Manuscript title: Satellite-derived Ecosystem Functional Types capture ecosystem functional heterogeneity at regional scale

Authors: Beatriz P. Cazorla et al.

06 Oct 2025 - Associate editor decision: Reconsider after major revisions, by Cornelius Senf

Dear authors,

Thank you very much for your response. While reviewer #2 had only few remarks, reviewer #1 remarked several instances where methodological choices were subjective and where better justifications (or even sensitivity analyses) are required. I recommend to revise your manuscript (major revision) to improve the manuscript with respect to the comments before a final decision can be made.

Sincerely,

Cornelius Senf

Dear Editors and Reviewers,

We thank the Editor and Reviewers for their support of this work and for their constructive comments, which provided valuable insights to refine the paper's content and analysis. In this revised version, we have addressed all issues highlighted by the Editor and the Reviewers. The main changes are summarized as follows:

1. **Justification of the EVI-based functional approach**
We explicitly state and clarify throughout the manuscript, particularly in the Introduction and Discussion, that the study focuses on a single ecosystem function: primary production dynamics, captured through EVI. We justify the use of EVI for this purpose and acknowledge that future applications could be strengthened by incorporating additional functional variables.

2. **Improved methodological transparency**
We provide a substantially strengthened justification for using four intervals per functional attribute and the resulting 64 EFT classes. In addition to detailing the ecological and statistical rationale for this approach, we explicitly discuss its implications for classification robustness and report evidence from the literature indicating that moderate changes in binning schemes exert limited influence on derived functional patterns. To enhance interpretability and reproducibility, we have also included complementary materials in the Supplementary: (i) a simplified EFT map derived through functional clustering; (ii) a schematic table summarising bin thresholds and representative value ranges; (iii) a table with examples of EFTs code combinations and their ecological interpretation; and (iv) supplementary figures illustrating the EFAs and the contribution of each attribute (productivity, seasonality, phenology) to the final EFT colour scheme.

3. **Strengthened Discussion of methodological considerations**
We have substantially enriched the Discussion to address several conceptual and methodological aspects raised by the reviewers. Specifically, we now discuss: (i) the implications of focusing on

EVI-based primary production as our core functional axis and the potential value of incorporating additional functional attributes; (ii) limitations related to footprint–scale mismatches between EC measurements and satellite observations; (iii) the complementary role of other temporal metrics such as SOS/EOS, anomalies, or interannual variability; and (iv) the possibility of developing simplified or multidimensional EFT schemes for broader applications, including Earth System Models. These additions provide a more comprehensive framework for interpreting our methodological choices and situating the study within the broader context of ecosystem functioning research.

4. **Corrections and refinements**
We improve clarity and consistency across the figures and text (e.g., by correcting the symbol descriptions in Fig. 1).

Overall, we have made substantial efforts to integrate all reviewer suggestions and to improve the clarity and robustness of the manuscript. Therefore, we consider that the manuscript has substantially improved in clarity and content.

In our response below, please find our point-by-point responses (indicated with "R") presenting, in detail, how we have addressed the Reviewer comments ("C"). In this document, we reproduce the Reviewer comments in bold font, and our responses are indicated in plain text. We numbered each comment and replied for ease of reference, and we also showed the changes made in the manuscript. The lines indicated correspond to the clean version without track change control.

Sincerely,

Beatriz P. Cazorla on behalf of the authors

Reviewers' COMMENTS

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RESPONSE TO COMMENTS FROM REVIEWER 1

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Reviewer: 1

Comments to the Author(s)
General assessment:

This study presents a timely analysis of ecosystem functional heterogeneity across Europe by testing whether satellite-derived Ecosystem Functional Types (EFTs), defined from MODIS EVI time series, are coupled with Net Ecosystem Exchange (NEE) patterns measured at eddy-covariance (EC) sites. By comparing EFTs with conventional Plant Functional Types (PFTs), the authors explore whether remote-sensing-based classifications provide a more dynamic alternative for ecosystem functional monitoring. The paper is well-structured, clearly written, and addresses an important research gap in functional biogeography. The authors provide robust empirical evidence across 50 EC sites and multiple biogeographic zones, reinforcing the potential of EFTs to serve as integrative descriptors of carbon dynamics. The methodological framework is rigorous, and the discussion is thoughtful and

comprehensive. However, several methodological choices and interpretative aspects could benefit from clarification, expansion, or further justification.

