Geoscientific

Model Development

Open Access

Discussions

EGU

GMDD

Interactive

comment

Interactive comment on "PM2.5 / PM10 Ratio Prediction Based on a Long Short-term Memory Neural Network in Wuhan, China" *by* Xueling Wu et al.

Xueling Wu et al.

wuxl@cug.edu.cn

Received and published: 16 December 2019

Manuscript number: gmd-2019-180 Xueling Wu *, Ying Wang, Siyuan He, Zhongfang Wu: "PM2.5 / PM10 Ratio Prediction Based on a Long Short-term Memory Neural Network in Wuhan, China". Dear editor and reviewer, We would like to thank you for the positive and constructive comments concerning our revised manuscript (ID: gmd-2019-180). These comments are all valuable and very helpful for revising and improving our paper. We have studied the comments carefully. Based on the comments, we have made corrections which we hope will meet with your approval. In the revised manuscript, all the corrections are marked in red. The responses to the reviewers'

comments are as follows (in blue font):

Responses to the Referee comment 2:

Point-by-point responses to the comments: 1. Comment: In particular, the authors should clarify the way they split their data. They state on line 271, "80% of the data were used as the training sample for modelling, and 20% of the data were used as the verification sample." It is important to specify how the hyper-parameters of their model were chosen. If they were chosen by optimising the performance against the verification dataset then it is possible that the algorithm has over-fit the hyper-parameters. Lines 272-274 seem to imply there was at least some hyper-parameter tuning performed. Ideally, the data should be split three ways, into a training, verification, and test, so that the hyper-parameters are tuned against the verification data, and the algorithm scored against the test data. The authors should reassure the reader that they have taken measures to ensure they have not overfit the hyper-parameters - for instance, perhaps they further split their training set. In addition, they state on line 279 that for Section 5.1 that there were 570 samples in the training data, and what I infer is 20 samples in the verification data (two days multiplied by ten sites, as per the training data). This appears not to be an 80%/20% split. In any case, the verification data are from one period in the season (end of December)-the algorithm may simply be good at predicting air quality in December but not the rest of the year. A more convincing approach would be to test against multiple cases from throughout the year. This is similar for the spatial prediction, which appears to only be tested at one site.

As such, the authors must reassure us that their approach to validation guards against overfitting in order for this to be suitable for publication. Response: Thank you for pointing this out. After considering your suggestions, we readjusted our model and code. Except for the data used for prediction, we divided the data set involved in the model construction into three parts: 40% of the data were used as the training samples for modeling, 30% of the data were used as the test samples, and the remaining 30% of the data was used as verification data. We tried to add a regularization term, but the

effect did not improve. After adjusting the number of neurons, the number of epochs, and the batch size, the loss function we obtained has converged without overfitting. Moreover, the revised model obtained higher prediction accuracy than the original one. We have generated the following learning curves for three prediction patterns, but in order to avoid the manuscript being too verbose, we do not intend to add the learning curve to the manuscript. The three curves in this figure are the losses of training samples, test samples and verification samples (train, test, and verifi) that increase with the number of epochs. We understand that our spatial and time prediction patterns do not completely cover the whole year and all regions, so we have added a random prediction pattern which randomly selects data from the whole year and the entire region for prediction to reduce fortuity of the other two prediction patterns. The correction is as follows (line 304-313):

Figure 1 Learning curves To determine the appropriate number of layers for the LSTM method, except for the data used for prediction, we divided the data set involved in the model construction into three parts: 40% of the data were used as the training samples for modeling, 30% of the data were used as the test samples, and the remaining 30% of the data was used as verification data. We tried to use various LSTM architecture layers for the comparison. After obtaining the results of various LSTM architecture layers, we found that the results obtained using the LSTM architecture with four layers were the best, with the first three layers and the dense layer as the last layer. The role of the dense layer is to complete the final output of unique values. Because the LSTM uses the activation function as the gate, the outputs of the gates must be between 0 and 1, and the output ranges of both types of activation functions must be satisfied. We determined that the activation function for setting the forget gate and the input gate was defined as a sigmoid function. After adjusting the number of neurons, the number of epochs, and the batch size, the loss function we obtained has converged without overfitting.

