

## Development of a Wireless Sensor-Based Shrimp Pond Water Quality Monitoring System

Andi Aulia Dwi Fachriana<sup>1</sup>

<sup>1</sup>Fishery Cultivation Technology, Pangkajene Islands State Agricultural Polytechnic

### ARTICLE INFO

Received: 17 November 2024  
Revised: 16 December 2024  
Accepted: 29 December 2024  
Available online: 11 January 2025

#### Keywords:

Shrimp Aquaculture  
Wireless Sensor Network  
Water Quality Monitoring  
Dissolved Oxygen

Corresponding Author:  
Andi Aulia Dwi Fachriana

Email:  
[andiaulia23093@gmail.com](mailto:andiaulia23093@gmail.com)

Copyright © 2025, Journal of Agrocomplex and Engineering, Under the license [CC BY- SA 4.0](https://creativecommons.org/licenses/by-sa/4.0/)



### ABSTRACT

**Purpose:** The study aims to design, develop, and validate a wireless sensor-based monitoring system for shrimp ponds, addressing the limitations of conventional manual monitoring in capturing dynamic fluctuations of critical water quality parameters.

**Subjects and Methods:** The system was equipped with low-power sensors to measure dissolved oxygen (DO), pH, temperature, and salinity, integrated with solar-assisted power, wireless transmission, and a cloud-based dashboard. Calibration and validation were first conducted under laboratory conditions, followed by an eight-week field deployment across three shrimp ponds. Accuracy was evaluated against standard reference instruments, while network performance and energy autonomy were continuously monitored.

**Results:** Laboratory calibration achieved high accuracy with RMSE values of 0.08 for pH, 0.18 mg/L for DO, 0.15 °C for temperature, and 0.42 ppt for salinity. Field trials generated more than 190,000 valid measurements, revealing consistent diurnal water quality dynamics. Sensor data showed strong concordance with manual reference measurements (concordance correlation coefficient > 0.95). The wireless communication network achieved a packet delivery ratio of 96.7% with median latency of 2.3 seconds. Solar-assisted nodes maintained uninterrupted operation for more than 30 days, ensuring system robustness in outdoor aquaculture conditions.

**Conclusions:** The developed wireless sensor-based monitoring system proved reliable for real-time aquaculture applications, offering both technical accuracy and practical benefits for farm management. The system enabled proactive interventions, such as timely aeration during pre-dawn oxygen depletion, thereby reducing shrimp stress and mortality risk. Future improvements will focus on enhancing sensor resistance to biofouling and integrating predictive analytics for decision support. Overall, the study demonstrates the feasibility of Internet of Things (IoT)-enabled solutions to advance sustainable and precision shrimp aquaculture.

### INTRODUCTION

Shrimp aquaculture has become one of the most rapidly expanding sectors in global food production, contributing significantly to food security and economic development in many coastal regions. Intensive cultivation systems, however, are highly sensitive to fluctuations in water quality parameters such as dissolved oxygen (DO), pH, temperature, and salinity (Mariu et al., 2023; Gorde & Jadhav, 2013; Nazneen et al., 2019).

Even short-term imbalances in these variables can induce stress, reduce growth rates, increase feed conversion ratios, and elevate the risk of disease outbreaks. Among these, low dissolved oxygen levels during pre-dawn hours remain a leading cause of mass mortality in shrimp ponds, often resulting in severe economic losses for farmers (Tenório et al., 2022; Mondal et al., 2025; Deans, 2022).

Traditionally, water quality in shrimp ponds has been monitored through manual spot-checks using portable devices. While such methods are inexpensive and widely adopted, they are inherently limited in frequency, labor-intensive, and incapable of capturing the dynamic, diurnal fluctuations characteristic of pond ecosystems (Li et al., 2019). Consequently, critical events such as nocturnal oxygen depletion often go undetected until after significant damage has occurred. This monitoring gap underscores the urgent need for continuous, automated, and real-time observation systems that can support proactive pond management (Wang, 2024; Kanwal et al., 2024; Bose et al., 2024).

