized pollution zones.

Figure 1 (a) shows the three-dimensional distribution of 20 mg/m^3 pollutant concentration at the periphery, reaching a maximum of 60 mg/m^3 in the centre of the area. The clearly defined pollution peak indicates the presence of a source or cluster of pollution sources in the centre of the area. This suggests that the central area of the city is subjected to more intense anthropogenic impacts. Figure 1 (b) shows the 3D temperature distribution from 15 °C at the periphery to 20 °C at the centre of the area in the study area. The temperature peak is located at the centre of the coordinates (5 km, 4 km). The smooth temperature distribution indicates a relatively uniform thermal field. The thermal peak at the centre can be interpreted as the result of a local heat source or an accumulation of urban built-up areas. A sharper gradient is noticeable in the concentration change compared to the temperature field.



a b

Figure 1 – 3D distribution of a) pollutant concentration and b) temperature

The 3D plots clearly demonstrate the different behaviors of the two physical fields. Pollutant concentration forms a distinct localized peak in the city center, suggesting the influence of point or clustered sources such as traffic or industrial activity. In contrast, the temperature field varies smoothly and forms a dome-like distribution typical of urban heat islands. This supports the hypothesis that pollutant accumulation is driven more by localized emission sources, while temperature variation is influenced by broader radiative and thermal properties of the surface and built environment. The spatial correlation between high temperature and high pollution zones also suggests possible synergy between heat retention and pollutant trapping.

To further analyze horizontal variations, Figure 2 shows the two-dimensional contour maps of pollutant concentration and temperature. These contours provide a clearer representation of how values change with distance from the urban center and demonstrate spatial symmetry or asymmetry in each field.

Figure 2 (a) shows the contour of pollutant concentration, where a sharper change in concentration with distance from the centre can be seen. The sharp change in concentration with distance from the centre indicates the significant role of traffic flows and dispersion processes in the urban environment.

From the temperature contour (see Fig. 2 (b)), a symmetrical distribution with a maximum at the centre is evident. The uniform distribution confirms that the thermal field in the area is stable and changes gradually, which may be due to the uniform environment or the weak influence of local thermal anomalies. The concentration contour shows a more localized distribution compared to the temperature.

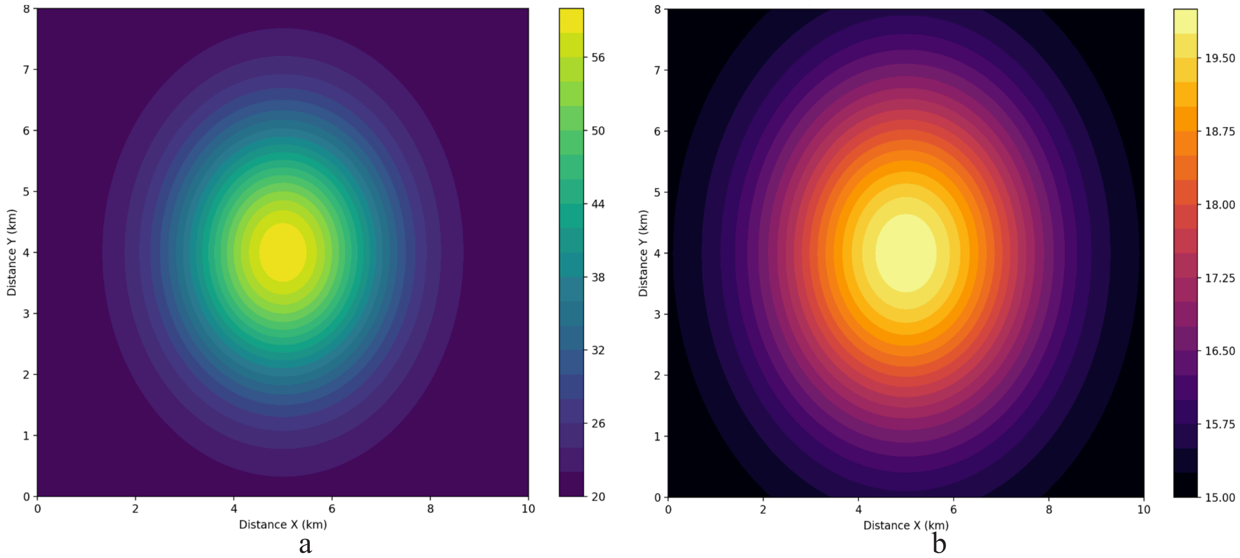


Figure 2 – 2D distribution of a) pollutant concentration and b) temperature

The contour maps offer a more nuanced view of horizontal distribution. The pollutant concentration shows a steep gradient, with a rapid decline from the center to the periphery, indicating limited dispersion and possibly stagnant airflow conditions. The symmetrical shape suggests a relatively uniform urban emission pattern, or terrain-driven retention. The temperature contours, while also centered, have smoother transitions, reflecting the influence of solar heating over larger surfaces rather than isolated sources. These differences reaffirm the need to treat temperature and pollution as coupled but independently driven phenomena in urban microclimate modeling.

