Reviewer #2

This study uses Self-Organizing Maps (SOM) and K-means clustering to reduce data dimensionality and identify the key components of variables such as Z500, which describe different large-scale meteorological patterns (LSMPs) that produce varying wind patterns. For each LSMP, wind data from HRRR is evaluated against two in-situ lidar buoys, with biases documented and presented. I found the manuscript technically sound, with interesting and valid methods to present the results. Below are several suggestions that could help improve the motivation and discussion sections:

We thank the reviewer for their thoughtful and constructive comments and suggestions, which has substantially improved the quality of the manuscript. We have addressed all the reviewer's concerns and revised the manuscript accordingly. Our point-by-point responses are in blue and the modifications to the manuscript are quoted in green.

In the introduction, you mentioned that the community relies on modeling data, but you didn't explain why. A transition paragraph discussing the sparsity of observational data offshore is needed. This would provide context as to why models are essential and why it's important to validate them.

Good point. The following paragraph has been added to Line 32-37 to discuss the sparsity of observational data.

As of October 2023, five wind energy lease areas were established off the California coast — two off Humboldt County and three off Morro Bay (BOEM, 2023). Observational datasets are ideal for assessing and characterizing the wind resource. The U.S. Department of Energy funded the installation of two research buoys in these areas, equipped with lidar and other instruments to collect wind measurements for resource assessment and model evaluation (Krishnamurthy et al., 2023). However, due to the challenges associated with deploying and maintaining offshore equipment, these measurements remain limited.

Although your focus is on validating HRRR, it might be worthwhile to mention other modeling datasets, especially since HRRR has a relatively short record. For instance, you could reference NOW-23 (offshore wind data developed by NREL) or the newly published Wind Toolkit (WTK-LED) by NREL. These datasets could also serve wind resource assessment purposes.

The following sentences have been included in the revision in Line 41-43.

The 2023 National Offshore Wind dataset (NOW-23) is the latest wind resource dataset for the offshore region in the U.S., launched by the National Renewable Energy Laboratory (NREL) (Bodini et al., 2024). The NOW-23 dataset delivers an updated and cutting-edge product to stakeholders.

The method you developed for validating HRRR model performance under different LSMPs can be applied to other model products as well. It might be helpful to mention this in the discussion to highlight the broader applicability of your approach.

Thank you for your insightful suggestion. We agree that the method developed for validating the HRRR model's performance under different LSMPs can be extended to other model products. Additionally, this approach can be applied to understand how environmental factors influence airflow evolution, benefiting predictive studies. By linking model performance with LSMPs, the results can also foster mechanism analysis, helping to explore the model's ability to capture underlying physical processes. We have included a discussion highlighting the broader applicability of this method in the revised manuscript in Line 331-.

This study introduces a new approach to characterizing offshore winds and associated model biases, linking them to LSMPs. The methodology used for evaluating HRRR performance under different LSMPs can be applied to other numerical weather prediction models. This approach not only identifies model strengths and weaknesses but also provides valuable insights into how environmental factors influence airflow, aiding predictive studies. By connecting model performance to LSMPs, this method promotes mechanism analysis, fostering studies on a deeper understanding of the physical processes behind wind patterns. Furthermore, the results are anticipated to guide the selection of cases for studying the influence of specific large-scale and local factors on winds off the California coast, which will aid in refining numerical weather prediction models, thereby enhancing the efficiency and reliability of offshore wind energy production.

Finally, while this paper proposes a useful method for validating models beyond just examining overall mean wind speeds, it would be valuable to discuss the implications for industry and data users. How should they interpret the identified biases when using these data for wind farm development? What practical guidance can be offered?

In the revised manuscript, we expand on how the identified biases can inform wind farm development and offer practical guidance on using model outputs. The following texts has been added.

The identified model biases have significant implications for wind farm development, particularly in offshore environments where accurate wind resource assessments are essential. For instance, the overestimation of wind speeds in certain LSMPs, such as pre-ridge and California-high conditions, could result in overestimating potential energy output. To address this, data users should approach HRRR model outputs cautiously under these conditions and incorporate model uncertainties into their assessments. Beyond the mean status of wind speed, future studies could link the wind power features like ramp frequency and intensity to LSMPs. Practical measures, such as utilizing ensemble forecasts or combining multiple models, can help mitigate the effects of these biases on wind farm siting and design decisions.