2. Comment: Could you discuss why you have focused on the PM2.5/PM10 ratio as

opposed to considering them separately? Response: Thank you for pointing this out. The explanation of using the PM2.5-PM10 scale is as follows (line 43-47): Since fine and coarse particles come from different sources, the PM2.5-PM10 scale model has different physicochemical properties, which can not only distinguish the type of aerosol in the PM but also provide the mixing ratio of dust and artificial aerosols (Sugimoto et al., 2015). The PM2.5-PM10 scale is the main indicator for macro analysis of the source of particulate pollution in a region, which is more practical than considering PM2.5 and PM10 separately.

3. Comment: line 75: "random precision", and Section 5.3 "random pattern prediction". Please could you clarify what this is - it was unclear to me. Are you randomly selecting a subset of points in space and then predicting them with the remaining, contemporaneous points? If so, how is this significantly different from the spatial prediction in Section 5.2? Please better explain this task near the beginning of the manuscript. Response: Thank you for pointing this out. We have added the explanation of these three prediction patterns to the Section 1-Introduction (line 80-84): The time precision mentioned in this article refers to the accuracy of inputting time-series data to predict the subsequent period results; the spatial precision refers to the accuracy of inputting all-time data of spatial points to predict the result of another spatial point; the random accuracy refers to the accuracy of inputting data of any time and space to predict the random selection data.

4. Comment: line 112,113: I found this sentence confusing. Are "monitoring station" and "monitoring site" different things? I'm unclear what the definition is on an "inspection standard"? Does this mean the "truth" data you are using for the verification. I'm unclear what "correlation factors" means. Response: Thank you for your thoughtful insights. "Monitoring station" and "monitoring site" have the same meaning, and we replaced "monitoring site" with "monitoring station". "Inspection standard" means truly data and "Correlation factors" refer to PM2.5, PM10, and gaseous pollutant data detected by the stations. We have redefined these meanings in the article (line 126-127):

Therefore, we used the truly air quality data from the ground monitoring stations as the inspection standard for verification and extracted the values of PM2.5, PM10, and gaseous pollutant with the data from the monitoring stations.

5. Comment: line 132: You verify your data processing against NASA data. Is NASA has a product, why not just use that? Response: Thank you for your thoughtful insights. The commonly used aerosol automatic observation network AERONET jointly established by NASA and CNRS is of good quality and easy to obtain, but the number of stations is limited, and there is no station coverage in the study area. The remote sensing data we collected are better in time and space continuity, and the AOD retrieval algorithm is also applicable to the study area.

6. Comment: line 175: "higher trend" and "lower trend". The word "trend" changes the meaning. I presume this should read "average temperature is higher in summer and lower in winter", as expected. Otherwise, I don't understand what it means. Response: Thank you for your thoughtful insights. We have modified the expression of this sentence (line 197-198): The average surface temperature and average temperature were higher in summer and lower in winter.

7. Comment: line 185: Is this standard published. If so, please cite. In my opinion, this can be a technical paper as opposed to a peer review paper (but the editor may feel differently). Response: Thank you for your thoughtful insights. This standard has been published, so we added a citation as follows (line 206-208): The national standard method is performed according to the method specified in the Chinese national standard GB/T13201-91 (http://www.mee.gov.cn/gzfw_13107/kjbz/qthjbhbz/qt/201605/t20160522_342349.shtml).

8. Comment: line 230: Could you clarify the optical subset approach? Was the RЁЕ2 score performed on the output of the LSTM as compared with the observations. If so, it may be better to put this section after the description of the LSTM and make that clear. Response: Thank you for your thoughtful insights. We clarified the optical

subset approach. In addition, we did not perform RËĘ2 scoring on the output of the LSTM, because the relative error rate can also reflect the accuracy intuitively. Since the maximum relative error and minimum relative error needs to be analyzed at the same time, it is more neatly to display the three relative error rates in a table. The explanation of optimal subset method is as follows (line 249-252): The process of the optimal subset method is that in a set containing multiple independent variables, freely selecting and combining from each independent variable, combining all independent variables and dependent variables to establish all possible equations, and then the best independent variable combination model is selected from all the fitted regression equations.

