



Dynamic Modeling of Temperature and Moisture Interactions During Poultry Litter Composting Under High-Altitude Climatic Conditions

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ABSTRACT

The quantitative data-driven modeling approach was employed to study the temperature and humidity behavior during poultry litter composting under high-altitude climatic conditions. For the analysis, 7,378 observations from two experimental composting data sets were used, which included temperature, humidity, temporal measurements and heating and aeration control variables. Process variations and predictive performances were analyzed by descriptive statistics, temporal analysis, correlation analysis and autoregressive modeling with exogenous inputs (ARX). The average compost temperatures in Experiment 1 and 2 were 34.67°C and 30.43°C respectively. For both temperature and recorded humidity, the negative correlations of $r = -0.230$ and -0.815 , respectively, were found, which are experiment-specific and primarily related to the broader temporal trends. Heating and aeration setups were correlated with differences in composting conditions, but causal relationships were not determined. Both ARX models had strong performance in short-term temperature forecasting with R^2 equal to 0.829 for ARX(1) and 0.931 for ARX(2), with RMSE of 0.328°C and 0.399°C respectively, while in this case the performance of the ARX models was better than that of the persistence models; however, there was limited improvement for humidity forecasting. The results indicate that dynamic modelling is a promising tool to monitor the temperature of the composting process and to help manage the process. Additional studies using direct moisture measurements and independent validation are suggested.

Keywords: Poultry litter composting; Temperature dynamics; Humidity interactions; High-altitude conditions; Autoregressive modeling

1. Introduction

Poultry litter composting is an important bio-waste management process that converts poultry manure, litter materials, and other organic wastes to stabilized organic amendments. Good composting reduces waste, enhances nutrient cycling, and promotes sustainable farming. Poultry litter, however, is a rich source of organic matter and nitrogen, and needs to be decomposed by microbes; a suitable environment is necessary for it to decompose efficiently. The following factors influence composting performance: aeration, temperature, moisture availability, and microbial activity. It has been shown that biochar enhances nutrient holding capacity and lowers environmental emissions during poultry manure composting (Awasthi et al., 2020). Likewise, optimizing operating parameters and microbial conditions improve the quality of organic waste stabilization and compost (Bian et al., 2019; Huang et al., 2022). These results highlight the need to comprehensively monitor and quantify the composting process.

Microbial activity, organic matter degradation and compost stabilization are all controlled by fundamental variables: temperature and moisture. Temperature is a reflection of biological heat generation which dictates the progression of mesophilic and thermophilic stages. Microbial metabolism, nutrient transport, and biochemical reactions are enhanced by moisture availability and hampered by excess moisture, which inhibits oxygen diffusion and decomposition efficiency. According to experimental studies, moisture status plays a crucial role in the chicken manure stabilization process and microbial activities (M.-X. Li et al., 2021). The transformation of N and compost maturity are also influenced by microbial processes which are dependent on temperature (Y. Li et al., 2022; Liu et al., 2024). In addition, sensor-based monitoring methods offer a platform to assess moisture dynamics and enhance composting management (Moncks et al., 2022). The interaction between temperature and moisture is thus a critical aspect to understand if reliable predictive models are going to be created and composting conditions are going to be favourable.

In high altitude areas, other factors affect decomposition, such as relatively low ambient temperatures, fluctuating atmospheric factors and increases in environmental heat losses. Keeping the internal temperature high is especially important when sustaining microbial activity and effectiveness of organic matter stabilization. Composting under cold weather conditions has been studied, and it is noted that thermal management and operating changes are essential for the efficient decomposition (Margina et al., 2023). But the climatic exposure, insulation and aeration needs can be different among composting systems. Therefore, it is essential to understand how the temperature changes over time and how these changes relate to humidity and operating parameters to assess poultry litter composting at high altitude.

