Correction of Sensible Heat Flux from Flux-Gradient Method to Eddy Covariance Method Based on Multi-Layer Perceptron

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Abstract. Understanding surface-atmosphere interactions is critical for environmental and meteorological studies. Sensible heat flux, a key component in this interaction, is typically measured using methods such as Eddy Covariance (EC) and Flux-Gradient (FG). The EC method, known for its high temporal resolution and direct measurement capabilities of wind speed, temperature, and humidity changes, requires the use of expensive and complex equipment, making it costly and challenging to implement. On the contrary, the FG method is more accessible and economical, relying on simpler instruments, but often lacks the precision of the EC method. To harness the benefits of both methods, this article uses the Multi-Layer Perceptron (MLP) machine learning method to enhance the accuracy of the FG method's sensible heat flux calculations. Through the MLP model, this paper aims to determine the optimal parameter settings for the specific measurement environment, thereby improving the FG method’s accuracy. The data was measured from Guandu Village, Anhui Province, China. This research seeks to demonstrate that the trained MLP model can be applied to similar measurement environments, thus enhancing the FG method's applicability and precision.

Keywords: sensible heat flux, eddy covariance method, flux-gradient method, multi-layer perceptron.

1. Introduction

The measurement of sensible heat flux is crucial for understanding surface-atmosphere interactions, which play a significant role in various environmental and meteorological processes. Sensible heat flux is a key component of the surface energy balance, which governs the exchange of energy between the Earth's surface and the atmosphere [1].

The Eddy Covariance (EC) method has been regarded as a significant approach for measuring sensible heat flux due to its ability to directly capture instantaneous variations in wind speed, temperature, and humidity [2]. This method offers high-temporal resolution data, providing detailed insights into micrometeorology. However, the EC method requires sophisticated and expensive equipment, such as three-dimensional ultrasonic anemometers and high-speed gas analyzers, which can be both costly and challenging to maintain [3-5]. In contrast, the Flux-Gradient (FG) method offers a more accessible alternative. It relies on relatively simple equipment, typically involving sensors for temperature, humidity, and wind speed positioned at two or more heights. The simplicity and costeffectiveness of the FG method make it an appealing option, especially for long-term and widespread implementation [4-5]. However, the FG method often compromises on accuracy and temporal resolution compared to the Explicit Central (EC) method.

To combine the strengths of both methods, this study explores the integration of a multi-layer perceptron (MLP) machine learning approach to enhance the FG method's accuracy. By using the high-resolution data from the EC method to train the MLP model, this paper aims to correct the sensible heat flux values calculated by the FG method on a 10-minute interval basis. This correction process will involve determining the optimal parameter settings for the MLP model within the specific measurement environment, ensuring that the model can adjust the FG method's results.

The ultimate goal is to improve the precision of the FG method's flux calculations, thereby establishing it as a more practical and cost-efficient option for diverse applications.

2. Materials and Methods

2.1. Materials, Eddy Covariance Method and Flux-gradient Method

The original data was measured from June 12th to June 25th, 2019, in Guandu Village, Anhui Province, China.

The sensible heat flux calculated by the EC method is expressed as:

$$H_{EC} = \rho C_p \overline{w'\theta'} \tag{1}$$

where $\rho = 1.16\ \mathrm{kg/m^3}$, is the air density. $C_p = 1004.0\ \mathrm{J/kg \cdot K}$ is the specific heat at a constant pressure of moist air. $\overline{w'\theta'}$ is the covariance between vertical velocity fluctuations and potential temperature fluctuations. This covariance is calculated every 10 minutes in this study. In this experiment, air temperature T is used to replace the potential temperature θ.

The sensible heat flux calculated by the FG method is expressed as:

$$H_{FG} = -\rho C_p u^* \theta^* \tag{2}$$

The Obukhov stability function for heat is represented by ϕ_h, for momentum is denoted as ϕ_m using a neutral condition to start calculation ($\phi_m = \phi_h = 1$), u* (friction velocity) and θ* (also use T instead of θ) are calculated by gradient relationship, the von Kármán constant (k) is 0.4, the geometric mean height is denoted as z_g [5].

The equations $u^* = k\frac{z_g}{\phi_m}\frac{\partial \bar{u}}{\partial z} = k\frac{z_g}{\phi_m}\frac{\bar{u}_2 - \bar{u}_1}{z_2 - z_1}$; $\theta^* = k\frac{z_g}{\phi_h}\frac{\partial \bar{\theta}}{\partial z} = k\frac{z_g}{\phi_h}\frac{\bar{\theta}_2 - \bar{\theta}_1}{z_2 - z_1}$; and $z_g = z - d$ use L (Monin Obukhov Length) to determine stability, which is denoted by $L = \frac{\bar{\theta} u^{*2}}{kg\theta^*}$, where $L > 0{:}\ \phi_m = \phi_h = 1 + 5\frac{z_g}{L}$; $L < 0{:}\ \phi_m = (1 - 16\frac{z_g}{L})^{-\frac{1}{4}}$, $\phi_h = (1 - 16\frac{z_g}{L})^{-\frac{1}{2}}$ [5]. And then, repeat the calculation until the difference between u^*_{new} and u^*_{old} is less than 1×10^{-1}.