Recent advances in wireless sensor networks (WSNs) and Internet of Things (IoT) technologies have opened new opportunities for precision aquaculture (Rastegari et al., 2023; Liu et al., 2022; Prapti et al., 2022). Several studies have demonstrated the feasibility of using distributed sensor nodes to measure environmental parameters in real time, transmitting data to centralized platforms for visualization and analysis. However, many existing prototypes face challenges such as limited deployment duration due to energy constraints, reduced data reliability in field conditions, and inadequate integration with user-friendly interfaces for farmers (Fountas et al., 2015; Mössinger et al., 2022; Saiz & Rovira, 2020; Garg et al., 2016).

Moreover, relatively few systems have been rigorously validated under long-term operational conditions in commercial shrimp ponds, leaving a gap between laboratory prototypes and field-ready solutions. This study addresses these challenges by developing and deploying a wireless sensor-based water quality monitoring system specifically designed for shrimp ponds. The system integrates low-power, solar-assisted sensor nodes with robust wireless communication and a cloud-based data platform, enabling continuous monitoring of DO, pH, temperature, and salinity.

The objectives of this research are threefold: (i) to evaluate the accuracy and reliability of the developed sensors under both laboratory and field conditions, (ii) to assess the stability of wireless data transmission and energy autonomy in a multi-week deployment, and (iii) to analyze the practical implications of real-time monitoring for aquaculture management. By bridging the gap between prototype development and field application, this work contributes to advancing sustainable and technology-enabled shrimp farming.

## METHODOLOGY

This study adopts a research and development (R&D) approach combined with laboratory experiments and field case studies. The primary objective is to design, construct, and evaluate a wireless sensor-based water quality monitoring system for shrimp ponds, capable of operating in real time with low power consumption. The development process was structured in several stages: identifying system requirements and performance specifications, designing the system architecture, calibrating sensors under controlled laboratory conditions, and conducting extended field trials in representative aquaculture ponds. The prototype consisted of floating sensor nodes built on a low-power microcontroller platform with LoRa communication, equipped with sensors for pH, dissolved oxygen (DO), temperature, and salinity. These nodes transmitted data to an edge gateway, which relayed the information to a backend time-series database and visualization dashboard with integrated early-warning notifications. The initial stage of the research focused on needs assessment and system specification, where accuracy targets were established (pH  $\pm 0.1$ ; DO  $\pm 0.2$  mg/L; temperature  $\pm 0.2$  °C; salinity  $\pm 0.5$  ppt). Communication performance was set at a minimum of 95% packet delivery ratio (PDR) with a median latency of less than five seconds. After hardware and firmware development, sensor calibration was performed in the laboratory using international standards: NIST buffer solutions (pH 4.01, 7.00, 10.01), two-point calibration for DO (sodium sulfite solution for 0% and air-saturated water for 100%), and KCl reference solutions for salinity. Stability tests were conducted through 72-hour immersion trials to evaluate repeatability and potential drift over time. Following laboratory

validation, the system was deployed in three intensive shrimp ponds (2,000–5,000 m<sup>2</sup> each) over an eight-week trial period corresponding to the grow-out phase (weeks 4–11 of the production cycle).

Sensor nodes were anchored at 0.5 m depth within the mixing zone and configured to acquire measurements every five minutes, with adaptive sampling at one-minute intervals during rapid fluctuations. As ground-truth references, manual spot-checks were performed three times daily (06:00, 12:00, 18:00) using calibrated laboratory-grade instruments. With this setup, each pond generated approximately 16,000 data points per parameter, resulting in a dataset of more than 190,000 observations across the three ponds, ensuring sufficient statistical robustness. The collected data were processed and analyzed to assess both technical performance and operational impact. Sensor accuracy was evaluated using mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). Agreement with reference instruments was examined using Bland–Altman plots and Lin’s concordance correlation coefficient (CCC). Reliability was tested through intra-class correlation (ICC) and drift analysis over weekly intervals. Network performance was evaluated in terms of PDR, received signal strength indicator (RSSI), signal-to-noise ratio (SNR), and transmission latency. In addition, energy autonomy was estimated by monitoring average daily battery consumption and projecting operational lifetime under limited solar input. Operationally, system responsiveness was measured by recording the time between critical DO drops below 4 mg/L and the issuance of alarms, as well as the corrective actions taken by farmers. Statistical analyses included normality testing (Shapiro–Wilk), paired t-tests or Wilcoxon signed-rank tests for sensor-reference comparisons, and linear mixed-effects models for examining pond-to-pond and temporal variability. Data quality assurance (QA/QC) protocols consisted of range checks, rate-of-change detection, and flatline detection, with flagged categories for “good,” “questionable,” or “bad” data. The overall success criteria were defined as meeting sensor accuracy thresholds, achieving PDR  $\geq 95\%$  with latency  $\leq 5$  seconds, and sustaining a minimum of 30 days of autonomous operation. Through this integrated methodology, the study not only delivers a technically robust prototype but also provides empirical evidence of the system’s effectiveness in supporting precision and sustainable shrimp aquaculture practices.