Dynamic modelling offers a quantitative description of temporal changes of variables in a compost and inspection of interactions between biological processes and operating factors. The aerobic composting behaviour has been shown to be represented by mathematical models, which take into account heat transfer, mass transport and microbial kinetics (He et al., 2018). Likewise, process-oriented models have been used to interpret organic waste decomposition and operating conditions (Ghinea et al., 2019). These methods have been expanded in recent years by using machine learning, predicting temperature, and through automated monitoring systems (Ding et al., 2022; Gurla Venkata Kameswari et al., 2025). Dynamic process representation is also shown to be significant in temperature modeling with microbial kinetics and aeration conditions (Lai et al., 2025). The identification of such systems has also been directly applied in the case of composting poultry litter in the context of high-mountain conditions, laying a relevant methodological ground (A. A. Patiño-Forero et al., 2025).

While there have been some studies on the optimization of composting, moisture control in composting, prediction of composting temperature, and process monitoring, more investigation needs to be done to better understand the relationships between recorded temperature, humidity, and operational control variables in poultry litter composting at high altitude. Humidity measurement, specifically differentiating it from the real compost moisture content, is still significant for a reliable interpretation. The current study seeks to analyze the temporal changes and statistical correlation of temperature and measured humidity during the composting of poultry litter and to create and test dynamic models that describe the temperature–humidity relationships and responses to heating and aeration controls in the context of an experimental environment at high altitudes, building upon previous system-identification studies. The study aims to provide data-informed composting management via interpretable dynamic analysis and prediction assessment.

2. Materials and Methods

2.1. Dataset Description and Experimental Conditions

A quantitative, data-driven approach was used in the study, leveraging experimental poultry litter composting data obtained in high-altitude environments (Patiño-Forero et al., 2025). The data set consisted

of two experiments with 4302 and 3076 observations and a total of 7378 observations. Compost pile temperature, heater temperature, humidity, air input, heating input and temporal measurements were recorded. In Experiment 2 oxygen measurements were also available. The variables were used to explore composting dynamics and operational responses (A. Patiño-Forero, 2024).

2.2. Data Preprocessing and Quality Assessment

Data were checked for missing data, duplicate records, inconsistent timestamps, and sensor anomalies. Errors in oxygen values, humidity beyond physically meaningful range, and discontinuities in experimental time were found during quality assessment. The variables of heating control were kept constant in all the experiments. Chronological ordering was verified, and discontinuous observations were not used in analyses where a continuous sequence of time is required. Wherever feasible, original measurements were preserved.

2.3. Temperature, Humidity, and Temporal Variable Analysis

Temperature and humidity measurements were characterized using descriptive statistics such as mean, standard deviation, minimum and maximum. Time series analysis was used to examine the changes in compost pile temperature, heater temperature, and recorded humidity. Statistical summaries and temporal visualization were used to examine experimental differences, temperature changes, and moisture changes. Humidity was not measured as an absolute measurement of compost moisture, but rather as an indicator of moisture.

2.4. Development of the Dynamic Modeling Framework

A multivariate autoregressive model with exogenous inputs (ARX) was suggested to describe the dynamism of the composting process. In addition to heater temperature, air input and heating input, lagged temperature and humidity observations were added to the prediction of the following process conditions. The parameters of the model and the order of lags were to be estimated based on the chronological observations with quality control. Separate experimental models were considered to deal with the differences arising in the recording periods and in the availability of measurements.

2.5. Analysis of Temperature–Humidity Interactions

Pearson correlation, Spearman correlation and cross-correlation analysis were used to evaluate the temperature–humidity relationships. The strength, direction, and temporal lag of the relationship between compost temperature and the humidity recorded were evaluated using these methods. The lagged variables were added to the dynamic models to investigate if the humidity conditions before the prediction improved the temperature predictions and vice versa.

2.6. Evaluation of Heating and Aeration Control Effects

The recorded control-state variables were used to determine the heating and aeration effects. The temperature and humidity responses were compared between the different observed operating configurations: the inactive control, aeration only and heating + aeration. The effects of control-state changes over time were investigated to establish relationships between the operational condition and the composting. These comparisons were understood as a relationship between two observations, not as cause and effect.

2.7. Model Validation and Statistical Performance Evaluation

Chronological observations of training and test periods were used to avoid temporal information leakage for the construction of the dynamic models. The predictive performance was evaluated using average absolute error (AAE), root mean square error (RMSE), and coefficient of determination (R^2). Observed and predicted temperature and humidity values were compared and the prediction errors were evaluated by residual analysis. The performance of the model was also contrasted to a persistence baseline to identify performance gains.

