Response to Referee #1

We sincerely thank the editor and all reviewers for your time and the constructive comments on our manuscript. We have carefully considered all the comments and suggestions. Below are our point-by-point responses detailing how we have addressed each issue in the revised manuscript. In the following, paragraphs in **black** are reviewers' comments; paragraphs in **blue** are point-to-point responses; paragraphs in **red** are revisions in the manuscript.

General Comments:

This study investigates the controlling factors and synoptic patterns of foehn events on the eastern foothills of the Taihang Mountains using long-term observations and interpretable machine-learning techniques. The application of machine learning to foehn analysis is innovative and highly commendable. In particular, the use of SHAP to quantify dominant factors and dynamic thresholds represents a valuable methodological contribution.

However, the scientific necessity of applying machine learning is not sufficiently clarified. The manuscript does not clearly demonstrate what additional physical insights are gained beyond those obtainable from conventional statistical or dynamical analyses. A more explicit justification of the added value of the machine-learning approach is needed.

In addition, the review of previous studies on foehn mechanisms is insufficient. Established dynamical explanations and controlling processes are not systematically synthesized, resulting in a discussion that lacks physical depth. Consequently, the interpretation of the results remains somewhat descriptive and would benefit from a stronger linkage to existing theoretical frameworks.

If these issues are adequately addressed, particularly by clarifying the role of machine learning and strengthening the mechanistic discussion, I would recommend publication of this study in ACP.

Response: We greatly appreciate the reviewer's summary on the novelty of this research and sincerely appreciate the reviewer's valuable and constructive comments. These comments have greatly helped us improve the scientific quality and clarity of our manuscript. We have carefully revised the manuscript according to all comments.

To clarify the role of machine learning, we first analyzed the limitations of conventional statistical or dynamical analyses by adding a more systematic review concerning influencing factors, seasonal variations, and synoptic patterns of foehn (please refer to our response to Comment 2). And then we analyzed the necessity of machine learning methods in our study by introducing their advantages in other non-foehn studies and the unresolved relevant issues for foehn research (please refer to our response to Comment 1 and Comment 7). Finally, through machine learning methods, this study reveals several new findings, such as the different thresholds of meteorological variables favorable for foehn occurrence in different seasons, which cannot be obtained through traditional methods. This confirms that applying machine learning methods to address the complexity of foehn problems is valuable and meaningful.

To strengthen the mechanistic discussion, we firstly have systematically expanded the review on foehn mechanisms and mountain circulation according to your suggestion. Secondly, in the "Abstract" and "Results", we integrated classical theories, such as the Froude number, which governs mountain airflow, and stable stratification, with our findings to further elucidate the dynamic processes of foehn occurrence over the Taihang Mountains (please refers to the response to Comment 6). This allowed for a deeper discussion and more insightful interpretation of the results.

Thanks again for your valuable suggestion. Further explanation please refer to Specific Comments.

Specific Comments:

Comment 1: L55: The manuscript should explicitly describe the limitations of conventional approaches and clearly articulate the rationale for adopting machine learning.

Response: We thank the reviewer for this valuable suggestion. We totally agree. We have added these contents and substantially revised the "Introduction section and Section 2.4" to address this concern:

The "Introduction section", Pages 2, lines 47-60:

“A range of frameworks to predict foehn events was developed in prior studies as well, including discriminant analysis-based foehn indices (Gutermann, 1971; Jansing et al., 2022; Widmer, 1966), physical mechanism-based threshold methods (Ayitikan et al., 2023), and decision tree-based classification approaches (Elvidge et al., 2020; Francis et al., 2023; Laffin et al., 2021). However, these methods commonly rely on manually selected thresholds, limiting their ability to resolve mixed atmospheric states or adapt to variable synoptic conditions (Stauffer et al., 2024). Although the automated identification methods have also been proposed (Plavcan et al., 2014), they are highly dependent on high-temporal-resolution (ideally sub-hourly) in-situ measurements, which limits their promotion in regions with sparse observation networks (Stauffer et al., 2024). In addition, one forecasting framework based on numerical weather prediction (NWP) models can provide spatially continuous predictions, but are constrained by grid resolution, parameterization uncertainties, and inherent errors of the NWP models, preventing accurate capture of localized terrain-induced circulations (Grajek & Bednorz, 2025; Maier et al., 2025). In summary, previous studies have either been based on analyses of static foehn characteristics or relied on NWP numerical models, with few having objectively and quantitatively isolated the key predictors of foehn formation. To improve foehn prediction, multiple interpretable machine learning methods merit consideration for identifying its controlling factors.”

The “Section 2.4”, Pages 6, lines 139-143:

“As our reviewing literature in the introduction, those conventional statistical methods struggle to analyze foehn formation due to the non-linear interactions among multiple atmospheric variables and the complex topographic modulation. These machine learning methods adopted in this study are able to automatically learn optimal decision boundaries and quantify factor importance via interpretable machine-learning techniques among the handling high-dimensional data and complex nonlinear relationships.”

New added references

Ayitikan, M., Li, X., He, Q., Musha, Y., Tang, H., Li, S., Zhong, Y., & Ren, G. (2023). Characteristics and Establishment of Objective Identification Criteria and Predictors for Foehn Winds in Urumqi, China. *Atmosphere*, *14*(8), 1206. https://www.mdpi.com/2073-4433/14/8/1206

Elvidge, A. D., Kuipers Munneke, P., King, J. C., Renfrew, I. A., & Gilbert, E. (2020). Atmospheric drivers of melt on Larsen C Ice Shelf: Surface energy budget regimes and the impact of foehn. *Journal of Geophysical Research: Atmospheres*, *125*(17), e2020JD032463.

Francis, D., Fonseca, R., Mattingly, K. S., Lhermitte, S., & Walker, C. (2023). Foehn winds at Pine Island Glacier and their role in ice changes. *The Cryosphere*, *17*(7), 3041-3062.

Grajek, Z., & Bednorz, E. (2025). Climatology and circulation conditions of potential foehn occurrence in the Polish Tatra Mountains. *Acta Geophysica*, *73*(1), 955-967. https://doi.org/10.1007/s11600-024-01372-w

Gutermann, T. (1971). Zur praktischen Anwendung des Föhntests von Widmer von Dr. Hans W. Courvoisier und.

Jansing, L., Papritz, L., Dürr, B., Gerstgrasser, D., & Sprenger, M. (2022). Classification of Alpine south foehn based on 5 years of kilometre-scale analysis data. *Weather and Climate Dynamics*, *3*(3), 1113-1138.