## RESULTS AND DISCUSSION

### Sensor Calibration and Laboratory Validation

The laboratory calibration results demonstrated that the sensors performed within the expected ranges of accuracy. Table 1 shows the summary of calibration results compared to the reference standards. The RMSE for pH and temperature sensors was below 0.1 and 0.2 °C, respectively, while the DO sensor achieved  $\pm 0.18$  mg/L accuracy. The salinity sensor exhibited the highest variability, though still within the  $\pm 0.5$  ppt target range.

Table 1. Sensor Calibration Results (n = 30 per parameter)

Parameter	Reference Range	RMSE (Sensor vs Reference)	Mean Bias	Target Accuracy	Achieved
pH	4.0 – 10.0	0.08	+0.02	$\pm 0.1$	✓
DO (mg/L)	0 – 15	0.18	-0.05	$\pm 0.2$	✓
Temp (°C)	20 – 35	0.15	+0.10	$\pm 0.2$	✓
Salinity (ppt)	5 – 35	0.42	+0.20	$\pm 0.5$	✓

Calibration results indicate that all sensors operate according to established standards. The pH, DO, and temperature sensors demonstrated stable performance with low error rates and minimal bias, thus being considered reliable for field use. Meanwhile, the salinity sensor exhibited the greatest variation compared to other parameters, but remained within the required accuracy limits. Overall, all instruments meet the eligibility criteria for use in a pond water quality monitoring system.

### Field Deployment and Data Acquisition

The system was then tested directly in the field by installing the device in three shrimp farming ponds (P1–P3) for eight weeks. During this period, the system successfully collected over 190,000 valid data sets, demonstrating sensor stability and connectivity reliability under real-world operational conditions. The recorded water quality dynamics provide a picture consistent with shrimp farming literature. As shown in Figure 1, daily fluctuations in DO and pH in Pond 1 during the third week demonstrate a clear biological rhythm: DO levels decrease progressively throughout the night due to reduced photosynthesis and increased respiration activity of microorganisms and plankton. This decline reaches a critical point near sunrise, potentially endangering shrimp health if left untreated. Meanwhile, pH oscillates daily, reflecting the intensity of photosynthesis during the day and respiration at night. These findings confirm that the wireless sensor-based system is capable of capturing water quality dynamics in real time, making it a valuable tool for early detection of suboptimal conditions in shrimp ponds.

### Accuracy Evaluation in the Field

To ensure system reliability during field use, sensor data was compared with periodic manual measurements. This comparison aimed to assess the extent to which sensor accuracy was maintained under real-world operational conditions, which are often more challenging than laboratory environments. Field validation results demonstrated a high level of agreement between the two data sources, as summarized in Table 2.

Table 2. Field Validation Statistics (Sensor vs Manual Reference, n = 504 pairs per parameter)

Parameter	MAE	RMSE	CCC	Evaluation
pH	0.07	0.09	0.98	Excellent
DO (mg/L)	0.16	0.20	0.96	Excellent
Temp (°C)	0.12	0.15	0.97	Excellent
Salinity (ppt)	0.38	0.45	0.93	Good

Field validation results showed that the sensor's performance was highly consistent with manual measurements. The pH, DO, and temperature parameters received "Excellent" ratings, indicating a very high level of suitability and sensor stability under various environmental conditions. Meanwhile, the salinity sensor demonstrated slightly lower accuracy than the other parameters, but remained in the "Good" category, making it suitable for field monitoring. These findings confirm that the system maintains measurement reliability despite the variability of operational conditions in the ponds.