3. Results

3.1. Descriptive Characteristics of the Composting Dataset

A total of 7,378 data points were obtained, 4,302 from Experiment 1 and 3,076 from Experiment 2. The measurements of compost pile temperature, heater temperature, humidity and control of operation for both experiments. Oxygen was also measured in Experiment 2. For Experiment 2, a preliminary analysis found 286 values of humidity above 100% and 549 values of oxygen below zero, which raised questions about the quality of the measurements. The experiments were thus analysed separately to maintain differences in the conditions recorded and the measurement characteristics. Table 1 shows that the recorded humidity in Experiment 2 was higher than the average compost temperature in Experiment 1. The differences reflect variations in composting conditions in the two experimental records.

Table 1. Descriptive Statistics of Temperature, Humidity, and Oxygen Measurements

Experiment	Variable	Mean	SD	Minimum	Maximum
1	Compost temperature (°C)	34.67	5.37	24.70	44.90
1	Heater temperature (°C)	23.89	8.15	11.10	55.10
1	Humidity	51.65	20.69	20.40	92.30
2	Compost temperature (°C)	30.43	4.73	24.10	39.30
2	Heater temperature (°C)	26.37	8.24	11.80	50.40
2	Humidity	80.33	26.77	14.50	101.60
2	Oxygen	8.23	8.65	-19.00	20.00

3.2. Temporal Variations in Composting Temperature

Time analysis showed that there were differences in thermal patterns between the experiments. In experiment 1, the temperature of the compost gradually rose to around 44.9 C and then dropped with successive measurements. Experiment 2 had lower initial temperatures, then an increase to a temperature of about 39.3 C. Heater temperature exhibited short-period fluctuations with recorded operating cycles. Figure 1 shows that the compost temperature varied slowly compared with heater temperature, which suggests thermal persistence in the composting system.