Laffin, M., Zender, C., Singh, S., Van Wessem, J., Smeets, C., & Reijmer, C. (2021). Climatology and evolution of the Antarctic Peninsula föhn wind-induced melt regime from 1979–2018. *Journal of Geophysical Research: Atmospheres*, *126*(4), e2020JD033682.

Maier, P., Klisho, T., Formayer, H., & Lehner, F. (2025). Analysing the future trends of foehn-enabling synoptic patterns over two valleys in the Eastern Alps in CMIP5 EURO-CORDEX models. *Theoretical and Applied Climatology*, *156*(3), 155. https://doi.org/10.1007/s00704-025-05365-7

Plavcan, D., Mayr, G. J., & Zeileis, A. (2014). Automatic and probabilistic foehn diagnosis with a statistical mixture model. *Journal of Applied Meteorology and Climatology*, *53*(3), 652-659.

Stauffer, R., Zeileis, A., & Mayr, G. J. (2024). Long-Term Foehn Reconstruction Combining Unsupervised and Supervised Learning [Article]. *International Journal of Climatology*, *44*(16), 5890-5901. https://doi.org/10.1002/joc.8673

Widmer, R. (1966). *Statistische Untersuchungen über den Föhn im Reusstal und Versuch einer objektiven Föhnprognose für die Station Altdorf* Dissertationsdruckerei Leemann].

Comment 2: L61–63: Since the study focuses on influencing factors, seasonal variations, and synoptic patterns, a more systematic review of previous foehn studies addressing these aspects is necessary.

Response: Thank you for your constructive suggestion. We have integrated a new added review covering these key aspects into the original review and substantially revised the "Introduction section" to make it more logical and systematic. At the same time, we have also discussed their limitations. The revised parts are as follows:

The "Introduction section", Pages 2, lines 45-60:

"Previous studies have made some important progress on the foehn mechanism. The primary physical mechanism of foehn formation, the synoptic patterns and seasonal variability favorable to foehn occurrence have been identified (Elvidge & Renfrew, 2016; Wiesner et al., 2024). A range of frameworks to predict foehn events was developed in prior studies as well, including discriminant analysis-based foehn indices (Gutermann, 1971; Jansing et al., 2022; Widmer, 1966), physical mechanism-based threshold methods (Ayitikan et al., 2023), and decision tree-based classification approaches (Elvidge et al., 2020; Francis et al., 2023; Laffin et al., 2021). However, these methods commonly rely on manually selected thresholds, limiting their ability to resolve mixed atmospheric states or adapt to variable synoptic conditions (Stauffer et al., 2024). Although the automated identification methods have also been proposed (Plavcan et al., 2014), they are highly dependent on high-temporal-resolution (ideally sub-hourly) in-situ measurements, which limits their promotion in regions with sparse observation networks (Stauffer et al., 2024). In addition, one forecasting framework based on numerical weather prediction (NWP) models can provide spatially continuous predictions, but are constrained by grid resolution, parameterization uncertainties, and inherent errors of the NWP models, preventing accurate capture of localized terrain-induced circulations (Grajek & Bednorz, 2025; Maier et al., 2025). In summary, previous studies have either been based on analyses of static foehn characteristics or relied on NWP numerical models, with few having objectively and quantitatively isolated the key predictors of foehn formation. To improve foehn prediction, multiple interpretable machine learning methods merit consideration for identifying its controlling factors."

New added references

Ayitikan, M., Li, X., He, Q., Musha, Y., Tang, H., Li, S., Zhong, Y., & Ren, G. (2023). Characteristics and Establishment of Objective Identification Criteria and Predictors for Foehn Winds in Urumqi, China. *Atmosphere*, *14*(8), 1206. https://www.mdpi.com/2073-4433/14/8/1206

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Elvidge, A. D., & Renfrew, I. A. (2016). The Causes of Foehn Warming in the Lee of Mountains [Article]. *Bulletin of the American Meteorological Society*, *97*(3), 455-466. https://doi.org/10.1175/BAMS-D-14-00194.1

Francis, D., Fonseca, R., Mattingly, K. S., Lhermitte, S., & Walker, C. (2023). Foehn winds at Pine Island Glacier and their role in ice changes. *The Cryosphere*, *17*(7), 3041-3062.

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Gutermann, T. (1971). Zur praktischen Anwendung des Föhntests von Widmer von Dr. Hans W. Courvoisier und.

Jansing, L., Papritz, L., Dürr, B., Gerstgrasser, D., & Sprenger, M. (2022). Classification of Alpine south foehn based on 5 years of kilometre-scale analysis data. *Weather and Climate Dynamics*, *3*(3), 1113-1138.

Laffin, M., Zender, C., Singh, S., Van Wessem, J., Smeets, C., & Reijmer, C. (2021). Climatology and evolution of the Antarctic Peninsula föhn wind-induced melt regime from 1979–2018. *Journal of Geophysical Research: Atmospheres*, *126*(4), e2020JD033682.

Maier, P., Klisho, T., Formayer, H., & Lehner, F. (2025). Analysing the future trends of foehn-enabling synoptic patterns over two valleys in the Eastern Alps in CMIP5 EURO-CORDEX models. *Theoretical and Applied Climatology*, *156*(3), 155. https://doi.org/10.1007/s00704-025-05365-7

Plavcan, D., Mayr, G. J., & Zeileis, A. (2014). Automatic and probabilistic foehn diagnosis with a statistical mixture model. *Journal of Applied Meteorology and Climatology*, *53*(3), 652-659.

Stauffer, R., Zeileis, A., & Mayr, G. J. (2024). Long-Term Foehn Reconstruction Combining Unsupervised and Supervised Learning [Article]. *International Journal of Climatology*, *44*(16), 5890-5901. https://doi.org/10.1002/joc.8673

Widmer, R. (1966). *Statistische Untersuchungen über den Föhn im Reusstal und Versuch einer objektiven Föhnprognose für die Station Altdorf* Dissertationsdruckerei Leemann].

Wiesner, L., McGowan, H., Sturman, A., & Dale, T. (2024). Subtropical Foehn Winds, Southeast Queensland, Australia. *Journal of Geophysical Research: Atmospheres*, *129*(13), e2023JD040410. https://doi.org/https://doi.org/10.1029/2023JD040410

Comment 3: L68–72: Elevation differences are a fundamental factor in foehn dynamics. The manuscript should provide clearer information on the topographic characteristics and elevation of the study area.

