**Manuscript: Spatiotemporal mapping of invasive yellow sweetclover blooms using Sentinel-2 and high-resolution drone imagery**

**Referee 2:**

Remote sensing of invasive species is an important research topic. Here, the authors combine Sentinel-2 data with drone imagery to map invasive yellow sweetclover blooms across western South Dakota in a multiannual approach using machine learning.

This study could be an interesting example of how remote sensing can be applied in monitoring plant invasions. Further details about data analysis need to be added to the methods. Some results need to be supported by data. Some parts of the discussion need to be moved to the results section, and the discussion would benefit from further interpretation of the results which includes citing external literature.

We sincerely thank the referee for their constructive feedback. We have added further details on data analysis in the Methods, moved results-related content from the Discussion to the Results section, and provided data support for key findings. The suggested revisions have improved clarity, strengthened data support, and placed the study within the broader context of remote sensing applications in plant invasion monitoring.

Note-The page and line number reference are based on the track changes/colored document provided in the supplementary. RC: Referee’s comment, AC: Author’s comment/response

I have a couple of questions/remarks:

RC1: L63: “However, previous studies often miss important data…”: Data on what?

AC1: We thank the referee for pointing this out. We have clarified in the revised manuscript that the missing data refer specifically to spatiotemporal information on invasion dynamics (e.g., species cover, spread rates, and environmental drivers). The revised statement in lines 64-67 is “However, previous studies often lack important spatiotemporal data on invasion dynamics, such as changes in species cover, spread rates, and environmental drivers, making it difficult to fully understand invasion processes that unfold continuously across space and time (Larson et al., 2020).”

RC2: L83: The spatial resolution depends on the size of the target species and/or age of the plant individual. Reformulate.

AC2: We thank referee for suggesting this correction. We have revised the statement in lines 87-90 as

“Invasive forbs such as MEOF develop yellow inflorescences that are prominent during flowering time and can be detected using 10 m resolution Sentinel-2 derived reflectance and quantitative indices, provided the plants meet the optimal size or developmental stage for detection (Saraf et al., 2023).”

RC3: L132: What do you mean by a generalized model?

AC3: We thank the referee for the comment. We have revised the sentence in lines 143-145as “Developing a generalized model that can be implemented across space and time allows for efficient mapping of irruptive invasive plant species that bloom episodically and form clustered patches.”

RC4: L141: From the logic of the introduction it is not clear why this validation step using PS imagery is required. Refine.

AC4: We thank referee for the suggestion. We have revised the third objective in lines 154-157 as: “(3) to further validate the predicted yellow sweetclover maps using PlanetScope imagery, which provides higher temporal resolution and independent data for cross-sensor validation, and to assess MEOF cover in regions lacking UAS coverage.”

RC5: L199: How were the ten sites selected?

AC5: We appreciate the referee’s concern and have added the following clarification to the manuscript in lines 217-222: “All 14 sites captured the observed range of MEOF percent cover, but they differed in total area covered by MEOF presence and the number of samples derived from each site. To ensure a balanced split, the 10 smaller sites were randomly selected for training the RF model, while the remaining four larger sites were reserved for validation. This approach ensured that both the training and validation sets contained approximately equal numbers of samples, providing an unbiased assessment of model performance.”

RC6: L204ff: So the cover of smaller plots were regarded as representative for the larger plots? Were they averaged? Please elaborate.

AC6: We appreciate the referee’s comment and have revised the sentence in lines 241-246 as “Within each 30 m × 30 m plot, a minimum of three 0.5 m × 0.5 m quadrats were sampled. Percent cover for each plot was calculated as the average of the quadrat measurements, with each quadrat considered representative of its portion of the plot. Within each quadrat, we estimated percent cover of MEOF by averaging the grids it occupied, allowing fine-resolution observations to be scaled up to the plot level while capturing spatial variability (John et al., 2018).”

RC7: L209ff: How do these samples compare to the samples described in L204ff? Were they sampled in a similar way?