### Network and Energy Performance

Evaluations of network performance and energy consumption demonstrated that the system was capable of operating with a high level of reliability. Network stability was reflected in the consistent delivery of data and relatively low delays, allowing water quality information to be received in near real-time without significant disruption. This is crucial considering that the dynamics of pond parameters such as DO and pH require continuous monitoring to prevent critical conditions. From an energy perspective, the solar-powered nodes demonstrated excellent operational resilience. Even under less-than optimal weather conditions, the system-maintained performance without manual intervention. This resilience demonstrates that the power management design and energy storage capacity are suitable for the long-term monitoring needs of ponds, which are typically located far from conventional power sources. These findings confirm that the combination of wireless networks and solar energy can support autonomous, sustainable, and efficient environmental monitoring in the context of shrimp farming.

## Discussion

### **Feasibility of Low-Power Wireless Sensor Networks in Aquaculture**

The study demonstrates that the use of a low-power wireless sensor network is a practical and effective approach for continuous water quality monitoring in shrimp ponds. Bhuiyan et al. (2017) said that, the system was able to operate consistently over extended periods, capturing rapid environmental changes that often go undetected with conventional manual sampling. Its ability to function reliably in outdoor aquaculture settings where humidity, temperature fluctuations, and biofouling present operational challenges indicates that the selected hardware,

communication topology, and power management strategies were appropriate. This confirms that such systems can be successfully integrated into routine farm management without requiring intensive technical maintenance from the users.

### ***Monitoring of Critical Diurnal Water Quality Dynamics***

The system's capability to continuously observe diurnal patterns of key parameters, particularly dissolved oxygen (DO) and pH, highlights its importance for effective pond management. These parameters are known to fluctuate throughout the day as a result of photosynthesis, respiration, feed input, and microbial activity. By providing real-time visibility of these daily variations, the system helps farmers understand the natural cycles within the pond and make informed operational decisions. This continuous stream of data also supports more accurate interpretation of pond health conditions, enabling interventions that are more-timely and evidence-based compared to traditional monitoring methods.

### ***Accuracy and Reliability Compared to Reference Instruments***

The high degree of alignment between sensor outputs and laboratory-grade reference instruments further reinforces the reliability of the developed monitoring platform (Wang et al., 2025; Feng et al., 2025). This agreement indicates that the calibration protocols, sensor selection, and signal processing techniques used in the system are suitable for field applications. Moreover, the system's consistent performance across multiple weeks of deployment shows that environmental stressors did not significantly degrade measurement stability. This reliability is particularly valuable for aquaculture operations, where inaccurate data could lead to improper management practices and potential losses.

### ***Practical Benefits for Farm Management and Decision-Making***

From a practical standpoint, the integration of an early warning mechanism proved highly beneficial. Alerts generated during early-morning declines in dissolved oxygen enabled farmers to respond quickly by activating aerators, thereby minimizing the risk of shrimp stress or mortality. Such proactive management is crucial in high-density farming systems where water quality deteriorates quickly. The ability to detect critical events in real time reduces dependence on manual checks, enhances operational efficiency, and can ultimately contribute to improved survival rates and production outcomes. This illustrates how sensing and automation technologies can provide tangible economic and welfare benefits to farmers.

### ***Comparison with Previous Aquaculture IoT Studies***

The findings of this study are aligned with earlier research on IoT-based systems for aquaculture, which also reported the potential of wireless sensors to support continuous monitoring and early warning functions (Tina et al., 2025; Alghamdi & Haraz, 2025). However, this research advances the field by demonstrating sustained performance during multi-week deployment under realistic farm conditions rather than short-term or laboratory-based trials. Such long-duration field validation is essential for assessing durability, data stability, and resilience against environmental challenges commonly encountered in commercial aquaculture operations.

### ***Observed Variability in Salinity Readings***

Although the system performed well overall, slightly higher variability in salinity data indicates an area for improvement (Walter et al., 2001). This inconsistency may be linked to electrode fouling, sediment accumulation, or the influence of fluctuating ionic concentrations. These factors can interfere with conductivity-based salinity measurements, especially in ponds with high organic loads. Future refinements could include improved protective housings, self-cleaning mechanisms, or adaptive calibration methods to reduce drift and enhance long-term stability. Addressing this issue would further strengthen the accuracy and reliability of the monitoring system.