Response: Thank you for your suggestion. We not only redrew Figure 1 from the original manuscript, but also added more descriptions regarding the topographic characteristics and elevation of the study area in the revised manuscript as follows:

The "Section 2.1", Pages 3, lines 82-91:

"The study area is the Taihang Mountain region in Northern China (Figure 1), with major cities including Taiyuan, the capital of Shanxi Province (the blue dot in Figure 1b, station elevation: nearly 800 m) and Shijiazhuang, the capital of Hebei Province (the middle red dot in Figure 1b, station elevation: 81 m). Topographically, the Taihang Mountains are one of China's most important mountain ranges, extending approximately 500 km in length and 40–50 km in width (Yusheng, 2010), roughly spanning 110–117°E and 35–41°N (the orange solid line in Figure 1b). They form a striking northeast – southwest oriented topographic barrier with steep eastern slopes facing the North China Plain and more gradual western slopes descending to the Loess Plateau. The average altitude of the mountains is 1,000 - 1,400 m, and the highest peak, Mount Wutai, which exceeds 3,000 m is located at the northern end of the Taihang Mountains (the northernmost tip of the orange solid line in Figure 1b). This pronounced topographic relief generates favorable conditions for foehn formation when moist air masses are forced to ascend the western slopes and descend adiabatically along the eastern leeward side."

Comment 4: L108–111: A brief explanation of the principles of each machine-learning model is needed. At minimum, the manuscript should describe the basic mechanism of the random forest model.

Response: Thank you for your suggestion. We have added the explanation of the principles of each machine-learning model in the revised manuscript as follows:

The "Section 2.4", Pages 5, lines 127-138:

"After cleaning and preprocessing the station observations and ERA5 reanalysis data, machine learning methods were employed to analyze the main influencing factors of foehn events on the eastern foothills of the Taihang Mountains. Six machine learning models were selected for this task: 1) K-Nearest Neighbor Classification (KNN), classifies samples based on the majority class among their k closest neighbors in the feature space (Cover & Hart, 1967); 2) Logistic Regression, estimates the probability of class membership using a logistic function to model the relationship between input features and the binary outcome (Kleinbaum, 2010); 3) Neural Network (NN), learns hierarchical representations through interconnected layers of neurons that apply nonlinear transformations to capture complex patterns in the data (Krizhevsky et al., 2017); 4) Decision Tree, recursively partitions the feature space into homogeneous regions based on feature values to make predictions (Salzberg, 1994); 5) Random Forest (RF), is an ensemble method that constructs multiple decision trees using bootstrap sampling (bagging) and random feature selection at each split, and predictions are made by aggregating votes from all trees, which reduces overfitting and improves generalization compared to single decision trees (Breiman, 2001); 6) Adaptive Boosting (AdaBoost), sequentially trains weak learners, adjusting sample weights to focus on misclassified instances and combining their predictions through weighted voting to form a strong classifier (Freund & Schapire, 1997)."

Comment 5: L138: Windward precipitation is generally important in foehn processes. The authors should clarify why precipitation was not included as a predictor in this study.

Response: This is a really good question. Based on literature review and our tests, we did not include precipitation in the model for the following main reasons.

Firstly, the objective of this study is to understand the main factors influencing foehn formation and improve foehn forecasting capability. In the existing physical mechanisms studies (Elvidge & Renfrew, 2016; Kusaka et al., 2021), foehn precipitation is more an outcome variable than a precursor signal. That's why we prioritize factors that have strong predictability for foehn occurrence including wind, temperature, pressure and humidity, rather than precipitation, which has shorter forecast lead times and is heavily influenced by terrain microscale terrain processes, resulting in lower predictability. Moreover, machine learning models require high-quality input data. Owing to its high spatiotemporal variability and observational uncertainties, precipitation did not enhance model performance or stability. Although precipitation was not directly included, other factors such as windward specific humidity (Q_{Wind}) related to atmospheric moisture conditions is included and demonstrated significant influence in SHAP analysis (Fig. 2d). These are the reasons why we did not include precipitation in the model.

References

Elvidge, A. D., & Renfrew, I. A. (2016). The Causes of Foehn Warming in the Lee of Mountains. *Bulletin of the American Meteorological Society*, *97*(3), 455-466. https://doi.org/https://doi.org/10.1175/BAMS-D-14-00194.1

Kusaka, H., Nishi, A., Kakinuma, A., Doan, Q.-V., Onodera, T., & Endo, S. (2021). Japan's south foehn on the Toyama Plain: Dynamical or thermodynamical mechanisms? [Article]. *International Journal of Climatology*, *41*(11), 5350-5367. https://doi.org/10.1002/joc.7133

Comment 6: L193 – 194: The explanation is difficult to understand. The mountain Froude number is typically defined by wind speed, static stability, and mountain height, rather than wind direction. This statement should be reconsidered and clarified.

Response: Thank you for your question. We had our explanation as below.

Yes, you are right. The mountain Froude number (Fr) is typically defined by wind speed, static stability, and mountain height. However, according to the classical theory, the wind speed refers to the velocity of the flow normal to the topographic barrier actually (Prósper et al., 2019; Wiesner et al., 2024), which means it is related to the wind direction.

Based on the classical theory (Prósper et al., 2019; Wiesner et al., 2024), the mountain Froude number (Fr) is defined by this formula:

$$Fr = \frac{u}{Nh}$$

Where u is the velocity of the flow normal to the topographic barrier, N is the Brunt Väisälä frequency, and h is the height of the topographic barrier. The Brunt Väisälä frequency, which also represents the static stability, was calculated by:

$$N = \sqrt[2]{\frac{g}{\theta}\frac{\partial\theta}{\partial z}}$$

Considering u is the velocity of the flow normal to the topographic barrier and Fr describes the air flowing over a mountain, we can use W_{Wind} and the angle (α) between W_{Wind} and the mountain orientation to represent Fr.

$$Fr = \frac{W_{Wind} \cdot \sin\alpha}{N \cdot h}$$

Taiyuan and Shijiazhuang lie at almost the same latitude. When the influence of small-scale terrain on wind direction is neglected, the wind directions on the windward and leeward slopes are consistent. Therefore, the above formula can be easily understood by the following new added Figure S8.