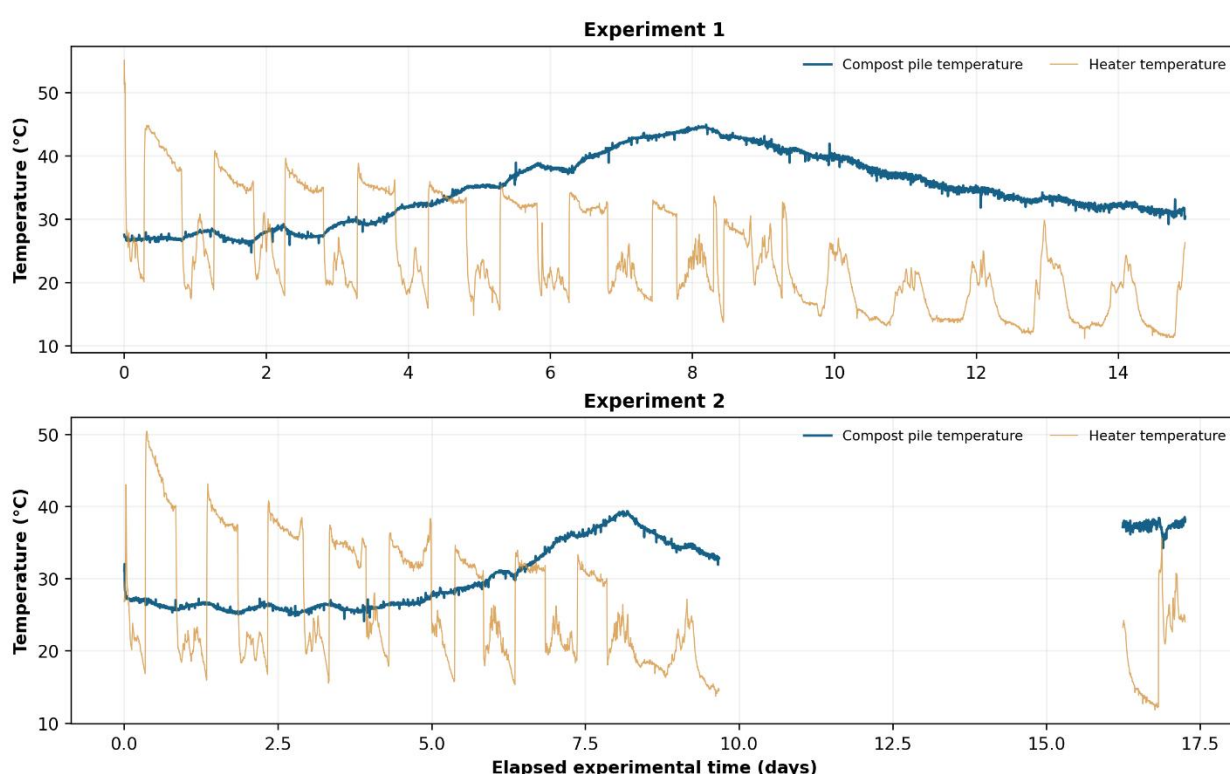


Figure 1. Temporal Variations in Compost Pile and Heater Temperature Across Two Experiments

3.3. Temporal Variations in Humidity Measurements

In both experiments, there was significant temporal variability in recorded humidity. Experiment 1 revealed that the average moisture of the plants decreased from 72.35 on days 1-5 to 26.55 on the later observed days. A similar downward trend was shown by Experiment 2, as the humidity readings ranging from 98.64 to 16.37 are valid results. But there were 286 readings in Experiment 2 that were above 100 which were not included in the valid-range summaries. The results indicate significant temporal variation in the measured humidity conditions as shown in Table 2, but cannot independently determine the change in compost moisture status.

Table 2. Temporal Distribution of Recorded Humidity During Poultry Litter Composting

Experiment	Observation Period	Valid Observations	Mean Humidity	SD	Readings Above 100
1	Days 1–5	1,444	72.35	9.40	0

1	Days 6–10	1,438	55.66	10.61	0
1	Days 11–15	1,420	26.55	3.26	0
2	Days 1–5	1,171	98.64	3.45	283
2	Days 6–10	1,329	73.84	18.17	3
2	Days 17–18	290	16.37	0.34	0

3.4. Relationships Between Temperature and Humidity

A negative correlation between the Compost temperature and humidity recorded was obtained. The Pearson correlation for Experiment 1 was found to be rather weak for a negative correlation value ($r = -0.230$), while for Experiment 2 the correlation was much more visible as a negative correlation ($r = -0.815$). The two Spearman correlations were -0.252 and -0.867 , respectively. Correlations between five-minute changes were weak, however (-0.011 and -0.005), suggesting that the strong correlations overall are mainly attributable to higher-level temporal relationships, and not to short-term fluctuations in the five-minute changes. Figure 2 shows the temperature–humidity relationships that were contrasted between the experiments.