AC7: We thank the referee for this comment. We have clarified in the revised manuscript that the historical samples were obtained using different field protocols but were integrated with our field-collected data to increase spatial and temporal coverage. The revised paragraph in lines 225-254 are as follows:

“We used a total of 22,972 MEOF percent cover samples collected across western South Dakota rangelands and surrounding regions during 2016-2023 (Table S1). This included 5,283 samples derived from UAS imagery collected during the peak blooming months (June–August) in 2023 (details in Sections 2.2 and 2.4) across western South Dakota rangelands. In addition, 17,689 MEOF cover samples were retrieved and synthesized from multiple federal, state, and non-governmental sources for 2016–2022 across four states: South Dakota, North Dakota, Montana, and Wyoming (Figure 1a; Table S1). Although the historical samples were obtained using different field protocols, they were integrated with our field-collected data to increase spatial and temporal coverage. These sources included RCMAP data from the USGS Center for Earth Resources Observation & Science, USGS Northern Rocky Mountain Science Center (Montana), the Bureau of Land Management (BLM) database, the Northern Great Plains Inventory & Monitoring Network, the National Ecological Observatory Network (NEON), and the Montana Natural Heritage Program. The source, year-wise distribution, and frequency of the samples are summarized in Tables S2 and S3. At the 10 m mapping scale, this compilation provided a suitable reference for model training and validation. Our field-collected surveys recorded the plant species composition, including dominant species and percent cover of all species present, using the conventional plot-based quadrat method. Within each 30 m × 30 m plot, a minimum of three 0.5 m × 0.5 m quadrats were sampled. Percent cover for each plot was calculated as the average of the quadrat measurements, with each quadrat considered representative of its portion of the plot. Within each quadrat, we estimated percent cover of MEOF by averaging the grids it occupied, allowing fine-resolution observations to be scaled up to the plot level while capturing spatial variability (John et al., 2018). We recorded flowering and non-flowering MEOF individuals separately. The separation was done to document phenological variability and population structure, which can be useful for understanding interannual flowering dynamics in future analyses. However, only the flowering MEOF percent cover was used for remote sensing–based mapping, as flowering individuals exhibit a distinct spectral signal that can be consistently detected in aerial and satellite imagery. This approach ensured that the satellite-derived cover estimates corresponded specifically to the detectable, flowering component of MEOF. For 2023, the GPS locations of the field-collected quadrat samples were utilized as the ground control points for enhancing the processing of drone imagery to derive percent cover samples.”

RC8: L215ff: Was there any non-flowering MEOF in your plots, and was the cover of non-flowering MEOF estimated?

AC8: Thank you for the comment. In our field surveys, we recorded flowering and non-flowering MEOF individuals separately. The separation was done to document phenological variability and population structure, which can be useful for understanding interannual flowering dynamics in future analyses. However, only the flowering MEOF percent cover was used for remote sensing–based mapping, as flowering individuals exhibit a distinct spectral signal that can be consistently detected in aerial and satellite imagery. This approach ensured that the satellite-derived cover estimates corresponded specifically to the detectable, flowering component of MEOF. We have clarified this in section 2.3 in lines 246-252 (paragraph added in the previous comment) to the revised manuscript.

RC9: L225: Hyperparameter tuning was performed to optimize which accuracy parameter?

AC9: We appreciate the referee’s comment. We have revised the statement in lines 267-269 as “ We tuned the Random Forest hyperparameters (mtry = 4, ntrees = 1500) to optimize model predictive performance, specifically by minimizing the Root Mean Square Error (RMSE) using 10-fold, 5-repeat cross-validation.”

RC10: L228: Which threshold was chosen for the binary classification?

AC10: We thank the referee for the question. We have revised the statement in lines 271-274 as “We converted the continuous Random Forest predictions to binary presence/absence using a threshold of 0.5, assigning pixels with predicted probability ≥ 0.5 as MEOF presence (assigned as 1) and pixels < 0.5 as absence (assigned as 0) (Josso et al., 2023; Steen et al., 2021).”

RC11: L237ff, L256, L318ff: If data based on an RF model is used to perform another analysis using RF (or any other kind of model), can this lead to error propagation?