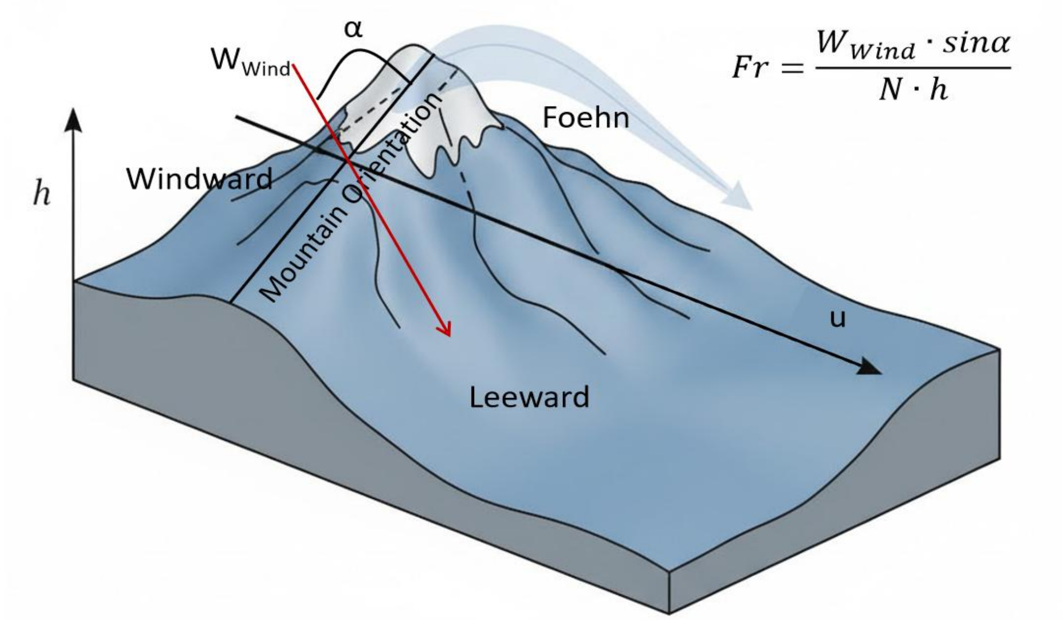

Figure S8: Schematic diagram illustrating the Froude number in relation to wind direction when the influence of small-scale terrain on wind direction is neglected. Fr is the Froude number; u is the velocity of the flow normal to the topographic

barrier; N is the Brunt Väisälä frequency; h is the height of the topographic barrier; and α is the angle between W_{Wind} and the mountain orientation.

According to the classical theory, there are significant nonlinear effects and blocking when Fr≪1, whereas for Fr≫1, the opposite occurs (Smolarkiewicz & Rotunno, 1989, 1990). Fr around 1 indicates a transitional regime between the two states and favorable conditions for the formation of downslope lee windstorms and hydraulic jumps (Prósper et al., 2019; Wiesner et al., 2024). Therefore, wind direction can be calculated or verified by aiming Fr (≈1) by the above formula, in which the airstream will descend the leeward slope smoothly while converting potential energy into kinetic energy, and this process accelerates wind speed and enhances adiabatic warming via isentropic drawdown, which are two key characteristics of foehn winds. Following your suggestion, we have added more explanation and revised the relevant section to clarify that the Froude number in the Taihang Mountains region is related to the wind direction of foehn occurrence as follows.

The "Section 3.1", Pages 10, lines 228-246:

"This wind-direction-dependent foehn formation mechanism is fundamentally supported by the Froude number (Fr) dynamics and terrain-airflow coupling effects, consistent with the principles of trans-barrier flow and orographic modification documented in foehn research (Durran, 1990). Froude number, defined as $Fr = \frac{u}{Nh}$, (where u is the flow velocity normal to the topographic barrier, N is the Brunt-Väisälä frequency, and h is the height of the topographic barrier), quantifies the balance between inertial forces and buoyancy restoring forces, thereby determining the flow behavior when encountering topographic obstacles (Prósper et al., 2019; Wiesner et al., 2024). When Fr≪1 there are significant nonlinear effects and blocking, whereas for Fr≫1 the opposite occurs (Smolarkiewicz & Rotunno, 1989, 1990). The Fr around 1 indicates a transitional regime between the two states and favorable conditions for the formation of downslope lee windstorms and hydraulic jumps (Prósper et al., 2019; Wiesner et al., 2024). Within this range, the airflow neither fully circumvents the range (Fr ≫ 1) nor is completely blocked (Fr ≪ 1), thereby sustaining a persistent downslope warming that favors foehn occurrence. Considering the u is the velocity of the flow normal to the topographic barrier, wind direction can be calculated or verified by aiming Fr (≈ 1) (Figure S8). Calculations show that the α (the angle between W_{Wind} and the mountain orientation) is equal to 41.81° and the wind direction is equal to 278.81°, which is really close the most conducive wind direction (275°) to the foehn development given by our SHAP method. Based on the obtained favorable wind direction (237°-294°, which means α = 33°-90°) identified in the SHAP model, the favorable Fr range is calculated as 0.82 to 1.5 for the formation of foehn on the eastern foothills of the Taihang Mountains. This finding not only agrees with classical theory but also extends it to a specific range for the first time, thereby enriching the global understanding of foehn dynamics. Such a result cannot be obtained from traditional theoretical studies."

New added references

Durran, D. R. (1990). Mountain Waves and Downslope Winds. In *Atmospheric Processes over Complex Terrain* (pp. 59-81). American Meteorological Society. https://doi.org/10.1007/978-1-935704-25-6_4

Prósper, M. A., Sosa Tinoco, I., Otero-Casal, C., & Miguez-Macho, G. (2019). Downslope windstorms in the Isthmus of Tehuantepec during Tehuantepecer events: a numerical study with WRF high-resolution simulations. *Earth System Dynamics*, *10*(3), 485-499. https://doi.org/10.5194/esd-10-485-2019

Smolarkiewicz, P. K., & Rotunno, R. (1989). Low Froude Number Flow Past Three-Dimensional Obstacles. Part I: Baroclinically Generated Lee Vortices. *Journal of Atmospheric Sciences*, *46*(8), 1154-1164. https://doi.org/https://doi.org/10.1175/1520-0469(1989)046<1154:LFNFPT>2.0.CO;2

Smolarkiewicz, P. K., & Rotunno, R. (1990). Low Froude Number Flow Past Three-Dimensional Obstacles. Part II: Upwind Flow Reversal Zone. *Journal of Atmospheric Sciences*, *47*(12), 1498-1511. https://doi.org/https://doi.org/10.1175/1520-0469(1990)047<1498:LFNFPT>2.0.CO;2

Wiesner, L., McGowan, H., Sturman, A., & Dale, T. (2024). Subtropical Foehn Winds, Southeast Queensland, Australia. *Journal of Geophysical Research: Atmospheres*, *129*(13), e2023JD040410. https://doi.org/https://doi.org/10.1029/2023JD040410

Comment 7: Discussion and Conclusion: Since similar conclusions might potentially be obtained using conventional statistical analyses, the authors should explicitly discuss the advantages of the machine-learning approach and clearly state the added scientific value of this study.

Response: We sincerely thank the reviewer for this constructive comment. This study yields several conclusions that cannot be obtained through traditional statistical or theoretical methods. We have explicitly discussed the new findings of the machine-learning approach in the revised manuscript as follows.