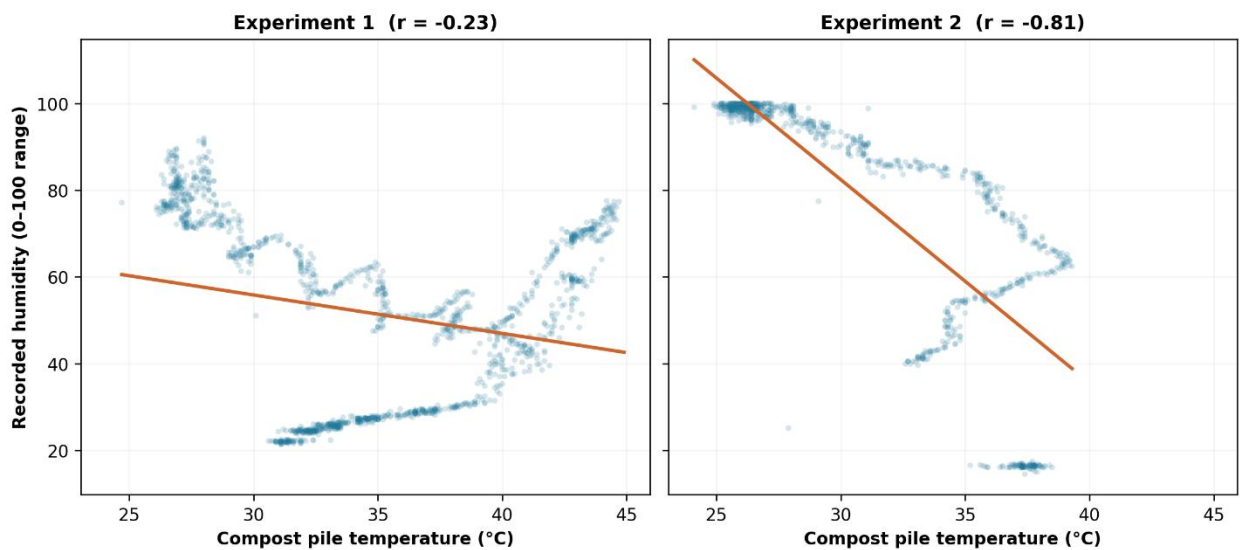


Figure 2. Relationships Between Compost Temperature and Recorded Humidity in Experiments 1 and 2

3.5. Effects of Heating and Aeration on Composting Dynamics

The three operational configurations that were recorded were used to evaluate heating and aeration conditions. The combined heating and aeration resulted in the compost having relatively high average humidity measurements for both experiments, while the highest average compost humidity measurement (42.33°C) occurred in Experiment 1 under the active aeration without heating. Table 3 shows the various compost conditions with operational configurations. These differences may, however, represent experimental timing, subliminal stages of composting and control responses and not separate causal effects of heating and aeration.

Table 3. Comparison of Composting Conditions Across Heating and Aeration Control States

Experiment	Air Input	Heating Input	Observations	Mean Compost Temp. ($^{\circ}\text{C}$)	Mean Valid Humidity
1	0	0	2,431	33.65	42.19
1	100	0	461	42.33	62.18
1	100	100	1,410	33.93	64.53
2	0	0	1,523	30.86	71.30
2	100	0	288	37.27	59.68
2	100	100	1,265	28.35	92.77

3.6. Dynamic Model Prediction Performance

Chronological partitions of 70%, 15%, and 15% were used for the training, validation and testing of the

autoregressive model with exogenous inputs (ARX). The lagged temperature, humidity, heater temperature and operational control measurements were used to fit ridge-regularized models. Five-minute lag times of 1, 2, 3, 6 and 12 were evaluated and chosen based on the evaluation of the mean absolute error for validation. The resulting models showed good short-term forecasting of temperature with values of $R^2 = 0.829$ and $R^2 = 0.931$, respectively, in Experiments 1 and 2. The models for humidity had R^2 values of 0.638 and 0.992, respectively, but their predictive errors were not consistently better than those of persistence-based predictions. Observed measurements versus one-step-ahead ARX predictions are displayed in Figure 3.