R0 - We thank the reviewer for the positive and encouraging evaluation of our work, as well as for the constructive comments that provided valuable insights further to strengthen the conceptual and methodological robustness of our manuscript. In our response below, we provide point-by-point responses (indicated with "R") that detail how we have addressed the Reviewer's comments ("C").

Major comments

C1 - *The study focuses exclusively on EVI-derived EFTs as proxies for ecosystem functioning, which primarily capture carbon uptake via vegetation greenness. This focus, while justified, represents only one dimension of ecosystem function. Consider acknowledging more explicitly in the introduction and discussion that EFTs in this implementation reflect carbon-related dynamics. The authors should also consider whether incorporating additional functional attributes (e.g., NDWI for water stress, land surface temperature, albedo, and evapotranspiration) could enhance EFT robustness, particularly in water-limited ecosystems such as the Mediterranean region.

R1 - We thank the reviewer for these constructive suggestions. Our decision to use EVI-derived EFTs is grounded in both ecological and remote-sensing evidence. EVI is particularly suitable for representing ecosystem functioning because it reflects canopy light absorption and photosynthetic activity, processes tightly linked to carbon uptake through APAR, GPP, and NEE (Huete et al., 1997; Running et al., 2004; Shi et al., 2017). 1) From an ecological perspective, primary production is the main pathway through which energy enters ecosystems and one of the most integrative indicators of overall ecosystem functioning (Virginia and Wall, 2001), being closely associated with multiple ecological processes and services (Paruelo et al., 2016). 2) From a remote-sensing standpoint, EVI has several well-documented advantages over other vegetation indices. It performs reliably across gradients of vegetation cover, maintains sensitivity in high-biomass systems, and reduces the influence of atmospheric effects and soil background (Huete et al., 1997). These properties explain why many ecosystem-process models (e.g., Potter et al., 2007; Running and Zhao, 2015) rely on EVI or NDVI to estimate APAR and NPP. In addition, using EVI avoids propagating uncertainties from PFT-based land-cover maps into the functional variables, a known issue in NPP and GPP products (Zhu et al., 2016; Wang et al., 2017). Several studies have also shown that EVI provides a straightforward and robust approach to estimating spatial patterns of annual GPP at global scales (Shi et al., 2017). EVI also offers practical benefits for functional classification. It is available at a finer spatial resolution (231 m) than MODIS GPP or NPP products (500 m), facilitating the detection of functional heterogeneity across European landscapes. For these reasons, ecological relevance, radiometric reliability, and spatial suitability, EVI provides an appropriate basis for identifying the carbon-related functional dynamics that are the focus of this study.

We agree that ecosystem functioning is multidimensional. Following the reviewer's suggestion, we now clarify in the Introduction (lines 89-94) as follows *"Among these functional attributes, those linked to carbon dynamics, particularly primary production, represent one of the most integrative dimensions of ecosystem functioning because they reflect the main entry of energy into ecosystems and are directly related to key carbon and energy exchanges (Virginia and Wall 2001; Pereira et al. 2013; Xiao et al. 2019). Moreover, primary production provides a holistic response to environmental changes and constitutes a synthetic indicator of ecosystem health (Costanza et al. 1992; Skidmore et al. 2015)"*. We also added in the Discussion (lines 333–340) that the EFTs used in this study primarily capture carbon-related dynamics, which serve as an integrative descriptor of ecosystem functioning. In addition, we have included a statement acknowledging that incorporating additional functional attributes related to water status, surface energy balance, or albedo (e.g., NDWI, land-surface temperature, evapotranspiration) could enrich future extensions of the multidimensional EFT framework as follows: *"EFTs derived in this study rely on EVI-based attributes, which primarily represent the dynamics of primary production. This focus is consistent with the fact that vegetation greenness and light absorption are tightly linked to APAR, GPP and NEE (e.g. Huete et al., 1997; Running et al., 2004; Shi et al., 2017), making EVI a direct and widely used indicator of ecosystem functional behaviour at large scales. The strong agreement between our EFTs and in situ NEE patterns confirms that EVI captures the dominant functional axis related to carbon uptake. Although additional attributes associated with water or energy fluxes (e.g., NDWI, land-surface temperature or albedo) could enrich multidimensional EFT frameworks in the future, the carbon-related dynamics encoded in EVI already provide a robust and ecologically meaningful foundation for functional ecosystem classification"* (lines 333–340) .