2.2. Multi-Layer Perceptron from Machine Learning

To harness the benefits of both EC and FG methods, this paper uses the multi-layer perceptron (MLP) machine learning approach to enhance the accuracy of the FG method's sensible heat flux calculations. The MLP model, a type of artificial neural network, is capable of capturing complex, non-linear relationships between input features and the target variable, making it suitable for this task [6].

This study implements an MLP model to correct sensible heat flux from the FG method. Excluding the dates that collected some incorrect data values, the data (1008 samples) on June 12th, 13th, 20th, 21st, 22nd, 24th, and 25th are used as training (80%) and validation(20%) set, and the data (1008 samples) on June 14th, 15th, 16th, 18th, 19th, 23rd (incorrectly collected data on 14th, 15th and 18th) are used as testing sets to yield the corrected sensible heat flux from FG to EC method and evaluate the performance of the model. The input features included the hour of the day and the sensible heat flux measured by the FG method. The output feature is the sensible heat flux measured by the EC method. The model was trained with 2 hidden layers with 100 neurons each. The maximum number of iterations was set to 500 to ensure convergence.

3. Analysis and Results

3.1. Evaluation of Corrected Sensible Heat Flux from MLP Model

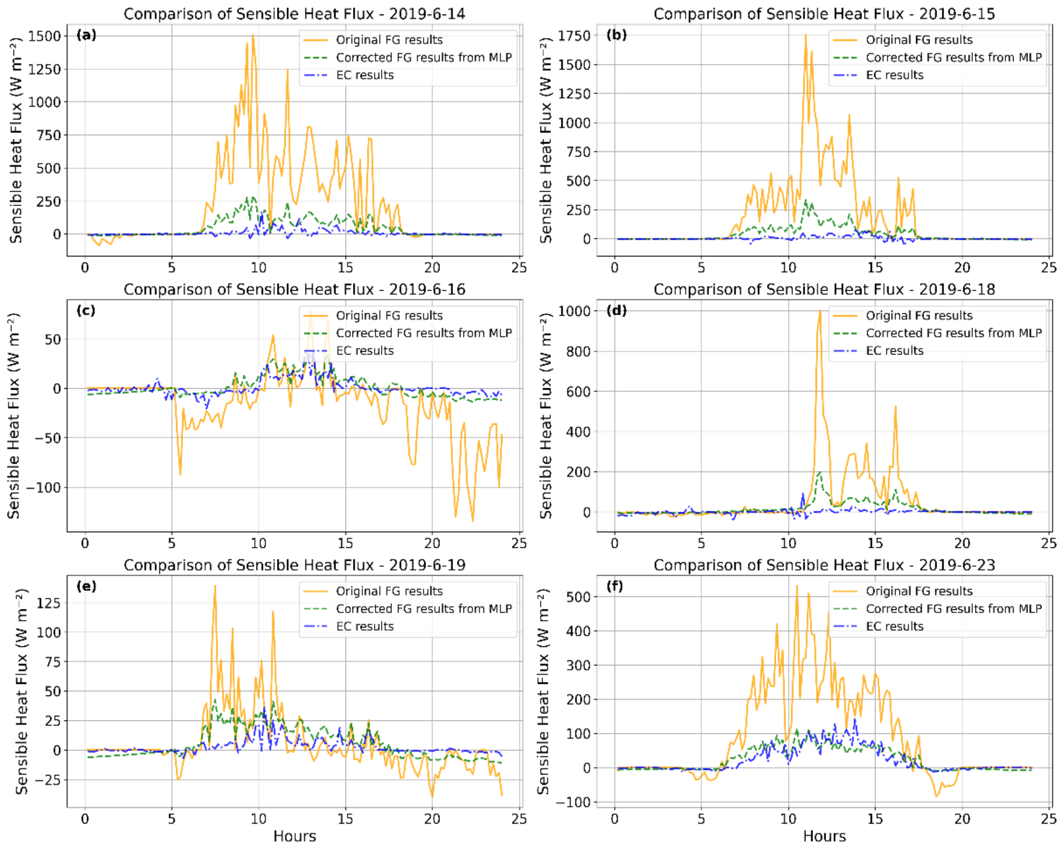

Figure 1. Comparison of sensible heat flux of original FG, corrected FG and EC

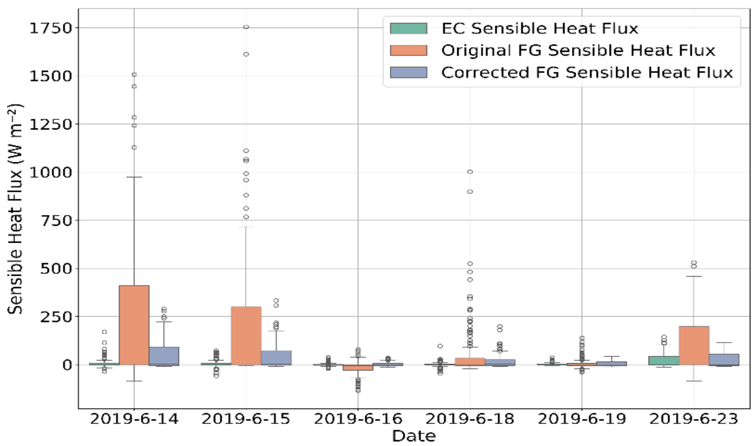

Figure 2. Box plot of sensible heat flux of original FG, corrected FG and EC

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The original FG sensible heat flux (orange line) shows evident discrepancies compared with EC results (blue line) on June 16th (Figure 1c), 19th (Figure 1e), and 23rd (Figure 1f). Besides, the original FG sensible heat flux (orange line) showed significantly unreasonable peaks (greater than 1000 W/m²) on June 14th (Figure 1a), 15th (Figure 1b), and 18th (Figure 1d) due to incorrectly collected data at the beginning.

After applying the trained model, on dates where the data were rightly measured, such as June 16th (Figure 1c), 19th (Figure 1e), and 23rd (Figure 1f), the corrected sensible heat flux data (green line) aligns much better with the EC computed results (blue lines), indicating improved consistency. The effectiveness of the MLP model is also evident on dates with original incorrect data collection, such as June 14th (Figure 1a), 15th (Figure 1b), and 18th (Figure 1d). On these dates, the significantly unreasonable peak values are corrected by the MLP model and provide more reasonable and sensible heat flux values. Although there are still discrepancies between the corrected flux data and those obtained by using the EC method, there has been a significant improvement. Studies have shown that MLP models are effective in correcting meteorological data discrepancies and improving accuracy. For instance, the advantages of machine learning models in correcting and predicting atmospheric data have been approved, such as fluxes for heat and momentum in unstable conditions [7]. This enhanced accuracy is critical for improving the reliability of meteorological data, particularly in operational applications where precise flux measurements are essential.