The "Discussion and Conclusion section", Pages 17, lines 362-379:

" By applying the SHAP-based explainable machine learning, we have quantified the critical dynamic thresholds for the foehn formation in this region and demonstrated their pronounced seasonal and spatial variability for the first time, instead of only setting fixed and empirical thresholds that lack seasonal and spatial adaptability (Ayitikan et al., 2023; Elvidge et al., 2020; Francis et al., 2023; Jansing et al., 2022; Laffin et al., 2021; Widmer, 1966). The threshold of the leeward 10-m wind speed (W_{Lee}) remains stably above 3 m/s year-round, yet its contribution to foehn occurrence is significantly stronger in winter than in summer. Differently, the threshold of the windward 2-m temperature (T_{Wind}) is seasonally variable, being −10 °C annually, −17 °C in winter, and 9 °C in summer, with stronger impacts in summer than in winter. The windward specific humidity (Q_{Wind}) is predominantly suppressive and its thresholds are 0.1 g/kg annually, 0.07 g/kg in winter and 0.75 g/kg in summer, exerting a greater influence in winter than in summer. The thresholds of leeward wind-direction (Dir_{Lee}) are given as the favorable range from 203° to 324°, with the range from 237° to 294° being most conducive to foehn formation. Based on these findings, the Froude number (Fr) range most favorable for foehn occurrence in the Taihang Mountains is identified as 0.82 to 1.5. This result cannot be obtained through traditional theoretical methods alone. Classical theory has only indicated that a Fr of approximately 1 favors foehn. This study, for the first time, extends this to a specific range, advancing the global understanding of foehn dynamics. These thresholds can directly guide the development of seasonally and slope-resolved (windward versus leeward) differentiated early-warning models. For example, winter warnings should particularly target persistent strong foehns with an extended lead time (up to 24 h) and focus on leeward wind speeds (W_{Lee}) exceeding 3 m/s and windward specific humidity (Q_{Wind}) above 0.07 g/kg, while summer warnings should focus on windward temperature (T_{Wind}) below 9 °C (Figure 4).”

The “Discussion and Conclusion section”, Pages 19, lines 396-409:

“Composite analysis of winter foehn events, which dominate among different seasons, reveals the following favorable synoptic background: 1) A pronounced pressure gradient with higher pressure on the windward side and lower pressure on the leeward side drives westerly flow across the range; 2) the ambient air mass is cold and dry, whereas the leeward slope becomes markedly warm and dry; 3) a 500-hPa cold trough in the westerlies affects the leeward slope, inducing westerly or north-westerly downslope flow and pronounced subsidence in the lower troposphere (850 hPa); 4) the thermal structure is characterized by a stable stratification with colder air at low levels on the windward side and colder mid-upper levels on the leeward side. Therefore, priority should be given to the surface pressure gradient, the low-level vertical motion (especially subsidence), and the position of westerly troughs and ridges across the range of Taihang Mountains. Through identifying the specific synoptic patterns favorable for foehn occurrence in the Taihang Mountains, we link large-scale synoptic conditions with local thresholds for the formation of foehn in this study. This cross-scale physical connection and its mutual validation are difficult to achieve with conventional statistical methods alone. Therefore, we also recommend that when developing foehn-warning models, it is better to combine the surface thresholds with favorable synoptic-pattern information to construct a reliable “synoptic pattern plus surface factors” framework that overcomes the physical interpretability limitations of traditional single-model approaches (Seluchi et al., 2003; Stauffer et al., 2024).

New added references

Ayitikan, M., Li, X., He, Q., Musha, Y., Tang, H., Li, S., Zhong, Y., & Ren, G. (2023). Characteristics and Establishment of Objective Identification Criteria and Predictors for Foehn Winds in Urumqi, China. *Atmosphere*, *14*(8), 1206. https://www.mdpi.com/2073-4433/14/8/1206

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Widmer, R. (1966). *Statistische Untersuchungen über den Föhn im Reusstal und Versuch einer objektiven Föhnprognose für die Station Altdorf* Dissertationsdruckerei Leemann].

Technical Comments:

Comment 1: Figure 1b: An elevation color bar and a horizontal distance scale should be added.

Response: Thank you for the suggestion. We have replotted the figure as follows.

Pages 4, lines 92:

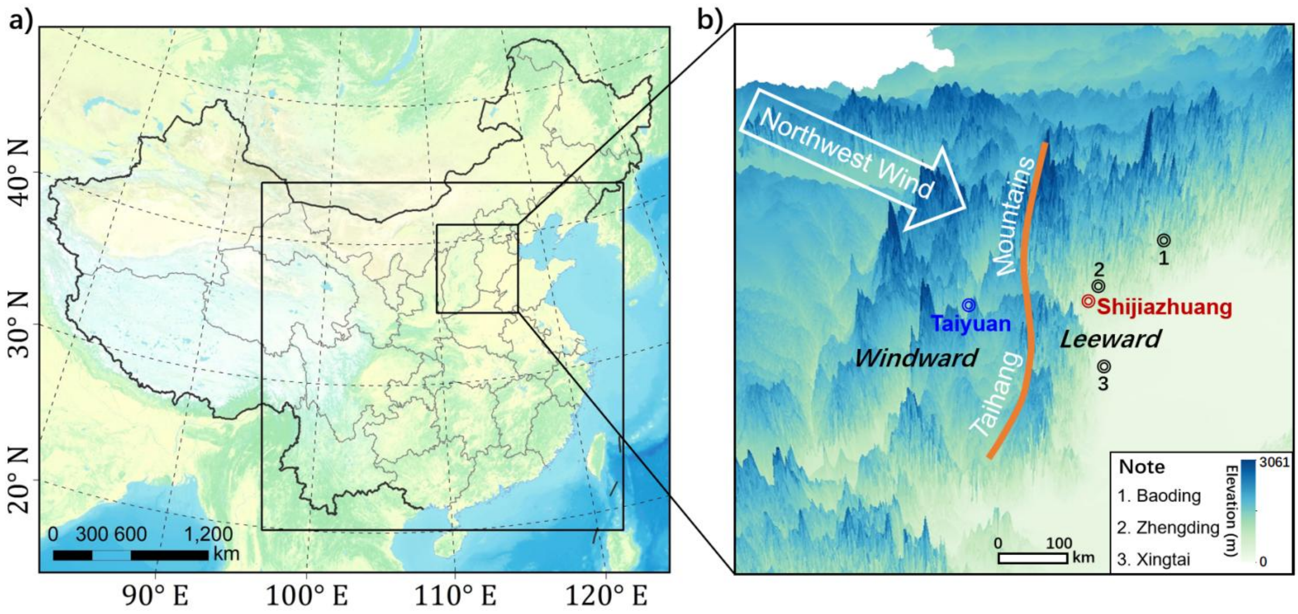

Figure 1: Regional map. (a) Major part of China (large black box) and the key area of foehn occurrence along the eastern foothills of the Taihang Mountains (small black box). (b) Geographical locations of meteorological stations in the region of Taihang Mountains, where blue and red dots indicate stations located on the windward and leeward sides, respectively.