9. Comment: Table 4: I presume this table shows only the top 10 scoring selections? Presumably you scored all combinations of predictors. Please explain. Response: Thank you for your thoughtful insights. I added an explanation for table 4 as follows (line 257-258): This table shows the top 10 scores for R2 scores and the corresponding factor combinations.

10. Comment: Line 258: Normally the first gate is expressed at deciding what to forget, rather than what to remember (I appreciate they are equivalent). Figure 7 shows a "Forget gate" so it would be helpful to standardise the terminology. Response: Thank you for your thoughtful insights. The correction is as follows (line 286-288): The input gate determines how much of the input xt of the network is saved to the cell state ct at the current moment, the forget gate determines how much the cell state ct-1 at the previous moment is retained to the current moment ct, and the output gate controls how much the cell state ct is output to the current output value ht of the LSTM.

11. Comment: "and the third switch controls whether c is the current output of the LSTM model" I'm not sure about this - correct me if I'm wrong, but isn't c_t combined with h_t-1, and x_t to create h_t, which is the output? Response: Thank you for your thoughtful insights. It is true that ht is created by xt with the combination of ct and ht-1. The correction is as follows (line 282-288): Fig. 6 emphasizes the calculation process

of the cell state c, and the overall process of the LSTM model is shown in Fig. 7. The key point of the LSTM model is how to control the state c. The idea of the LSTM model is to use three control switches to control it. The switches implemented in the algorithm are known as "gates", which are fully connected layers whose input is a vector, and the output is a real vector between 0 and 1 (Srivastava and Lessmann, 2018). The input gate determines how much of the input x_t of the network is saved to the cell state c_t at the current moment, the forget gate determines how much the cell state c_{t-1} at the previous moment is retained to the current moment c_t, and the output gate controls how much the cell state c_t is output to the current output value h_t of the LSTM.

12. Comment: Section 4: I see the link to your code, that you used Keras and their LSTM implementation, which is great. If possible, could you cite Keras directly in the manuscript, and state that you used their implementation of LSTMs. Response: Thank you for your thoughtful insights. I cited Keras in the manuscript as follows (line 301-302): The implementation of the LSTM models is based on Keras which is a high-level neural network Application Programming Interface written in Python.

13. Comment: line 273: "with the first three layers being the LSTM layer and the last layer being the dense layer". I presume this means that you have three LSTM units follows by a dense layer. However, each LSTM unit can be thought of comprising multiple layers, so this terminology is confusing. In addition, could you explain to the reader the purpose of the final dense layer. Response: Thank you for your thoughtful insights. This sentence does means that we have three LSTM units follows by a dense layer. To avoid misunderstandings, we adjusted the description and explained the purpose of the dense layer as follows (line 307-310): We tried to use various LSTM architecture layers for the comparison. After obtaining the results of various LSTM architecture layers, we found that the results obtained using the LSTM architecture with four layers were the best, with the first three layers and the dense layer as the last layer. The role of the dense layer is to complete the final output of unique values.

14. Comment: line 282: I don't understand the difference between a "multilayer per-

ceptron" and an "artificial neural network". In addition, I would have thought the LSTM, multilayer perceptron and artificial neural network, all rely on back propagation, so I don't understand the terminology "back propagation artificial neural network". Please clarify. Response: Thank you for your thoughtful insights. The reason why we discriminate between MLP and BP is that MLP is a back propagation neural network model with a three-layer architecture after adjusted in Python by us, while the BP neural network acquired by the clementine software with non-adjustable parameters. After careful consideration, we decided to delete the comparison with MLP to avoid ambiguity.