C2 - * The current approach partitions EVI_mean, EVI_SD, and EVI_DMAX into four bins each, generating 64 EFT classes. However, the justification for choosing four intervals remains vague, and it is unclear how sensitive the results are to this choice. Could you please clarify the rationale behind selecting four intervals per metric? Would the patterns hold if three or five bins were used instead? A supporting table defining the intervals or example ranges for each bin would significantly improve interpretability.

R2 - The choice of four intervals per metric was not arbitrary, but grounded in ecological interpretability, statistical balance, and methodological precedent. For EVI_DMAX, we defined four intervals to match the four seasons of temperate climates (spring, summer, autumn, winter), which provides a phenologically meaningful discretization of the timing of peak photosynthetic activity and makes the resulting classes naturally interpretable from an ecological perspective in terms of the main limiting factors to photosynthetic activity (e.g., for a Mediterranean region., typically temperature and radiation in the winter, and water in the summer).

For parallelism with phenology, the surrogates of primary production (For EVI_mean) and seasonality (EVI_SD) were also divided in four bins. For this, we used annual quartiles averaged over the 14-year period. Quartile-based thresholds offer a statistically balanced partition of the value range, ensuring proportional representation of classes, facilitating spatial comparability across regions, and maintaining methodological coherence with previous EFT applications (Alcaraz-Segura et al., 2006, 2013; Cazorla et al., 2021, 2023). In combination, EVI_mean and EVI_SD summarize the magnitude and intra-annual variability (seasonality) of primary production, while EVI_DMAX captures the timing dimension (phenology), thus providing a parsimonious characterization of key aspects of ecosystem functioning.

This discretization also aligns with the functional classification principles of Noble and Gitay (1996), who emphasize starting from the simplest structure that preserves ecological interpretability. Using four categories per metric yields 64 potential EFT classes (4 × 4 × 4), which strikes a balance between capturing regional functional variability and retaining a classification that is analytically manageable and supported by a comprehensible legend. Substantially increasing the number of intervals per metric would generate a very large number of possible EFTs, many with very low spatial representation, thereby complicating interpretation and reducing reproducibility. Conversely, too coarse schemes with fewer bins per variable would risk masking relevant functional differences.

Importantly, recent evidence also supports the robustness of EFT classifications to the number of bins used. Liu et al. (2023) assessed the effect of using 2x2x2=8 bins versus 4x4x4=64 bins. They found that the number of bins used to classify Ecosystem Functional Attributes (EFAs) into Ecosystem Functional Types exerted only a limited influence on estimates of Ecosystem Functional Diversity (EFD). These findings indicate that using four intervals provides a sufficiently robust functional discretization, as increasing or decreasing the number of bins does not substantially alter broader functional patterns.

In addition, we use fixed class boundaries across years, allowing us to apply the same EFT classification to each year of the time series. This temporal consistency facilitates the detection and interpretation of interannual changes in ecosystem functioning, in line with previous work on functional heterogeneity (e.g., Cazorla et al. 2023).

In the revised manuscript (Section 2.2, lines 142–148), we now explicitly describe how the thresholds for the four-class discretization were derived. Specifically, we state that for each quartile, we calculated the interannual mean across the 14-year period and used these values as fixed breaks between classes (Supplement S2, Table S1). These breaks were then applied consistently to each year as the thresholds for EVI_mean and EVI_SD to assign EFT classes (Table S1). We have added this in the main text as follows: *"For each quartile, we calculated the interannual mean of the 14-year period and used them as breaks between classes. These breaks were applied back to each year as the thresholds for EVI_Mean and EVI_sSD to set EFT classes (S2, Table S1). We used this four-class discretization and fixed class boundaries to obtain a coherent and ecologically interpretable classification (Noble and Gitay 1996) that applies consistently across years. This approach enables interannual comparisons of spatial functional heterogeneity and maintains continuity with previous EFT implementations (Alcaraz-Segura et al. 2013, Cazorla et al. 2021, 2023). Moreover, recent methodological assessments indicate that EFT derivation is relatively robust to the number of bins used to discretize EF attributes (e.g., Liu et al. 2023)"*. A new table, included below, has been added to the Supplementary Material to summarize the intervals and representative value ranges for each bin, as indicated in line 151.