AC11: Thank you for the comment. We acknowledge that using Random Forest (RF)–derived percent cover estimates as input for further analyses could introduce some degree of error propagation. To minimize this, we calibrated the RF-derived values against independent field observations using a leave-one-out jackknife procedure. We used linear regression for calibration because it provides a simple and transparent way to correct systematic biases in the RF predictions. This approach ensures that each predicted value is validated independently of the data used for model training, reducing overfitting and mitigating bias.

RC12: L239: Why did you decided to use linear regression and not any other type of approach?

AC12: We appreciate the referee’s comment. We have clarified the calibration procedure and the rationale for using linear regression in section 2.4 in the revised manuscript. We have revised the statement in lines 288-292 as “We used linear regression to calibrate RF-derived percent cover estimates because it provides a simple and transparent way to correct systematic biases. To ensure unbiased predictions and minimize overfitting, we applied a leave-one-out jackknife procedure, where each observation was predicted independently of the data used to fit the model (Wolter, 2007).”

RC13: L250: I think the methods needs a workflow diagram to visualize how which data was used for what purpose.

AC13: We thank the referee for the suggestion. We have added the reference to workflow diagram (Figure 2) in lines 292-295 and cited it accordingly throughout the methods section.

RC14: L289: How were the data resampled?

AC14: We thank the referee for the comment. We have added the sentence in lines 334-337 to clarify the procedure: “All variables were resampled to 10 m resolution and projected in Albers Equal Area projection and WGS 84 datum. We used bilinear interpolation for predictor variables to preserve data integrity during resampling.”

RC15: L309: Write RF out and cite it earlier in the manuscript.

AC15: We thank the referee for pointing this out. We now spell out Random Forest (RF) at its first mention in the Introduction and cite Breiman (1984) there. In the Methods and later sections, we use the abbreviation RF consistently.

RC16: L309: Overlaid or extracted?

AC16: As suggested, we have replaced the ‘overlaid’ with ‘extracted’ in the sentence in lines 360-361. The revised sentence is “We constructed a predictor variable database by extracting observed sample points from the satellite-derived predictor variables (rasters) for training the RF model.”

RC17: L330: Distinguishing flowering MEOF pixel?

AC17: We thank the referee for the comment. We have corrected the sentence in lines 380-382 as “The developed RF classification model exhibited an overall accuracy of 98.76% and kappa of 0.97 in distinguishing flowering MEOF pixels.”

RC18: L345: RF predictions of what?

AC18: We thank the referee for the suggestion. The title of Section 3.2 has been revised to “Regional-scale Random Forest predictions of MEOF cover” in the manuscript.

RC19: L348: Name the predictors or at least the most important groups.

AC19: As suggested, we have included the names of the predictors and added the following statement to the manuscript in lines 396-404: “The top 13 predictor variables included climatic variables — mean annual precipitation (MAP), coefficient of variation of MAP (MAPcv), mean annual temperature (MAT), coefficient of variation of MAT (MATcv), snow depth (SnowDepth), and coefficient of variation of snow depth (SnowDepth\_cv); topographic variables — elevation (Elevation) and slope (Slope); proximity to roads (Dist\_Roads); and remote sensing indices capturing moisture and vegetation properties —Normalized Difference Moisture Index (NDMI), coefficient of variation of Normalized Difference Water Index (NDWIcv), coefficient of variation of Land Surface Water Index (LSWIcv), and coefficient of variation of Tasseled Cap Wetness (TCWcv; Table 2).”

RC20: L362ff: Support this result statement with data.

AC20: We thank the referee for the comment. We have removed the statement regarding MEOF cover following moisture gradients, as the available data do not consistently support this pattern.

RC21: L377ff: Could mass blooming be affected rather by ground water parameters than precipitation? Were any patterns observed regarding closeness to floodplains? Maybe further analysis focusing on watersheds could also help to understand the mass blooming.