15. Comment: Section 5.3: as mentioned above, I don't understand what is being done in this section. Response: Thank you for your thoughtful insights. The output of the random prediction pattern in Section 5.3 is randomly selected data in any time and space. This pattern is different from the time and space pattern. The applicability of LSTM reflected by the random prediction pattern is more obvious than the other two patterns. The explanation for section 5.3 is in the manuscript as follows (line 358-362): The random pattern prediction was based on the completely random selection of time and space aspects and can reflect the effect of air quality prediction under various climatic conditions well. The superiority of the LSTM model prediction in the random prediction pattern was more obvious than in the other patterns, which indicates that under irregular conditions, the LSTM model is more suitable for making predictions.

16. Comment: line 24: "Aerosols are a general term" -> "Aerosol is a general term". Response: Thank you for your thoughtful insights. We apologize for our mistakes. The correction is as follows (line 25): Aerosol is a general term for solid and gas particles suspended in air.

17. Comment: Please define all your acronyms on first use, for instance RH, DVV etc. Response: Thank you for your thoughtful insights. The correction is as follows (line 12-15): First, the aerosol optical depth (AOD) in 2017 in Wuhan was obtained based on Moderate Resolution Imaging Spectroradiometer (MODIS) images, with a 1 km spatial resolution, by using the Dense Dark Vegetation (DDV) method. Second,

the AOD was corrected by calculating the planetary boundary layer height (PBLH) and relative humidity (RH).

18. Comment: line 74: "intelligent models", please clarify what this means. Response: Thank you for your thoughtful insights. We replaced "intelligent models" with "machine learning models". The correction is as follows (line 79-80): However, with the introduction of new machine learning models, the traditional regression model reflects the inability to balance time, space and random precision.

19.Comment: line 89: "classic" -> "classical". Response: Thank you for your thoughtful insights. The correction is as follows (line 99-101): Finally, the space and time scales and random PM2.5/PM10 predictions were determined and performed, respectively, via the LSTM model, and the prediction results of the LSTM model and other classical models were compared and analyzed.

20. Comment: line 108: -> "Our environmental monitoring station only monitors data in real-time". I'm also not sure what this sentence is meant to mean. Are you saying that the instrument doesn't provide information about the future? Please clarify. Response: Thank you for your thoughtful insights. The supplement is as follows (line 122-123): The data that our environmental monitoring station can monitor is only real-time data with no predicting subsequent data in advance.

21. Comment: line 110: "which have", is ambiguous - is this referring to the AOD or the atmospheric aerosols? It seems redundant to say that PM is linked to atmospheric aerosols. Please clarify this sentence. Response: Thank you for your thoughtful insights. "Which have" refers to AOD. The correction is as follows (line 123-124): The AOD which has a great relationship with PM is an important parameter in the study of atmospheric aerosols.

22. Comment: line 140: "The shortest distance between points exceeds 3 km, and the average distance exceeds 10 km." I don't know what the word "exceeds" means in this context. Can we replace it with "is" instead? Response: Thank you for your thoughtful

insights. The correction is as follows (line 155): The shortest distance between points is more than 3 km, and the average distance is about 10 km.

A special thanks to you for your insightful and valuable comments.

We greatly appreciate the editors and reviewers for their helpful work and hope that the corrections will meet your approval. Once again, thank you very much for your valuable and helpful comments and suggestions. With best wishes Yours sincerely, Xueling Wu Institute of Geophysics and Geomatics, China University of Geosciences No. 388 Lumo Road, Wuhan 430074, P. R. China Email: snowforesting@163.com