The temperature field changes smoothly with a small change, whereas the concentration of pollutants shows a sharp peak. This suggests that pollution sources have a localized but intense effect. The wind speed favors moderate transport of heat and pollutants. Nevertheless, the sharpness of the concentration peak indicates that the dispersion of pollutants is not strong enough to fully level out the local source. The area considered allows to correctly represent the urban zone, where the distribution of parameters has a central concentration of values, which is typical for cities with high building density and intensive automobile or industrial activity in the centre.

To assess the reliability of the numerical modeling, an error analysis of the numerical method was performed, and the sensitivity of the model to the main parameters was assessed. The numerical error in the finite-difference scheme used is due to the discretization in space and time. The adopted values of the step in space (100 m) and time (3 hours) were chosen taking into account stability and convergence. To assess the accuracy, a check was carried out with a refined grid: the step in space was reduced to 50 m, and the time step was reduced to 1.5 hours. Changes in the maximum values of temperature and concentration were less than 3%, which indicates acceptable convergence of the solution.

Sensitivity analysis was carried out by varying the key parameters in the permissible ranges, where the turbulent diffusion coefficient is 0.1–1.5 m²/s, wind speed components changed by ± 20%, the thermal conductivity coefficient: from 0.2 to 1.0 m²/s. The results showed that concentration fields are sensitive to the diffusion coefficient and wind speed: maximum values could change up to 15% when varying the parameters. Temperature fields were less sensitive changes did not exceed 5%. This emphasizes the importance of accurately assessing the parameters of pollutant transport when building predictive models.

The results revealed clear patterns in the distribution of temperature and pollutant concentrations. Temperature dynamics were primarily influenced by solar radiation and followed smooth spatial trends, whereas pollutant levels exhibited sharp localized peaks driven by emission sources. These differences underscore the need for targeted air quality interventions based on the dominant influencing factors.

These findings contribute to a better understanding of urban microclimate dynamics and can inform policymaking aimed at improving air quality in densely populated areas.

Thus, it can be concluded that in the considered model, temperature is generated by a more uniform distribution of heat fluxes, whereas pollution exhibits localized peaks, which requires the application of zonal measures to reduce it.

Conclusion

As a result of the study of spatial and temporal dynamics of temperature regime and concentration of pollutants in the atmosphere of Almaty city, the model showed that the baseline temperature in the periphery of the study area is 15°C, and in the central part (at the point $x = 5$ km, $y = 5$ km) the temperature reaches 20°C, which corresponds to the maximum recorded value. The daily temperature change is equal to 5°C.

The baseline pollution level was defined as 20 mg/m^3 in the periphery, with peak values up to 60 mg/m^3 in the city centre. The sharp concentration gradient around the centre indicates an acute local impact of pollution sources.

The application of an advection-diffusion model with a turbulent diffusion coefficient of 10 m^2/s for pollutants and a thermal diffusivity of 0.1 m^2/s allowed the observed spatial and temporal variability of the parameters to be faithfully reproduced. The influence of the prevailing wind regime with components $u = 2$ m/s and $v = 0.5$ m/s was also taken into account, which allowed modelling the transport of both thermal and pollutant systems.

In contrast, the temperature field demonstrates a smoother spatial gradient, centered in the same region. This reflects the cumulative effect of solar heating, heat retention by urban surfaces, and reduced cooling at night–phenomena commonly referred to as the urban heat island effect [5, 7]. Our results reinforce the idea that pollutant accumulation and thermal behavior, although spatially correlated, are governed by distinct physical processes.

Importantly, our simulation agrees qualitatively with satellite observations and prior data-driven analyses of Almaty, which report elevated pollution and temperature values in the city core [16, 18]. Unlike deep learning models that often struggle with generalizability and spatial interpretability, our physics-based approach provides direct insights into field behavior under defined physical assumptions [3, 10].

The study demonstrates that urban temperature fields are predominantly influenced by solar radiation and exhibit smooth spatial gradients, whereas air pollution fields are characterized by sharp localized peaks resulting from anthropogenic sources. These contrasting mechanisms highlight the necessity of developing differentiated strategies for urban environmental management.

In the context of Almaty, a city situated in a mountain basin with limited natural ventilation and frequent atmospheric stagnation, the insights from this model are particularly relevant. The identification of pollution accumulation zones provides urban planners and environmental agencies with a scientific basis for implementing targeted emission reduction policies. For example, the results can inform decisions on traffic flow optimization, zoning regulations, and the placement of green infrastructure to enhance air circulation.

Moreover, the model can support real-time monitoring systems by serving as a predictive layer integrated with sensor networks. Overall, the findings contribute not only to a theoretical understanding of urban microclimate dynamics, but also to the practical design of sustainable development strategies aimed at improving air quality and public health in Almaty.