AC21: We thank the referee for these insightful suggestions. We agree that local groundwater availability and soil moisture may influence MEOF blooms in addition to precipitation. While we observed higher cover near floodplain regions in certain years, this pattern was not consistent across all years. We have added a statement in the manuscript noting that future analyses incorporating watershed and hydrological variables could help clarify the environmental drivers of mass blooming events. We have added the following statements in lines 505-513 in the discussion section 4.1: “There is a possibility that MEOF blooms could be influenced not just by precipitation but also by local groundwater availability or soil moisture, particularly in areas near floodplains. While we observed some higher cover near floodplain regions in certain years, the pattern was not consistent across all years. Future analyses focusing on watersheds and hydrological variables could help clarify the environmental drivers of bloom events. Overall, our findings suggest that climate contributes to interannual variation in MEOF cover, while previous studies suggest that spatial heterogeneity and local environmental conditions further modulate vegetation dynamics across the Northern Great Plains (Fore, 2024).”

RC22: L378-383: “This unexpected result may be due to the large disparity in spatial resolution between Sentinel-derived variables at 10 m and the 1 km climate variables, with the 10,000-fold difference in spatial resolution contributing to an underestimation of precipitation as a significant variable. Therefore, we created a MEOF percent cover map series for 2016 through 2023 and compared it with precipitation anomaly maps during the same period computed using the Daymet dataset product.”: This sounds like a results. And I don’t really understand the latter part. Please reformulate.

AC22: We thank the referee for this helpful comment. In response, we have split the first couple of paragraphs of Section 4.1 into Results and Discussion. Observed MEOF patterns are now fully described in the Results section, while the Discussion focuses on interpretation. We also explicitly acknowledge that mass blooming may be influenced not only by precipitation but also by local groundwater availability or soil moisture, particularly near floodplains, and we suggest future analyses incorporating hydrological variables. These changes clarify the role of climate versus local environmental factors and improve the logical flow of the manuscript.

***The three paragraphs added in the result section in lines 427-476:***

“We created a MEOF percent cover map series for 2016–2023 and compared it with precipitation anomaly maps to assess the potential relationship between MEOF cover and interannual climatic variability. These precipitation anomaly maps showed that the western SD witnessed above-average precipitation in a few regions for 2018 and 2023 and most of the western SD for 2019 (Figure S4). The central and eastern counties in 2019 and the central and southern counties in 2023 showed a greater range of MEOF covers showing a consistent pattern of MEOF resurgence with the return of wet conditions. Despite 2016 being a relatively normal or slightly dry year, sweetclover cover remained moderate with less spatial variability, indicating less widespread establishment. The widespread establishment of MEOF could be seen increasing in 2018, with a high Coefficient of Variation (CV) of 0.5 and the percent cover reached a peak in the subsequent year of 2019. For the years 2020, 2021 and 2022, most regions experienced average to below-average rainfall conditions. During these years, the MEOF percent cover reached up to 50%, with a sharp drop in percent cover in 2021, where the maximum cover was only 43%. This showed drought conditions likely limit growth and establishment. The year 2020 and 2022 acted as transitional years, possibly due to lagged ecological response. For dry years, the majority of western SD predicted less than 50% cover.

Overall, we found a high percent cover range in the western counties of western SD including Butte, Meade, Pennington, Custer, Fall River, Jackson, Bennet and Oglala Lakota counties. Central South Dakota counties showed fluctuating trends, with moderate to high coverage in some years (e.g., 2018, 2019, 2023) and relatively low coverage in other years (e.g., 2020, 2021), whereas the eastern counties (i.e., Corson, Dewey, and Stanley) consistently exhibited relatively low percent cover (<20%) for the majority of years. In the eastern region, MEOF appeared to be more scattered and patchier with fewer patches of higher percent cover near floodplains, which are situated at lower elevations and benefit from high moisture availability especially in the years 2018 and 2019. During the summer fieldwork of 2022, we observed MEOF predominantly in the first year of its life cycle. In the following year, we observed ample coverage of MEOF blooms in Butte County, SD forming patches substantial enough to be captured by the drones. This temporal pattern arises from the biennial growth period of MEOF. Additionally, we predicted MEOF percent cover estimates for the year 2024 using our trained model (Figure S5). However, this 2024 prediction has not yet been validated due to the unavailability of field data. Validation of model performance for 2024 and subsequent years remains a key focus for future work.