Comment 2: Figure 1b: The red labels in the figure are difficult to read. Please improve their visibility.

Response: We have improved their visibility. Thank you. Please see our reply to technical comment 1.

Comment 3: Figure 5h: The legend label "Yes" is unclear. It would be more appropriate to replace it with "Foehn" or another clearer term.

Response: We have replaced it. Thank you for your suggestion.

Pages 15, lines 299:

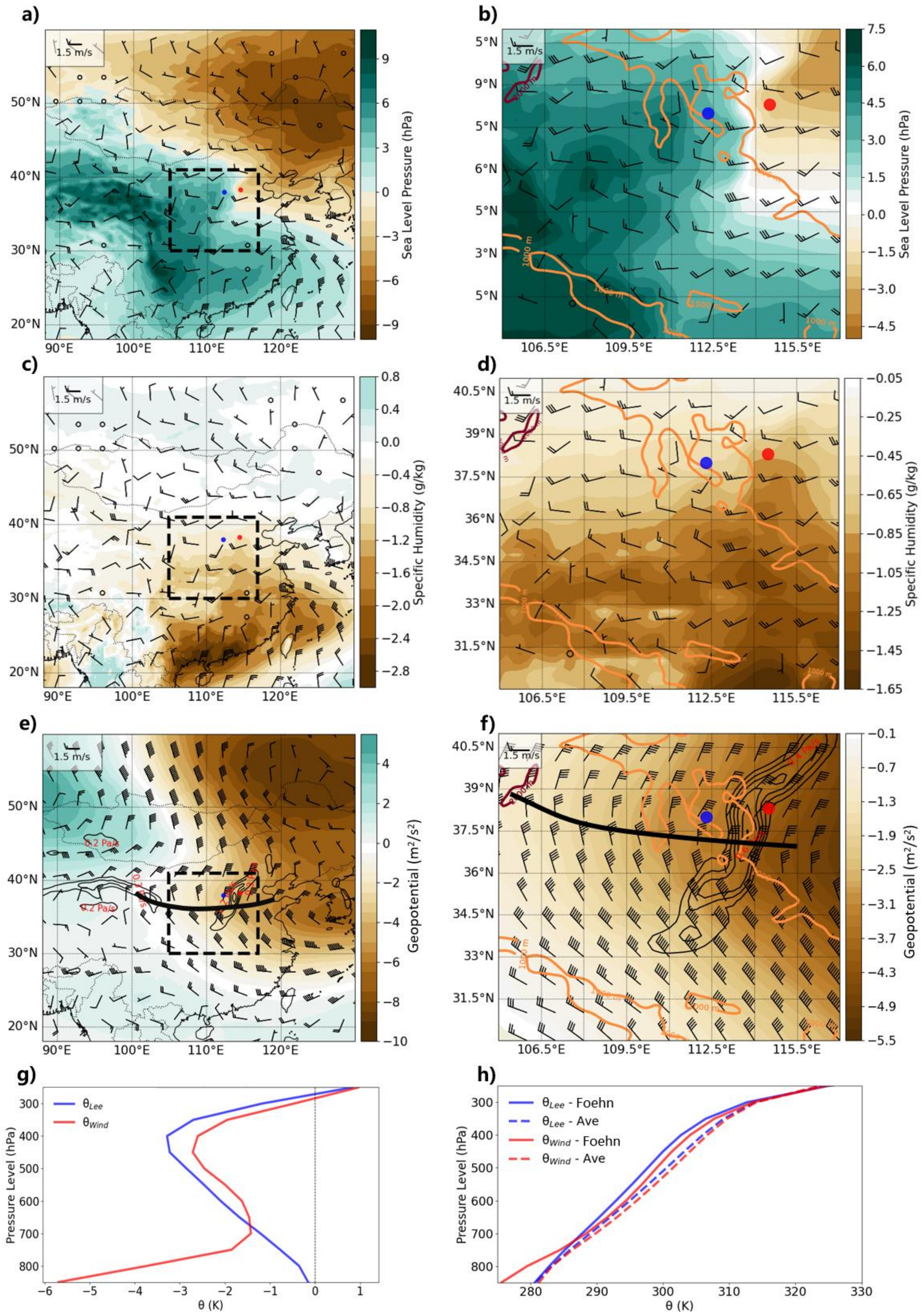

Figure 5: Anomalies of meteorological fields relative to the climatological mean during foehn events in winter on the eastern foothills of the Taihang Mountains: (a–b) Sea-level pressure (shaded) and 10 m wind field; (c–d) Surface specific humidity and 10 m wind field; (e–f) 500 hPa geopotential height (thick black contour denotes the westerly transverse trough), wind field, and 850 hPa vertical velocity (black contours, solid lines indicate subsidence); (g) Vertical profiles of potential temperature on the windward and leeward sides. Blue and red dots mark the windward and leeward stations, respectively; the orange solid line indicates the position of the Taihang Mountains (defined by the 1,000 m elevation contour); the black dashed box in the left column outlines the domain shown in the right column. (h) Vertical profiles of potential temperature on the windward and leeward sides; "Foehn" and "Ave" denote the foehn events and the climatological mean, respectively.

Response to Referee #3

We sincerely thank the editor and all reviewers for your time and the constructive comments on our manuscript. We have carefully considered all the comments and suggestions. Below is our point-by-point response detailing how we have addressed each issue in the revised manuscript. In the following, paragraphs in **black** are reviewers' comments; paragraphs in **blue** are point-to-point responses; paragraphs in **red** are revisions in the manuscript.

General Comments:

This is an interesting paper that employs interpretable machine-learning techniques to investigate the key controlling factors, dynamic thresholds, and synoptic patterns of foehn winds on the eastern foothills of the Taihang Mountains in China. The authors have conducted a lot of analysis and synoptic analysis, which are good for elaborating the main arguments. Overall, the paper employs novel methods, presents solid analysis, and draws clear conclusions.

Response: We greatly appreciate the reviewer's comment on the novelty of our research.

Specific Comments:

Comment 1: Line 139: This study explicitly used the potential temperature difference (Δθ > 2K) as one of the defining criteria for foehn events in Table 1. However, in the subsequent machine learning modeling (Table 2), the 28 predictor variables used for training and interpreting the model did not include any variables related to potential temperature (such as θWind, θLee, or Δθ). This needs clarification.

Response: This is a really good question. We have our explanations below.