The corrected tables are as follows: Table 5 The results and relative error rates of the time pattern predictions. Measured value Predicted value Relative error rate (%) LSTM BP SVM CHAID LSTM BP SVM CHAID 0.8212 0.6335 0.7786 0.6698 0.4853 22.8604 5.1875 18.4364 40.9036 0.7436 0.5610 0.6961 0.7841 0.4853 24.5491 6.3878 5.4465 34.7364 0.6629 0.7346 0.7074 0.8353 0.6753 10.8069 6.7129 26.0069 1.8706 0.6950 0.7949 0.6850 0.5628 0.6753 14.3746 1.4388 19.0216 2.8345 0.7816 0.7347 0.6871 0.8092 0.5145 5.9982 12.0906 3.5312 34.1735 0.6311 0.7605 0.5864 0.7032 0.6487 20.5089 7.0829 11.4245 2.7888 0.7959 0.7347 0.6870 0.8568 0.6973 7.6931 13.6826 7.6517 12.3885 0.8743 0.8067 0.6474 0.7451 0.6973 7.7307 25.9522 14.7775 20.2448 0.7204 0.6553 0.8106 0.7446 0.8206 9.0291 12.5208 3.3592 13.9089 0.9854 0.7128 0.7154 0.6760 0.8206 27.6610 27.4000 31.3984 16.7242 0.7079 0.7249 0.8321 0.6089 0.7959 2.4048 17.5449 13.9850 12.4311 0.9455 0.7790 0.7064 0.7285 0.7959 17.6108 25.2882 22.9508 15.8223 0.7200 0.4924 0.6692 0.8172 0.6931 31.6131 7.0556 13.5000 3.7361 0.8600 0.6521 0.6192 0.6907 0.6931 24.1694 28.0000 19.6860 19.4070 0.6571 0.6432 0.7011 0.8522 0.5812 2.1242 6.6961 29.6911 11.5508 0.9189 0.7175 0.6195 0.7146 0.5812 21.9150 32.5824 22.2331 36.7505 0.7640 0.7673 0.6549 0.5406 0.7870 0.4291 14.2801 29.2408 3.0105 0.9273 0.7896 0.6354 0.7155 0.7870 14.8513 31.4785 22.8405 15.1299 0.6277 0.4614 0.7308 0.5392 0.6951 26.4993 16.4250 14.0991 10.7376 0.8896 0.6904 0.6685 0.6694 0.7534 22.3909 24.8539 24.7527 15.3103 Mean: 15.7613

C10

16.1330 17.7017 16.2230 Maximum: 31.6111 32.5824 31.3984 40.9036 Minimum: 0.4319 1.4388 3.3592 1.8706

Table 6 The results and relative error rates of the spatial pattern prediction. Models LSTM BP SVM CHAID Mean: 27.9231 34.1333 34.0207 33.7718 Maximum: 178.0639 222.9295 204.7317 230.1367 Minimum: 0.0764 0.1124 0.9026 0.2396

Table 7 The results and relative error rates of the random pattern prediction. Measured value Predicted value Relative error rate (%) LSTM BP SVM CHAID LSTM BP SVM CHAID 0.5870 0.6031 0.5762 0.6091 0.4928 2.7428 1.8399 3.7649 16.0477 0.6213 0.6581 0.6561 0.6826 0.6795 5.9231 5.6012 9.8664 9.3675 0.9843 0.4662 0.6247 0.6185 0.7422 52.6364 36.5336 37.1635 24.5962 0.8000 0.4198 0.4772 0.5231 0.4928 47.5250 40.3500 34.6125 38.4000 0.4638 0.4654 0.4773 0.5136 0.4928 0.3450 2.9107 10.7374 6.2527 0.7010 0.5762 0.6811 0.6675 0.6795 17.8031 2.8388 4.7789 3.0670 0.2222 0.2470 0.4292 0.3971 0.3737 11.1611 93.1593 78.7129 68.1818 0.5929 0.6418 0.6543 0.6598 0.6795 8.2476 10.3559 11.2835 14.6062 0.9571 0.5875 0.6246 0.6698 0.6164 38.6167 34.7404 30.0178 35.5971 0.7576 0.7095 0.5959 0.6398 0.4928 6.3490 21.3437 15.5491 34.9525 0.6277 0.6368 0.6935 0.6802 0.6795 1.4497 10.4827 8.3639 8.2523 0.8896 0.6508 0.7551 0.7353 0.7422 26.8435 15.1192 17.3449 16.5692 Mean: 18.3036 22.9396 21.8496 22.9909 Maximum: 52.6364 93.1593 78.7129 68.1818 Minimum: 0.3450 1.8399 3.7649 3.0670

Please also note the supplement to this comment:
https://www.geosci-model-dev-discuss.net/gmd-2019-180/gmd-2019-180-AC2-supplement.pdf

---