Year-wise evaluation of model performance revealed considerable variation in normalized RMSE (nRMSE), which ranged from 0.12 in 2022 to 0.65 in 2023 (Table S9). The year-wise sample distribution of observed MEOF cover could be a partial reason for these differences. In 2018, the observed cover exhibited the greatest variability (CV = 0.51) and reached a maximum cover of 81%. However, the nRMSE remained low (0.19), indicating that the model effectively captured patterns in years with a broader range of values. Conversely, 2023 exhibited the highest error (nRMSE = 0.657) despite having the 100% maximum cover and the lowest variability (CV = 0.25). This high error occurred despite a relatively large sample size, likely due to spatial clustering and the reduced ability of the model to predict extreme cover values. Consequently, the model's capacity to generalize to high-cover conditions was restricted. Similarly, 2020 had a moderate maximum cover (56%) but relatively high error (nRMSE = 0.55), which may reflect imbalances in sample distribution across cover classes. In contrast, the most optimal overall performance was achieved in 2022 (max = 57%, CV = 0.38) (nRMSE = 0.124), which implies that predictive accuracy is enhanced by balanced sampling across cover ranges. These results emphasize that the distribution and variability of cover values across years have a significant impact on predictive performance, although increasing the sample size improves model stability.”

***Revised paragraphs in the Discussion section in lines 495-536:***

“The occurrence of sweetclover years is predominantly associated with wetter conditions, suggesting that precipitation plays a key role in the resurgence of MEOF (Gucker, 2009). Despite this, climate variables such as annual precipitation or snow depth, did not rank among the top predicting variables. This may be due to MEOF’s biennial life cycle, where precipitation from the previous year can influence current-year cover (Klebesadel, 1992; Van Riper and Larson, 2009). We tested this by including biennial precipitation (MAP2). However, due to its high correlation with annual precipitation (MAP) and the higher relative importance of MAP, neither variable alone, at the coarser 1 km resolution, adequately captured the biennial dynamics. This unexpected result may be due to the large disparity in spatial resolution between Sentinel-derived variables at 10 m and the 1 km climate variables, which likely contributed to an underestimation of precipitation’s importance in the model (Latimer et al., 2006). There is a possibility that MEOF blooms could be influenced not just by precipitation but also by local groundwater availability or soil moisture, particularly in areas near floodplains. While we observed some higher cover near floodplain regions in certain years, the pattern was not consistent across all years. Future analyses focusing on watersheds and hydrological variables could help clarify the environmental drivers of bloom events. Overall, our findings suggest that climate contributes to interannual variation in MEOF cover, while previous studies suggest that spatial heterogeneity and local environmental conditions further modulate vegetation dynamics across the Northern Great Plains (Fore, 2024).

Despite experiencing ample moisture in some areas in 2016 or 2018, the ‘sweetclover year’ super blooms were limited only to 2019. This phenomenon may be attributed to MEOF’s biennial life cycle, which plays a significant role and acts as a lag effect provided average or above average conditions persist (Van Riper and Larson, 2009). A distinct drop in coverage is seen in the years of 2020 and 2021 across the south, with a recovery in 2022–2023. Moreover, MEOF with >40% percent cover was found in mostly regions that received above-average precipitation during both dry and wet years, highlighting the importance of moisture in regulating dominance. This aligns with previous studies showing that sweetclover cover can fluctuate substantially from year to year, driven by its biennial growth habit and strong germination response in years with high precipitation (Turkington et al., 1978). Although the RF model did not identify precipitation as the top predictor, our predicted MEOF cover maps showed that years of high cover (e.g., 2018 and 2019) coincided with favorable moisture conditions, whereas lower cover in 2020–2021 corresponded with drier years. This pattern supports the hypothesis that ‘sweetclover years’ of high MEOF abundance occur when favorable moisture conditions are maintained, allowing successful establishment and dominance despite losses from evapotranspiration. These favorable moisture conditions likely facilitate the successful establishment and dominance of MEOF across the Northern Great Plains rangelands, consistent with broader patterns observed for invasive species in semi-arid rangelands (Brooks et al., 2004; D’Antonio and Vitousek, 1992) . Similar patterns have been observed for exotic annual grasses such as Cheatgrass (*Bromus tectorum* L.*)*, Red brome (*Bromus rubens* L.) or Medusahead (*Taeniatherum caput-medusae* (L.) Nevski), which often increase under periods of favorable precipitation (Chen and Weber, 2014; Dahal et al., 2023).”