Potential temperature θ is calculated from temperature T and pressure P （$\theta = T(\frac{1000}{P})^{0.286}$）. This equation shows that the combined changes in T and P lead to changes in θ—that is, T and P are the causes, while θ is the result. Therefore, we prefer using θ, a variable that reflects the outcome to distinguish whether foehn occurs. In the subsequent machine learning modeling, we actually consider θ as a predictor in the 28 predictor variables in our earlier work, however, the model did not perform well. Therefore, we did not include θ in the model.

Comment 2: Line 192-194: There remains a gap between the statistical association and the physical causation. To bridge this, it is recommended to: (a) Whether the Fr (Froude) number is directly calculated from observational data and indeed falls within this specific range during foehn wind events. (b) Why the Fr between 0.8 and 1.2 is conducive to the foehn development? There seems still some physical process gap between your proofs and current conclusions.

Response: Thank you for your question. We had our explanations as below.

Based on the classical theory (Prósper et al., 2019; Wiesner et al., 2024), the mountain Froude number (Fr) is defined by this formula:

$$Fr = \frac{u}{Nh}$$

Where u is the velocity of the flow normal to the topographic barrier, N is the Brunt Väisälä frequency, and h is the height of the topographic barrier. The Brunt Väisälä frequency, which also represents the static stability, was calculated by:

$$\mathrm{N} = \sqrt[2]{\frac{\mathrm{g}}{\theta}\frac{\partial\ \theta}{\partial\ \mathrm{z}}}$$

Considering u is the velocity of the flow normal to the topographic barrier and Fr describes the air flowing over a mountain, we can use W_{Wind} and the angle (α) between W_{Wind} and the mountain orientation to represent Fr.

$$Fr = \frac{\mathrm{W}_{Wind} \cdot \sin\alpha}{N \cdot h}$$

Taiyuan and Shijiazhuang lie at almost the same latitude. When the influence of small-scale terrain on wind direction is neglected, the wind directions on the windward and leeward slopes are consistent. Therefore, the above formula can be easily understood by the following new added Figure S8.

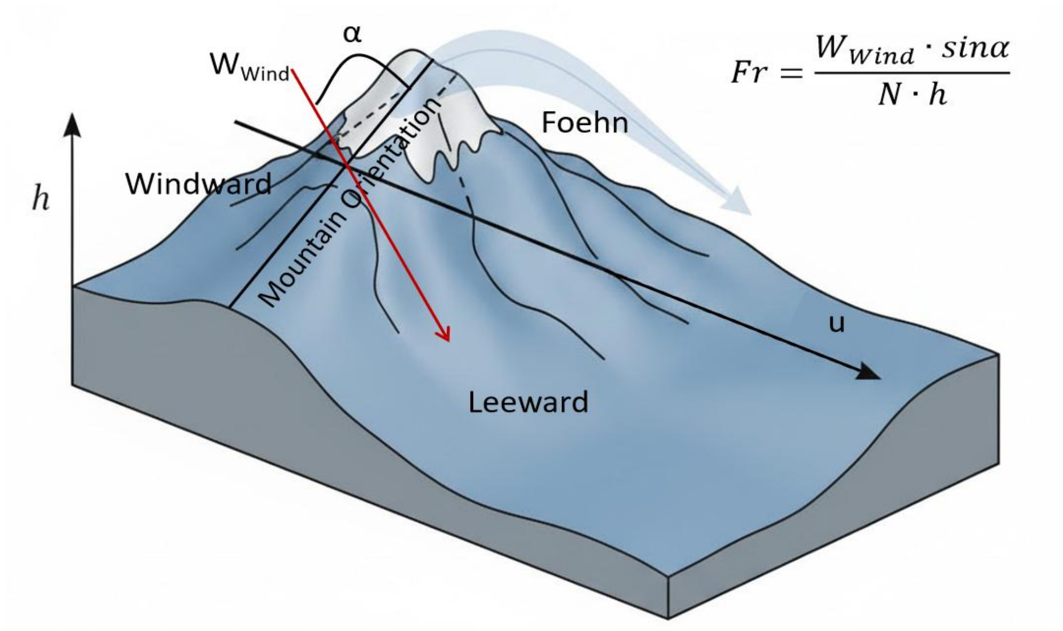

Figure S8: Schematic diagram illustrating the Froude number in relation to wind direction when the influence of small-scale terrain on wind direction is neglected. Fr is the Froude number; u is the velocity of the flow normal to the topographic barrier; N is the Brunt Väisälä frequency; h is the height of the topographic barrier; and α is the angle between W_{Wind} and the mountain orientation.

According to the classical theory, there are significant nonlinear effects and blocking when Fr≪1, whereas for Fr≫1, the opposite occurs (Smolarkiewicz & Rotunno, 1989, 1990). Fr around 1 indicates a transitional regime between the two states and favorable conditions for the formation of downslope lee windstorms and hydraulic jumps (Prósper et al., 2019; Wiesner et al., 2024). Therefore, wind direction can be calculated or verified by aiming Fr (≈1), in which the airstream will descend the leeward slope smoothly while converting potential energy into kinetic energy, and this process accelerates wind speed and enhances adiabatic warming via isentropic drawdown, which are two key characteristics of foehn.

Here is the specific calculating process which will better answer your questions (a) and (b):

First, we verified the most conducive wind direction by aiming Fr:

$$Fr = \frac{W_{Wind} \cdot \sin\alpha}{N \cdot h} = 1$$

W_{Wind} = 3 m/s according to SHAP analysis; α is the aiming unknown quantity; N is usually

0.01−0.03s^{-1}, here we calculated N = 0.01s^{-1} according to the results in Figure 5h; h = the difference between the minimum mountain height (between the two stations) and the altitude of the pre-mountain weather station, approximately 200 m. And the answer α is equal to 41.81°, which is really close the most conducive angle (90°-52°=38°) to the foehn development in line 226.

Then we can calculate the favorable Fr range by the conducive wind direction (237°-294°, which means α = 33°-90°) given by SHAP method in the "Section 3.1". And the answer Fr is equal to 0.82-1.5 (Thank you for your question, we calculated again and revise the 0.8-1.2 by this more precise consequence), which is conducive to the foehn development.

It is worth noting that this conclusion cannot be provided by traditional theoretical research. Following your suggestion, we have added more explanation and revised the relevant section to fix this gap in the revised manuscript as follows.