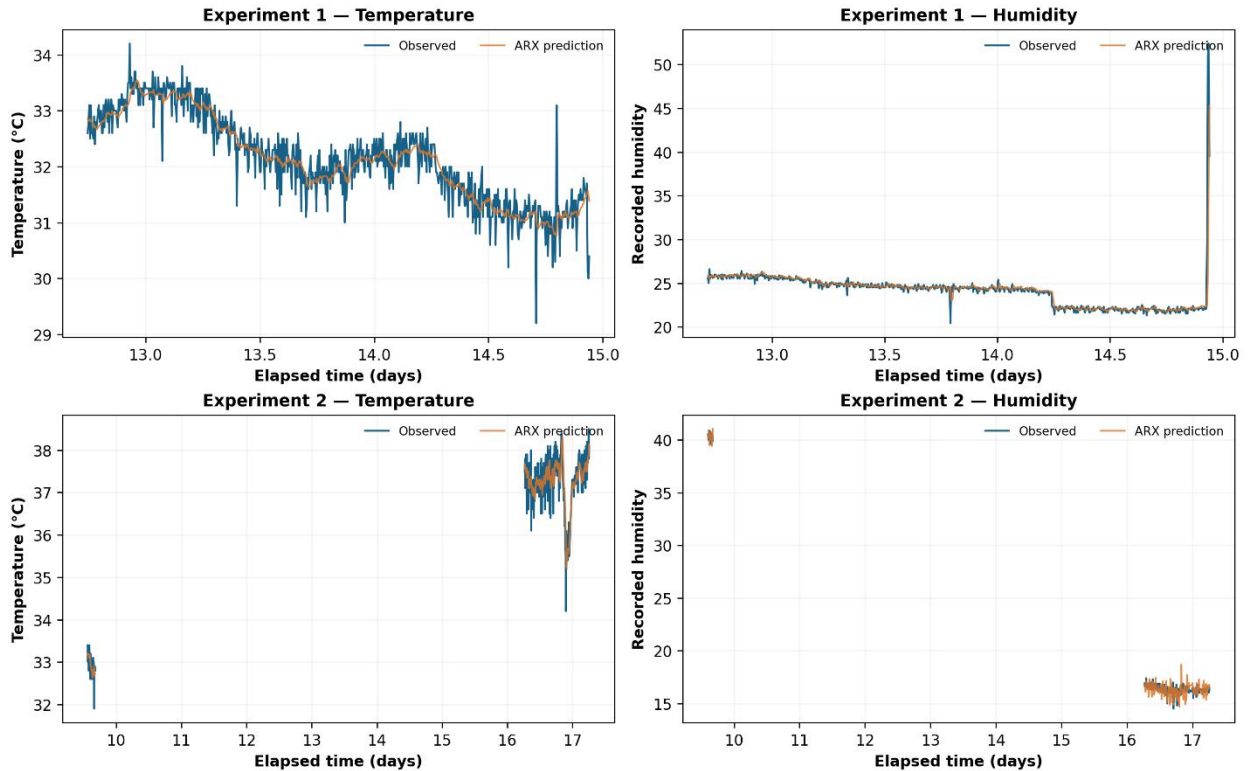


Figure 3. Observed and Predicted Temperature and Humidity Using the ARX Dynamic Model

3.7. Comparison of Observed and Predicted Temperature and Humidity

The performance of the proposed model was tested by comparing the model's prediction results with the experimental ones, showing that the behavior of the compost temperature in the short term is well predicted by the ARX framework and has relatively lower prediction errors. The findings of Experiment 1 were 0.328 °C, and Experiment 2 recorded 0.399 °C. These values were better than the persistence baselines of the same values. The results for the prediction of humidity were less consistent: the models developed relatively high coefficients of determination, but their RMSE values were higher than the persistence baselines in both experiments. The results are presented in Table 4 and confirm that dynamic modeling is appropriate for temperature prediction and further development of the model is needed for humidity prediction.

Table 4. Dynamic Model Prediction Performance and Comparison with Persistence Baseline

Experiment	Predicted Variable	Selected Lag	MAE	RMSE	R^2	Baseline RMSE
1	Temperature	12	0.242	0.328	0.829	0.435
1	Humidity	3	0.322	1.326	0.638	1.104
2	Temperature	6	0.309	0.399	0.931	0.487
2	Humidity	6	0.460	0.590	0.992	0.419

3.8. Model Accuracy, Residual Analysis, and Validation

The residual analysis showed that the prediction error from the temperature models was relatively low with the mean biases of 0.014°C and 0.032°C for Experiments 1 and 2, respectively. The first-order residual autocorrelation values were about -0.006 and 0.060, respectively, which show some residual short-term dependence. The level of humidity showed more residual variation, especially when drastic changes occurred in the recorded humidity. In Experiment 1, a first-order residual autocorrelation of 0.481 and 0.391

was found for the humidity models, indicating that there was still some unaccounted-for temporal structure. The residual distributions for most observations were approximately centered around zero with occasional larger errors as shown in Figure 4. These findings demonstrate that the proposed framework can be useful in short-term temperature forecasting, while it has limitations for humidity forecasting and generalization in changing experimental conditions.