RC23: L390: What does CV stand for?

AC23: We have spelled out CV and revised statement as “ The widespread establishment of MEOF could be seen increasing in 2018 with high Coefficient of Variation (CV) of 0.5 and then it’s percent cover reached a peak in the subsequent year of 2019.”

RC24: L377-396: This sounds like a results section. Please reformulate.

AC24: As suggested, we have split the first couple of paragraphs of Section 4.1 into two parts. The portion describing observed MEOF patterns has been moved to the Results section, while the remaining portion stays in the Discussion. We also added relevant citations to support interpretation and maintain a logical flow. The added paragraphs in the Results section and the revised Discussion paragraphs are provided in our response to a previous comment.

RC25: L415ff: How did the time-series maps support the hypothesis? I don’t see this in your line of argumentation.

AC25: We thank the referee for this comment. To clarify how the time-series maps support our hypothesis, we have revised the statement in lines 524-530 as follows: “Although the RF model did not identify precipitation as the top predictor, our predicted MEOF cover maps showed that years of high cover (e.g., 2018 and 2019) coincided with favorable moisture conditions, whereas lower cover in 2020–2021 corresponded with drier years. This pattern supports the hypothesis that ‘sweetclover years’ of high MEOF abundance occur when favorable moisture conditions are maintained, allowing successful establishment and dominance despite losses from evapotranspiration.”

RC26: L398-423: This section lacks external references. Support your interpretation with references to existing literature.

AC26: We thank the referee for this suggestion. As recommended, we have moved this section to the Results. The remaining portion in the Discussion now includes references to maintain logical flow and situate our findings within the existing literature.

RC27: L427: Why does particularly the bloom trigger changes in soil nitrogen content? Is it not generally an N-fixing species?

AC27: We thank the referee for this helpful suggestion. We have revised the statement in lines 483-487 as follows: “These blooms cause a sudden increase in annual net primary production, triggering relevant changes in the ecosystem such as increases in soil nitrogen content due to N-fixation, temporary plant composition modifications, attraction of predators, etc. (Jaksic, 2001), as well as changes in the local climate: an increase in evapotranspiration and a decrease in albedo (He et al., 2017).”

RC28: L443-446: The ecological consequences are an interesting aspect to be discussed. I think this aspect could be elaborated further.

AC28: We thank the referee for this suggestion. To elaborate on the ecological consequences of MEOF invasion, we have added the following statements: “Furthermore, the database supports investigation of the ecological consequences of MEOF invasion. For example, MEOF’s nitrogen-fixing ability may alter soil nutrient dynamics, potentially facilitate its own dominance while affect native plant communities. Increased MEOF cover could lead to declines in native species richness, shifts in plant community composition, and changes in ecosystem processes such as nutrient cycling and primary productivity, particularly in nitrogen-limited prairie ecosystems. Understanding these impacts is critical for predicting long-term vegetation changes and developing targeted management strategies.”

RC29: L465: Which data show that local moisture dynamics and human disturbance play a critical role? Explore this further.

AC29: We thank the referee for this comment. To clarify which data support the role of local moisture dynamics and human disturbance, we have revised the statement as follows: “Overall, our results suggest that local moisture dynamics, captured by NDMI and NDWIcv, and human disturbances, reflected by proximity to roads, are stronger determinants of MEOF distribution at fine spatial scales than coarser-resolution climatic variables (snow depth, MAP, MAT, and their variability). Although climate may establish broad-scale suitability, our data indicate that MEOF invasion patterns in western South Dakota are primarily influenced by local hydrological conditions and human-mediated dispersal.”

RC30: L478: Is there any way to deal with unbalanced data sets? Can you really relate the increased RSME with the imbalanced date set?