From Figure 2, it is evident that after applying the MPL model, the original FG sensible heat flux outliers (orange box) which are greater than 1000W/m² on June 14th, 15th, and 18th had a significant reduction to less than 400W/m². For instance, on June 14th, the outliers of the original sensible heat flux exceeded 1500W/m², but after model correction, the outliers dropped to approximately 250W/m², indicating a substantial decrease. However, there are visible discrepancies compared to the sensible heat flux results calculated using the EC method (green box). This suggests that the trained MPL model still does not adequately correct excessive outliers, potentially due to an insufficient amount of training and validation sets. From Figure 2, on June 16th, 19th, and 23rd, it can be seen that for the original sensible heat flux obtained from accurate data collection and calculation, the trained MPL model exhibits good correction performance. This demonstrates that the MPL model has the potential for application in flux data correction [8]. Overall, the application of the MLP model results in a more accurate and consistent alignment of the sensible heat flux with the EC method, reducing errors and improving the quality of the data. This underscores the potential of machine learning techniques in refining and correcting meteorological data, ensuring better prediction and analysis capabilities.

3.2. Root Mean Square Error Comparison

Table 1. RMSE between the original FG and EC sensible heat flux and the corrected FG and EC sensible heat flux

Date	Original FG vs EC RMSE	Corrected FG vs EC RMSE
2019-6-14	400.55	76.44
2019-6-15	364.65	70.75
2019-6-16	34.79	7.73
2019-6-18	155.42	35.85
2019-6-19	25.20	10.90
2019-6-23	128.16	21.38

Root Mean Square Error (RMSE) measures the standard deviation of the prediction errors. This study assumes the corrected sensible heat flux from the MPL model as the prediction value and EC sensible heat flux as the true value. A lower RMSE indicates better model performance.

The RMSE can be calculated through $\mathrm{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_p)^2}$.

Table 1 provides a detailed comparison of the RMSE between the original FG and EC sensible heat flux, as well as the corrected FG and EC sensible heat flux over June 14^{th}, 15^{th}, 1^{6th}, 18^{th}, 19^{th}, and 23^{rd} (dates generated data as testing sets). The analysis highlights the effectiveness of the MLP model in reducing errors and improving the accuracy of sensible heat flux measurements.

Overall, the RMSE values for the corrected FG sensible heat flux are consistently smaller than those for the original FG sensible heat flux, indicating that the MLP model significantly reduces the discrepancies between the FG and EC sensible heat flux values.