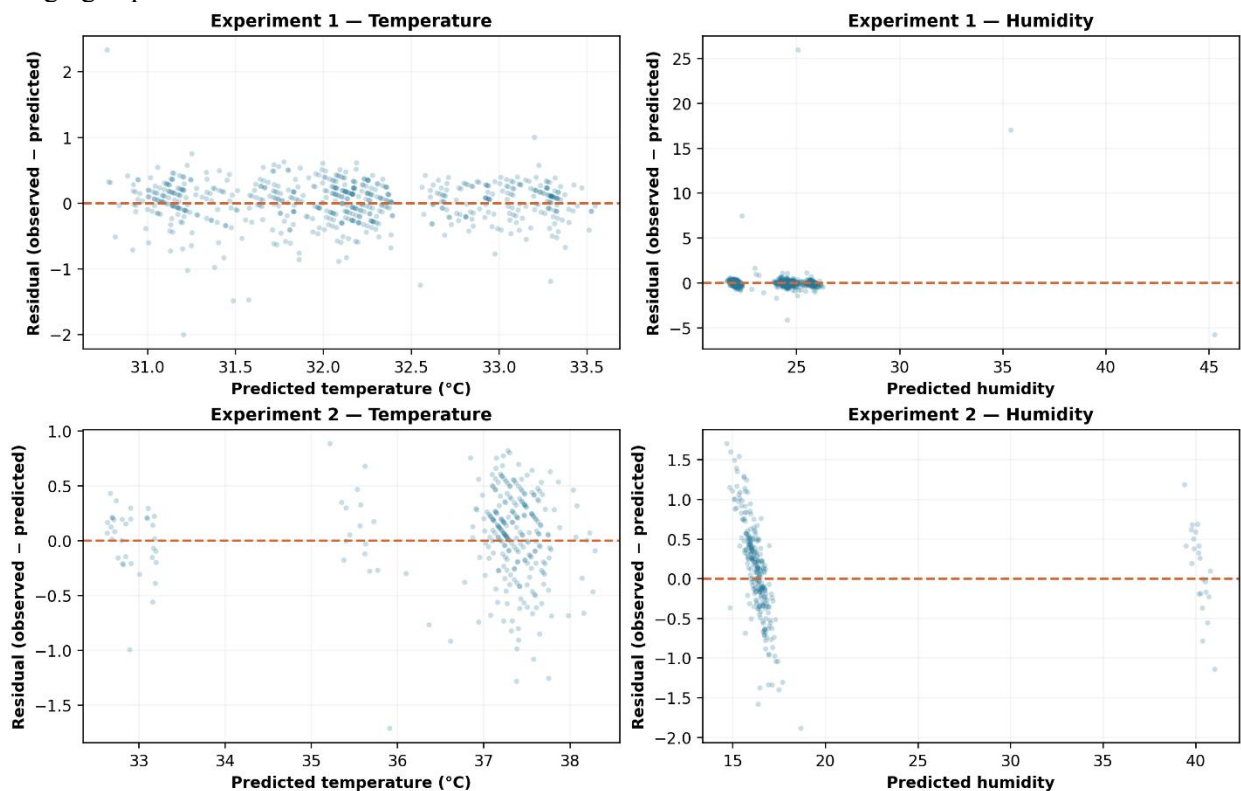


Figure 4. Residual Analysis of Temperature and Humidity Predictions Across Both Experiments

4. Discussion

The results established that there were significant differences between the two poultry litter composting experiments in terms of temperature dynamics. The mean compost temperature was 34.67°C for Experiment 1 and 30.43°C for Experiment 2, reflecting different thermal conditions and process development. The temperature changes are gradual, indicating that heat buildup and dissipation are occurring in the composting system. The control of temperature is especially crucial as this is the site of microbial decomposition which is dependent on temperature conditions. It has been proven from previous investigations that the temperature developed in the poultry manure composting depends on the configuration of the reactors and aeration (Qasim et al., 2018, 2019). In addition, microbial activity and organic matter transformation drive composting progress but were not directly measured in the current data set (W. Wan et al., 2020; W. Wang et al., 2025).