AC30: We thank the referee for this comment. To address concerns regarding unbalanced datasets, we added a couple of statements in the manuscript and revised this paragraph in lines 581-599 as follows:

“It is important to note that reducing the sample size from 22,972 to 11,235 due to high spatial correlation did not substantially affect model performance. However, in comparison to Saraf et al., (2023), a much larger overall sample size was required to improve predictive accuracy. We developed a single generalized RF model across all years (2016–2023) and applied it to predict MEOF cover annually. Thus, while temporal imbalance in samples (e.g., more samples from bloom years such as 2019 and 2023) influenced the overall distribution of training data, spatial balance and adequate coverage across the full percent cover range were the most critical factors for model accuracy. We found that increasing the sample size and ensuring a more balanced distribution significantly improved model performance, raising R² from 0.55 (Saraf et al., 2023) to 0.76. RMSE increased from 7% to 15%, reflecting the inclusion of a wider range of percent cover values rather than insufficient sample size or overall imbalance. Saraf et al., (2023) reported that their model underestimated high percent cover due to a limited sample size (n = 1,612). In contrast, our model utilized a larger and more evenly distributed sample (n = 11,235) across years, improving predictive accuracy and the representation of extreme cover values. These findings suggest that balanced sample sizes enhance both the predictive range and accuracy of RF models, although temporal imbalance in certain years may still influence RMSE and require further investigation. Moreover, it is noteworthy to highlight that it is difficult to fully stratify samples temporally for a biennial species like MEOF, which remains dormant during certain seasons and blooms only under specific environmental conditions.”

RC31: L497: Why did you not use the manually delineated polygons for modelling instead of the modelled cover values to avoid problems of error propagation?

AC31: We thank the referee for this comment. To clarify, we have added an explanation in lines 615-620 as follows: “We manually delineated MEOF presence and absence polygons on the UAS imagery, which were used to train and validate the RF classification model. The resulting classified image was then used to derive continuous, wall-to-wall fractional cover estimates across the UAV sites. We used these model-derived continuous MEOF cover values, rather than the manual polygons, for regression analyses in order to generate numerous spatially explicit cover samples and to capture gradients of invasion across the landscape.”

RC32: L539ff: The whole section sounds like results. Reformulate and/or remove.

AC32: We thank the referee for this suggestion. In response, we have removed “Section 4.6 Validation with Planet Imagery” and incorporated the content in lines 659-668 into Section 4.5 “Validation for 2023 estimates.” The revised paragraph reads as follows:

“In addition to UAS validation, we used four-band (visible and near-infrared), 3 m resolution Dove Classic and SuperDove PlanetScope (PS) imagery for 2019 and 2023 through the NASA CSDA program (Planet Labs PBC, 2023) to further assess model predictions (Figure 7). PS scenes were selected for locations with predicted high MEOF cover, and false-color combinations (green-green-blue) were applied to enhance visualization of MEOF blooms. These imagery data offered an independent and freely available means to complement the UAS-based validation by visually verifying the spatial patterns of predicted MEOF cover across sites where field data were unavailable. In general, the validation results indicate that the RF model effectively depicts spatial variation in MEOF cover throughout the study area, thereby providing a reliable foundation for evaluating invasion intensity on a landscape scale.”

RC33: L548-550: Support this statement with data. It would rather belong to results. In the discussion, further interpretation of the results are needed.

AC33: We thank the referee for this comment. The statement in lines L548–550 has been removed, and the paragraph has been rephrased in lines 659-668 for inclusion in the Discussion section (Section 4.5), focusing on interpretation rather than presenting results. The revised paragraph, which now places the PlanetScope validation within the broader discussion of model reliability and spatial variation, is provided in the previous comment.

RC34: L569: Do you mean PlanetScope data when referring to high-resolution mapping? What could be limitations of PlanetScope data?

AC34: We thank the referee for this comment. We have revised the sentence in lines 684-689 to clarify that high-resolution mapping refers to both Sentinel-2 and PlanetScope data, and also highlighted the challenges with uneven predictor spatial resolutions: “High-resolution mapping, even at Sentinel-2 (10 m) or PlanetScope (3 m) resolution, is complicated by the uneven spatial resolution of independent variables, making it more difficult to understand their relative roles in characterizing the niche of invasive species. Mapping at very high resolution, such as 3 m PlanetScope imagery, has its own limitations, including fewer spectral bands, lower radiometric calibration, and higher noise levels in vegetation indices, which can affect the accuracy of species-specific detection.”

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