### ***Toward the Implementation of Precision Aquaculture***

The successful integration of wireless sensor nodes, cloud-based data storage, and mobile visualization tools underscores a clear movement toward precision aquaculture (Mustapha et al., 2021). By combining automated data collection with accessible dashboards, the system provides

farmers with actionable insights that support more precise, data-driven decision-making. This technological framework can also enable long-term trend analysis, predictive modeling, and integration with other smart farming tools. Overall, the research presents a technological pathway that not only enhances monitoring capabilities but also contributes to the broader digital transformation of aquaculture management practices.

## CONCLUSION

This study successfully developed and validated a wireless sensor-based water quality monitoring system tailored for intensive shrimp aquaculture. Laboratory calibration confirmed that the pH, dissolved oxygen, temperature, and salinity sensors achieved the target accuracy, with RMSE values well within acceptable thresholds. Field deployment across three ponds over an eight-week period demonstrated the system's robustness in capturing diurnal fluctuations of critical water quality parameters, particularly the pre-dawn decline in dissolved oxygen and the midday increase in pH. The sensor readings exhibited strong agreement with manual reference measurements (CCC > 0.95), while the wireless transmission network achieved a high packet delivery ratio (96.7%) and stable latency, ensuring reliable real-time data flow. The integration of solar-powered nodes enabled continuous operation with more than 30 days of autonomy, confirming the system's suitability for remote aquaculture environments. From a practical standpoint, the real-time alerts provided by the system allowed proactive interventions, such as timely activation of aerators, which can significantly reduce shrimp stress and mortality. Compared to conventional manual monitoring, this approach represents a step forward toward precision aquaculture, empowering farmers with continuous, accurate, and actionable information. Future improvements should focus on enhancing sensor stability under biofouling conditions and extending the system with predictive analytics and decision-support tools. Nonetheless, the findings confirm that wireless sensor networks represent a viable and effective solution for sustainable shrimp pond management.

## REFERENCES

Alghamdi, M., & Haraz, Y. G. (2025). Smart Biofloc Systems: Leveraging Artificial Intelligence (AI) and Internet of Things (IoT) for Sustainable Aquaculture Practices. *Processes*, 13(7), 2204. <https://doi.org/10.3390/pr13072204>

Bhuiyan, M. Z. A., Wu, J., Wang, G., Wang, T., & Hassan, M. M. (2017). e-Sampling: Event-sensitive autonomous adaptive sensing and low-cost monitoring in networked sensing systems. *ACM Transactions on Autonomous and Adaptive Systems (TAAS)*, 12(1), 1-29. <https://doi.org/10.1145/2994150>

Bose, R., Sutradhar, S., Mondal, H., Bhattacharyya, D., & Roy, S. (2024). Integrating environmental monitoring and bird attack prevention in fish farming: a combined solution for improved pond management. *Discover Applied Sciences*, 6(3), 81. <https://doi.org/10.1007/s42452-024-05621-x>

Deans, F. S. C. (2022). *The influence of climate change on marine bacterioplankton communities and greenhouse gases in New Zealand waters* (Doctoral dissertation, University of Otago).

Feng, Z., Zheng, L., & Xue, N. (2025). Physics-informed calibration model for enhanced accuracy in particulate matter monitoring integrating clustering algorithms with field validation. *Expert Systems with Applications*, 277, 127313. <https://doi.org/10.1016/j.eswa.2025.127313>

Fountas, S., Carli, G., Sørensen, C. G., Tsiropoulos, Z., Cavalaris, C., Vatsanidou, A., ... & Tisserye, B. A. (2015). Farm management information systems: Current situation and future perspectives. *Computers and electronics in agriculture*, 115, 40-50. <https://doi.org/10.1016/j.compag.2015.05.011>

Garg, K. K., Wani, S. P., & Patil, M. D. (2016). A simple and farmer-friendly decision support system for enhancing water use efficiency in agriculture: tool development, testing and validation. *Current Science*, 1716-1729.

Gorde, S. P., & Jadhav, M. V. (2013). Assessment of water quality parameters: a review. *J Eng Res Appl*, 3(6), 2029-2035.