The "Section 3.1", Pages 10, lines 228-246:

"This wind-direction-dependent foehn formation mechanism is fundamentally supported by the Froude number (Fr) dynamics and terrain-airflow coupling effects, consistent with the principles of trans-barrier flow and orographic modification documented in foehn research (Durran, 1990). Froude number, defined as $\mathrm{Fr} = \frac{u}{Nh}$, (where u is the flow velocity normal to the topographic barrier, N is the Brunt-Väisälä frequency, and h is the height of the topographic barrier), quantifies the balance between inertial forces and buoyancy restoring forces, thereby determining the flow behavior when encountering topographic obstacles (Prósper et al., 2019; Wiesner et al., 2024). When $\mathrm{Fr} \ll 1$ there are significant nonlinear effects and blocking, whereas for $\mathrm{Fr} \gg 1$ the opposite occurs (Smolarkiewicz & Rotunno, 1989, 1990). The Fr around 1 indicates a transitional regime between the two states and favorable conditions for the formation of downslope lee windstorms and hydraulic jumps (Prósper et al., 2019; Wiesner et al., 2024). Within this range, the airflow neither fully circumvents the range ($\mathrm{Fr} \gg 1$) nor is completely blocked ($\mathrm{Fr} \ll 1$), thereby sustaining a persistent downslope warming that favors foehn occurrence. Considering the u is the velocity of the flow normal to the topographic barrier, wind direction can be calculated or verified by aiming Fr (≈ 1) (Figure S8). Calculations show that the α (the angle between W_{Wind} and the mountain orientation) is equal to 41.81° and the wind direction is equal to 278.81°, which is really close the most conducive wind direction (275°) to the foehn development given by our SHAP method. Based on the obtained favorable wind direction (237°-294°, which means α = 33°-90°) identified in the SHAP model, the favorable Fr range is calculated as 0.82 to 1.5 for the formation of foehn on the eastern foothills of the Taihang Mountains. This finding not only agrees with classical theory but also extends it to a specific range for the first time, thereby enriching the global understanding of foehn dynamics. Such a result cannot be obtained from traditional theoretical studies."

New added references

Durran, D. R. (1990). Mountain Waves and Downslope Winds. In *Atmospheric Processes over Complex Terrain* (pp. 59-81). American Meteorological Society. https://doi.org/10.1007/978-1-935704-25-6_4

Prósper, M. A., Sosa Tinoco, I., Otero-Casal, C., & Miguez-Macho, G. (2019). Downslope windstorms in the Isthmus of Tehuantepec during Tehuantepecer events: a numerical study with WRF high-resolution simulations. *Earth System Dynamics*, *10*(3), 485-499. https://doi.org/10.5194/esd-10-485-2019

Smolarkiewicz, P. K., & Rotunno, R. (1989). Low Froude Number Flow Past Three-Dimensional Obstacles. Part I: Baroclinically Generated Lee Vortices. *Journal of Atmospheric Sciences*, *46*(8), 1154-1164. https://doi.org/https://doi.org/10.1175/1520-0469(1989)046<1154:LFNFPT>2.0.CO;2

Smolarkiewicz, P. K., & Rotunno, R. (1990). Low Froude Number Flow Past Three-Dimensional Obstacles. Part II: Upwind Flow Reversal Zone. *Journal of Atmospheric Sciences*, *47*(12), 1498-1511. https://doi.org/https://doi.org/10.1175/1520-0469(1990)047<1498:LFNFPT>2.0.CO;2

Wiesner, L., McGowan, H., Sturman, A., & Dale, T. (2024). Subtropical Foehn Winds, Southeast Queensland, Australia. *Journal of Geophysical Research: Atmospheres*, *129*(13), e2023JD040410. https://doi.org/https://doi.org/10.1029/2023JD040410

Comment 3: Line 290: Please add a brief explanation in the discussion (or other appropriate place) to more explicitly link the stable stratification with the physical mechanism of foehn occurrence.

Response: Thank you for your constructive suggestion. We have added more explanations in the discussion, highlighted in red in the following paragraph:

The "Section 3.3", Pages 16, lines 328-344:

"Figures 5g, h reveal the atmospheric stratification stability through vertical potential-temperature (θ) profiles. The foehn events exhibit lower θ than the climatological mean between 700 and 300 hPa, with the largest deficit near 450 hPa on the leeward side (Figure 5h). This result shows that the presence of a mid-tropospheric cold air mass positively contributes to the foehn formation. Compared with climatology, the leeward side exhibits lower θ above 650 hPa, whereas the windward side shows a markedly lower θ within the 850–700 hPa lower troposphere (Figure 5g). It indicates that a pattern, which is colder in lower troposphere on the windward side and colder in upper layer on the leeward side, provides a stable atmospheric environment highly conducive to foehn events. In fact, both the windward and leeward sides are within a stably stratified environment (θ increases with height) overall (Figure 5h). Previous results showed that the stable stratification inhibits vertical mixing of the lower tropospheric airflow, leading to blocking of the cold air in the lower windward layer, while the warmer and drier air in the upper layer flows over the mountain and sinks along isentropic surfaces on the leeside (i.e., isentropic drawdown mechanism (Elvidge & Renfrew, 2016; Wiesner et al., 2024)). Also, the stable stratification provides favorable dynamic conditions for the development of mountain waves and hydraulic jumps (Wiesner et al., 2024), which further accelerate the sinking of leeward airflow and enhance the foehn effects of temperature increase and humidity decrease. The large-scale environmental conditions we identified in Figure 5e, f further reveal the synoptic patterns responsible for the formation of stable stratification during foehn events in the Taihang Mountains, linking large-scale synoptic conditions with local foehn formation mechanisms and deepening the systematic understanding of foehn development."

New added references

Elvidge, A. D., & Renfrew, I. A. (2016). The Causes of Foehn Warming in the Lee of Mountains. *Bulletin of the American Meteorological Society*, *97*(3), 455-466. https://doi.org/https://doi.org/10.1175/BAMS-D-14-00194.1

Wiesner, L., McGowan, H., Sturman, A., & Dale, T. (2024). Subtropical Foehn Winds, Southeast Queensland, Australia. *Journal of Geophysical Research: Atmospheres*, *129*(13), e2023JD040410. https://doi.org/https://doi.org/10.1029/2023JD040410

Comment 4: Line 315: It is suggested that the outlook section propose the future development of a regression model to predict specific foehn intensity metrics (such as wind speed or warming magnitude), and to again utilize the SHAP method to reveal its influencing factors. This would represent a natural and valuable deepening of the current classification-based research.

Response: Thank you for your constructive suggestion. This is a really good point, enabling the classification-based research extending and deepening. We added this revision in the Discussion and Conclusion Session as follows:

The "Discussion and Conclusion section", Pages 19, lines 417-420:

"Furthermore, our future research will further develop a regression model to predict specific foehn intensity metrics (e.g., foehn wind speed and warming magnitude), and apply the interpretable method to quantify and reveal the key influencing factors governing these intensity indicators. These will serve as a useful reference for understanding foehn winds in other regions of the world."