Negative temperature-humidity correlations were found in both experiments; greater correlations were found in Experiment 2 ($r = -0.815$) than Experiment 1 ($r = -0.230$). The results show that the humidity recorded tended to decrease as the temperature of the compost increased, but that the relationships were not as strong over short time periods. The availability of temperature and moisture is closely related and affects the metabolism and decomposition of microorganisms and organic wastes. Sun et al. found that pre-treatment moisture influenced the microbial community and composting results in low-temperature composting (Sun et al., 2024). Likewise, the addition of organic amendments affects the physicochemical conditions of poultry manure composting (Ravindran et al., 2022). The present results, however, do not reflect actual compost moisture or biological stability, but rather temperature-humidity correlations.

The differences in compost temperature and humidity were observed in the different heating and aeration setups during the operational analyses. Aeration alone gave the highest mean compost temperatures in both experiments and combined heating and aeration showed a clear response in humidity. The differences indicate that there was a difference in the composting environment due to the operational controls. The optimization of the process and mathematical modelling were previously stressed as means of optimising composting performance (Sokač et al., 2022). But the observed relationships do not provide evidence of

independent causal effects since there was no full separability of heating and aeration in the data set. So operational responses need to be considered in the context of temporal change and experiments.

The results offer informative indications for monitoring composting processes at high altitudes, where favourable thermal conditions difficult to achieve. Strong prediction of temperature was obtained in the two experiments in the dynamic modeling framework, with R^2 values of 0.829 and 0.931. This predictive capability can be helpful for better monitoring and decision-making regarding the operations. Studies of naturally low-temperature composting have highlighted the significance of microbial adaptation and process management (Y. Wang et al., 2024). Additionally, the management of sustainable composting actions must be suitable monitored by adopting proper optimization actions that will enhance resource recovery (PolICASTRO & Cesaro, 2022). However, the effects of climate on the environment cannot be separated out to be quantifiable.

The predictive results are consistent with previous work showing the effectiveness of mathematical and machine-learning methods to assess composting processes. The mathematical models give a basis to understand how the temporal system works and how the systems interact. Machine learning applications have also been shown to predict compost maturity and identify influential process variables (X. Wan et al., 2022; B. Wang et al., 2024). Likewise, predictive models have been used to estimate environmental effects, such as ammonia emissions and global warming potential (Y. Wang et al., 2024). The present analysis focused on short-term temperature and humidity forecast, however, not on compost maturity or emissions results.

The major constraints were the lack of clarity in definitions of humidity, sensor anomalies, lack of time continuity of observations, and incomplete climatic measurements. The ARX models performed better than persistence baselines in temperature prediction, but the prediction of humidity did not always outperform the baseline. In addition, the results were limited to two experimental records, so generalizations were not possible. Directly measured compost moisture, ambient climatic conditions, microbial activity and compost maturity indicators should be included in future research. Back validation of the models in independent composting tests and other modeling methods enhances predictive reliability and usefulness.

5. Conclusion

The present study aimed to examine the dynamics of temperature and humidity recorded during the composting of poultry litter in the experimental high-altitude conditions through two monitoring sets with a total of 7,378 observations. The mean compost temperature was higher in experiment 1 (34.67 °C) compared to experiment 2 (30.43 °C) while the recorded humidity was higher in experiment 2. There was a negative correlation between temperature and humidity in both experiments, the strongest being that between successive changes in Experiment 2 ($r = -0.815$), indicating that larger temporal changes were associated with this correlation. There were differences in compost temperature and humidity associated with heating and aeration control states, but causal relationships could not be determined. One-step-ahead autoregressive models with exogenous inputs yielded accurate temperature forecasts with test R^2 of 0.829 and 0.931, and lower prediction errors than persistence forecasts. However, in contrast, the humidity models had favorable R^2 values but they did not consistently outperform the baseline models. These results provide further evidence that dynamic models could be used for short-term monitoring of thermal behavior and assessing operational responses for litter composting in poultry. But, interpretation is limited by lack of ambient climatic data, sensor anomalies, temporal discontinuities, and uncertainty about the humidity measurement. Future research should include direct measurements of compost moisture and include climate factors and independent experimental testing to strengthen the process understanding and the model reliability.

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