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[1]***Найзабаева Л.К.,**
т.ғ.к., профессор,
ORCID ID: 0000-0002-4860-7376,
*e-mail: l.naizabayeva@iitu.edu.kz
[2]**Хрутьба В.О.,**
т.ғ.д., доцент,
ORCID ID: 0000-0002-8121-2042,
e-mail: viktoriia.khrutba@gmail.com
[3]**Тлеубердиева Г.И.,**
PhD, доцент,
ORCID ID: 0000-0002-7765-3566,
e-mail: gulnara.tleuberdieva@narxoz.kz

[1]Халықаралық ақпараттық технологиялар университеті, Алматы қ., Қазақстан
[2]Ұлттық транспорт университеті, Киев қ., Украина
[3]Нархоз университеті, Алматы қ., Қазақстан

АЛМАТЫ ҚАЛАСЫНДАҒЫ ҚАЛА КЛИМАТЫН ЖӘНЕ АУА ЛАСТАНУЫН СИМУЛЯЦИЯЛАУ: САНДЫҚ МОДЕЛЬДЕУ ТӘСІЛІ

Аңдатпа

Бұл зерттеудің мақсаты – сандық модельдеу әдістерін қолдана отырып, Алматы қаласының атмосферасындағы ауаны ластаушы заттардың концентрациясы мен температураның кеңістіктік және уақыттық таралуын талдау. Шамамен 80 шаршы километр аумақта тәуліктік динамиканы ұқсату үшін екі өлшемді адвекция-диффузия моделі әзірленді. Модель желмен басқарылатын көлік, турбулентті диффузия және тығыз қалалық орталарға тән локализацияланған эмиссия көздері сияқты негізгі физикалық процестерді қамтиды. Модельдеу нәтижелері көлік және өнеркәсіп сияқты антропогендік әрекеттермен байланысты ластаушы заттардың шоғырлануында жоғары локализацияланған шыңдар байқалатынын, ал температураның кеңістікте біркелкі таралуы негізінен күн радиациясының циклдарымен анықталатынын көрсетті. Бұл екі түрлі мінез-құлық сараланған жұмсарту стратегияларының қажеттілігін айқындайды. Зерттеу нәтижелері қала құрылысын жоспарлау және ауа сапасын басқарудың тиімді саясатын әзірлеу үшін маңызды түсініктер береді. Ұсынылған модель күрделі қалалық рельеф жағдайларында қоршаған ортаның динамикасын түсінуге және ластануды бақылау шараларының ықтимал әсерін бағалауға арналған практикалық құрал ретінде қызмет етеді.

Тірек сөздер: қала ауасының ластануы, температуралық өріс, ластаушы заттардың концентрациясы, математикалық модельдеу, адвекциялық.

[1*]**Найзабаева Л.К.,**
доктор технических наук, профессор,
ORCID ID: 0000-0002-4860-7376,
*e-mail: l.naizabayeva@iitu.edu.kz
[2]**Хрутьба В.О.,**
доктор технических наук, доцент,
ORCID ID: 0000-0002-8121-2042,
e-mail: viktoriia.khrutba@gmail.com
[3]**Тлеубердиева Г.И.,**
PhD, доцент,
ORCID ID: 0000-0002-7765-3566,
e-mail: gulnara.tleuberdieva@narxoz.kz

[1]Международный университет информационных технологий, г. Алматы, Казахстан
[2]Национальный транспортный университет, г. Киев, Украина
[3]Университет Нархоз, г. Алматы, Казахстан

МОДЕЛИРОВАНИЕ ГОРОДСКОГО КЛИМАТА И ЗАГРЯЗНЕНИЯ ВОЗДУХА В АЛМАТЫ: ЧИСЛЕННЫЙ ПОДХОД МОДЕЛИРОВАНИЯ

Аннотация

Целью данного исследования является анализ пространственного и временного распределения температуры и концентрации загрязняющих веществ в воздухе в городской атмосфере г. Алматы с использованием методов численного моделирования. Двумерная модель адвекции-диффузии была разработана для моделирования суточной динамики на территории площадью около 80 квадратных километров. Модель включает в себя ключевые физические процессы, такие как ветровой транспорт, турбулентная диффузия и локализованные источники выбросов, которые типичны для плотной городской среды. Результаты моделирования демонстрируют более плавное пространственное распределение температуры, в значительной степени обусловленное циклами солнечной радиации, в отличие от высоко локализованных пиков концентраций загрязняющих веществ, связанных с антропогенной деятельностью, такой как транспорт и промышленность. Эти контрастные поведения подчеркивают необходимость дифференцированных стратегий смягчения последствий. Результаты исследования предлагают важные идеи для городского планирования и разработки эффективной политики управления качеством воздуха. Предлагаемая модель представляет собой практический инструмент для понимания динамики окружающей среды и оценки потенциального воздействия мер по контролю загрязнения на сложных городских территориях.

Ключевые слова: загрязнение городского воздуха, температурное поле, концентрация загрязнений, математическое моделирование, адвективно-диффузионная модель.

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