C3 - *While visually appealing, the EFT map (Fig. 1) is difficult to interpret due to the high number of classes. The dense legend makes it hard to discern regional patterns or relate the map to key findings. Consider providing a simplified version of the map by aggregating the EFTs into broader clusters (e.g., via PCA, hierarchical clustering, or functional similarity groupings).

R3 - We appreciate the reviewer's suggestion. In the revised manuscript, we have added a simplified version of the EFT map in the Supplementary Material (Fig. S7), produced by clustering EFTs based on their functional similarity. We also indicate in the main text where this simplified map can be consulted (lines 221-222). This aggregated map enhances visual interpretability and allows large-scale spatial patterns to be more easily identified, while the full-resolution (64-class) EFT map is retained in the main text for methodological completeness.

Additionally, to support visual interpretation of original functional classification, we provide in the Supplementary Material a figure showing the three Ecosystem Functional Attributes (EFAs) used to derive the EFTs (Fig. S1), namely: (a) the annual mean of EVI (EVI_mean, representing annual primary production), (b) the seasonal standard deviation of EVI (EVI_SD, describing seasonality), and (c) the date of maximum EVI (EVI_DMAX, characterizing phenology). Furthermore, to help readers understand how each functional dimension contributes to the final EFT colour scheme, we include three additional maps in which the EFTs are coloured by each individual attribute: productivity (Fig. S4), seasonality (Fig. S5), and phenology (Fig. S6). These maps allow readers to visually disentangle each EFA's contributions to the composite EFT map, thereby improving the interpretability of the patterns shown in the main text.

Finally, we provide the proportion of area represented by each EFT class (Fig. 2, main text), showing that a subset of well-represented classes dominates the study region. Together, all these substantially enhance the accessibility and clarity of the EFT representation.

C4 - *The authors analyse NEE seasonal dynamics as the basis for comparing EFTs and PFTs. However, ecosystem function varies across multiple temporal scales. Please clarify why only seasonal cycles were analysed. Could complementary metrics, such as daily anomalies, interannual variability, or cumulative annual fluxes, provide additional insight into functional distinctiveness across EFTs?

R4 - We thank the reviewer for this insightful comment. Our analysis focused on seasonal NEE cycles because they aligned with the EVI-based EFT framework, which characterizes ecosystem functioning through intra-annual dynamics (mean or area under curve, standard deviation or seasonality, and date of maximum or phenology). Seasonal patterns also provide the most robust and comparable temporal signal across sites, given MODIS's 16-day temporal resolution and FLUXNET's heterogeneous temporal coverage. For these reasons, seasonal cycles constitute the most consistent basis for evaluating functional differences between EFTs and PFTs at the European scale.

Complementary metrics, such as daily anomalies, interannual variability, and cumulative annual fluxes, capture different temporal dimensions of ecosystem functioning, often dominated by short-term meteorological variability or year-specific climate anomalies. Because they operate on temporal scales different from those used to define EFTs, they are not expected to increase discriminative power among EFTs themselves. This is consistent with previous work (e.g., Cazorla et al. 2023), where interannual variability was analysed as a property of EFT dynamics rather than as an input for defining EFT classes. These metrics can therefore be valuable to study additional facets of ecosystem functioning (e.g., stability, resilience, or sensitivity to climate extremes), but they do not align with the temporal structure used for functional classification.

To acknowledge this distinction, we have added a sentence in the Discussion noting that such metrics may complement EFT-based assessments (lines 426–428), "*..Also other temporal metrics, such as daily anomalies or interannual variability, can provide complementary information on short-term or year-to-year ecosystem responses, but they are not expected to improve the discrimination among EFTs, which is intrinsically based on intra-annual functional patterns.*"

C5 - *The MODIS spatial resolution (~230 m) does not always match the EC tower footprint (~50–200 m), which varies depending on meteorological conditions and site characteristics. Please address whether a footprint-weighted EVI averaging was considered or feasible. At a minimum, discussing the potential impact of footprint mismatch on EFT-NEE comparisons would enhance methodological transparency.