Kanwal, S., Abdullah, M., Kumar, S., Arshad, S., Shahroz, M., Zhang, D., & Kumar, D. (2024). An optimal internet of things-driven intelligent decision-making system for real-time fishpond water quality monitoring and species survival. *Sensors*, 24(23), 7842. <https://doi.org/10.3390/s24237842>

Li, W., Tian, L., Guo, S., Li, J., Sun, Z., & Zhang, L. (2019). An Automatic Stationary Water Color Parameters Observation System for Shallow Waters: Designment and Applications. *Sensors*, 19(20), 4360. <https://doi.org/10.3390/s19204360>

Liu, T., Liu, J., Wang, J., & Xu, J. (2022). Optimization of the intelligent sensing model for environmental information in aquaculture waters based on the 5G smart sensor network. *Journal of Sensors*, 2022(1), 6409046. <https://doi.org/10.1155/2022/6409046>

Mariu, A., Chatha, A. M. M., Naz, S., Khan, M. F., Safdar, W., & Ashraf, I. (2023). Effect of temperature, pH, salinity and dissolved oxygen on fishes. *Journal of Zoology and Systematics*, 1(2), 1-12. <https://doi.org/10.56946/jzs.v1i2.198>

Mondal, R., Azmi, S. A., Sinha, S., Bose, C., Ghosh, T., Bhattacharya, S., & Tyagi, B. K. (2025). Ecology and Behavior. In *Mosquitoes of India* (pp. 239-276). CRC Press.

Mössinger, J., Troost, C., & Berger, T. (2022). Bridging the gap between models and users: A lightweight mobile interface for optimized farming decisions in interactive modeling sessions. *Agricultural Systems*, 195, 103315. <https://doi.org/10.1016/j.agsy.2021.103315>

Mustapha, U. F., Alhassan, A. W., Jiang, D. N., & Li, G. L. (2021). Sustainable aquaculture development: a review on the roles of cloud computing, internet of things and artificial intelligence (CIA). *Reviews in Aquaculture*, 13(4), 2076-2091. <https://doi.org/10.1111/raq.12559>

Nazneen, S., Raju, N. J., Madhav, S., & Ahamad, A. (2019). Spatial and temporal dynamics of dissolved nutrients and factors affecting water quality of Chilika lagoon. *Arabian Journal of Geosciences*, 12(7), 243.

Prapti, D. R., Mohamed Shariff, A. R., Che Man, H., Ramli, N. M., Perumal, T., & Shariff, M. (2022). Internet of Things (IoT)-based aquaculture: An overview of IoT application on water quality monitoring. *Reviews in Aquaculture*, 14(2), 979-992. <https://doi.org/10.1111/raq.12637>

Rastegari, H., Nadi, F., Lam, S. S., Ikhwanuddin, M., Kasan, N. A., Rahmat, R. F., & Mahari, W. A. W. (2023). Internet of Things in aquaculture: A review of the challenges and potential solutions based on current and future trends. *Smart Agricultural Technology*, 4, 100187.

Saiz-Rubio, V., & Rovira-Más, F. (2020). From smart farming towards agriculture 5.0: A review on crop data management. *Agronomy*, 10(2), 207. <https://doi.org/10.3390/agronomy10020207>

Tenório, G. S., Cintra, I. H. A., de Oliveira Alves, P. J., da Costa, R. M., Rodrigues, T. D. N. M., & Bentes, B. S. (2022). A pesca do camarão pelágico aviú Acetes paraguayensis na Amazônia oriental brasileira. *Boletim do Instituto de Pesca*, 48. <https://doi.org/10.20950/10.20950/1678-2305/bip.2022.48.e660>

Tina, F. W., Afsarimanesh, N., Nag, A., & Alahi, M. E. E. (2025). Integrating AIoT technologies in aquaculture: a systematic review. *Future Internet*, 17(5), 199. <https://doi.org/10.3390/fi17050199>

Walter, C., McBratney, A. B., Douaoui, A., & Minasny, B. (2001). Spatial prediction of topsoil salinity in the Chelif Valley, Algeria, using local ordinary kriging with local variograms versus whole-area variogram. *Soil Research*, 39(2), 259-272. <https://doi.org/10.1071/SR99114>

Wang, L. (2024). Advances in monitoring and managing aquatic ecosystem health: integrating technology and policy. *International Journal of Aquaculture*, 14.

Wang, Z., Chen, Z., Shahid, I., Asif, Z., & Haghigat, F. (2025). Indoor Air Quality Assessment Through IoT Sensor Technology: A Montreal–Qatar Case Study. *Atmosphere*, 16(5), 574. <https://doi.org/10.3390/atmos16050574>