In Table 1, for the dates that had incorrect data measurement, the MLP model's correction is particularly effective. The RMSE between the original FG and EC sensible heat fluxes are 400.55, 364.65 and 155.42 on June 14^{th}, 15^{th}, and 18^{th} respectively. The RMSE between the corrected FG and EC sensible heat flux are 76.44, 70.75, and 35.85 on June 14^{th}, 15^{th}, and 18^{th} respectively. In addition, the effect of the reduction of RMSE is also dominant on dates (June 16^{th}, 19^{th}, and 23^{rd}) with correct data collection.

The analysis confirms that the MLP model is highly effective in correcting sensible heat flux data. By significantly lowering the RMSE, the corrected FG data aligns much more closely with the EC method's computed results. This consistency is crucial for improving the reliability and accuracy of meteorological data supporting existing literature on the advantages of machine learning models in atmospheric data correction and highlighting the MLP model's potential to enhance data accuracy.

4. Conclusion

This study demonstrates the effectiveness of integrating the Multi-Layer Perceptron (MLP) machine learning model to enhance the accuracy of the Flux-Gradient (FG) method for sensible heat flux calculations, by utilizing the sensible heat flux data from the Flux-Gradient (FG) method and the Eddy Covariance (EC) method on June 12^{th}, 13^{th}, 20^{th}, 21^{st}, 22^{nd}, 24^{th}, and 25^{th} as the training and validation set. The analysis of the corrected FG sensible heat flux on June 14^{th}, 15^{th}, 16^{th}, 18^{th}, 19^{th}, and 23^{rd} indicates that the MLP model significantly reduces discrepancies between the FG and EC methods. The corrected FG sensible heat flux values showed an improved alignment with the EC method, as evidenced by lower Root Mean Square Error (RMSE) values. Despite these improvements, the MLP model still shows some limitations in fully correcting excessive outliers, likely due to an insufficient amount of training and validation set. On June 14^{th}, 15^{th}, and 18^{th}, although the magnitude of outliers has already significantly reduced, it still has not been adequately corrected. Overall, the integration of MLP models with traditional FG measurements presents a promising approach to enhance the accuracy and reliability of sensible heat flux measurements, offering a scalable and cost-effective solution for various environmental and meteorological applications.

In summary, with the use of sufficient and accurate data to train the MPL model, a more optimal model can be achieved, which can be effectively utilized in real-life scenarios.

References

[1] Thakur, G., Schymanski, S.J., Mallick, K. et al. (2022) Downwelling longwave radiation and sensible heat flux observations are critical for surface temperature and emissivity estimation from flux tower data. Sci. Rep., 12: 8592. https://doi.org/10.1038/s41598-022-12304-3.

[2] Moncrieff, J. B., Massheder, J. M., de Bruin, H., Elbers, J., Friborg, T., Heusinkveld, B., Kabat, P., Scott, S., Soegaard, H., & Verhoef, A. (1997) A system to measure surface fluxes of momentum, sensible heat, water vapour and carbon dioxide. Journal of Hydrology, 188-189: 589–611. https://doi.org/10.1016/s0022-1694(96)03194-0.

[3] Siebicke, L. and Emad, A. (2019) True eddy accumulation trace gas flux measurements: proof of concept. Atmos. Meas. Tech., 12: 4393–4420. https://doi.org/10.5194/amt-12-4393-2019.

[4] Arya, P. S. (2001) Introduction to Micrometeorology. Elsevier.

[5] Lee, X. (2023) Fundamentals of Boundary-Layer Meteorology. Springer.

[6] Anwar Faizaan Reza, Singh, R., Rohit Kumar Verma, Singh, A., Ahn, Y.-H., & Saikat Sinha Ray. (2024) An integral and multidimensional review on multi-layer perceptron as an emerging tool

in the field of water treatment and desalination processes. Desalination, 586: 117849–117849. https://doi.org/10.1016/j.desal.2024.117849.

[7] Wulfmeyer, V., Pineda, J.M.V., Otte, S. et al. (2023) Estimation of the Surface Fluxes for Heat and Momentum in Unstable Conditions with Machine Learning and Similarity Approaches for the LAFE Data Set. Boundary-Layer Meteorol., 186: 337–371. https://doi.org/10.1007/s10546-022-00761-2.

[8] Xu, T., Guo, Z., Liu, S., He, X., Meng, Y., Xu, Z., Xia, Y., Xiao, J., Zhang, Y., Ma, Y., & Song, L. (2018) Evaluating Different Machine Learning Methods for Upscaling Evapotranspiration from Flux Towers to the Regional Scale. Journal of Geophysical Research: Atmospheres, 123(16): 8674–8690. https://doi.org/10.1029/2018jd028447.