R5 **-** We thank the reviewer for raising this important point. A mismatch between MODIS pixel size (~231 m) and the variable EC footprint (typically 50–200 m) is unavoidable in RS-flux integration, because MODIS has a fixed spatial resolution, whereas the EC footprint changes continuously with micrometeorological conditions such as wind direction, atmospheric stability, and surface roughness (Schmid 1997; Kljun et al. 2015). Footprint-weighted averaging was not feasible in our study because daily or sub-daily footprint estimates are not available for most FLUXNET sites and years, a limitation commonly acknowledged in previous RS-flux integration studies (Ryu et al. 2011; Chu et al. 2021). Additionally, we acknowledge that EC towers are not always located at the centre of a MODIS pixel; in some sites they may be positioned near pixel edges or even close to pixel boundaries, which can increase the potential for representativeness mismatch (Chu et al. 2021). However, EC sites are generally installed within large, functionally homogeneous land patches to ensure that measured fluxes originate from a uniform surface (Aubinet et al. 2012). This site-level homogeneity means that both the tower footprint and the surrounding MODIS pixels usually sample similar functional landscapes. Moreover, because our EFTs describe regional-scale patterns of primary production rather than site-level variability, moderate pixel–footprint or tower-location mismatches are unlikely to substantially affect the interpretation of EFT–NEE comparisons. We discuss this limitation explicitly in the revised manuscript as follows: *"Second, the footprint or spatial resolution of the EC measurements varies depending on the micrometeorological conditions (wind direction, wind speed, atmospheric stability) and the ratio of measurement to vegetation height, e.g., forest flux footprints are generally larger than grassland footprints (oscillates between 50 m and 200 m) (Schmid 1997; Kljun et al. 2015). In contrast, the MODIS pixels used have a constant spatial resolution of ~231 m, generating an unavoidable scale mismatch. However, because EC towers are typically placed in relatively large and functionally homogeneous land patches (Aubinet et al. 2012), the MODIS pixel and the flux footprint generally sample comparable surfaces, limiting the practical impact of this mismatch on the regional-scale patterns captured by our EFTs. Nonetheless, we acknowledge that some challenges regarding spatial representativeness remain (Chu et al. 2021)."* (lines 409–416).

We also clarify in the Discussion why higher-resolution sensors could not be used for our study period. Sentinel-2 data are available only from 2015 onward, preventing temporal overlap with the FLUXNET2015 dataset. Landsat offers higher spatial resolution, but its 16-day revisit interval and frequent cloud contamination in Europe would result in large data gaps and insufficient temporal continuity for deriving reliable seasonal EVI metrics (Zhu and Woodcock 2014). In contrast, MODIS provides cloud-screened, temporally consistent 16-day composites throughout the entire 2001–2014 period, ensuring a harmonized time series across all sites. Finally, we note in the Discussion (lines 416–422) that future work could reduce scale mismatches by using higher-resolution sensors when sufficiently long time series become available, or by applying footprint modelling when appropriate micrometeorological data exist. *"Future studies may reduce this mismatch by using higher-resolution sensors such as Sentinel-2 (10 m/pixel), but currently is not possible because the time period of Sentinel-2 data is not covered by FLUXNET data (i.e., Sentinel-2 starts taking data in 2015 and the available FLUXNET 2015 database goes up to this year). Alternatively, footprint modelling could be applied when appropriate micrometeorological data exist, but footprint-weighted averaging was not feasible in our study because daily or sub-daily footprint estimates are unavailable for most FLUXNET sites and years, a limitation commonly acknowledged in previous RS–flux integration studies (Chu et al. 2021). "*

C6 - *With 64 possible EFTs, only 20 are represented in the EC network. This granularity may be problematic for integration into Earth system models, which typically rely on a smaller number of categories. Have the authors considered simplifying the EFT classification, for example, by grouping rare classes or employing dimension-reduction techniques? Providing a roadmap for EFT integration into models would enhance the study's relevance.

R6 - We thank the reviewer for this insightful comment. Although our EFT scheme includes 64 potential classes, only 20 are represented in the EC network, and these correspond to the most abundant EFTs in Europe, jointly covering 73.1% of the study area. Thus, the EC network captures the dominant functional strategies across the continent.

Regarding model integration, we agree that Earth system models typically use fewer land surface categories. However, previous studies have shown that EFT-based classifications can already be incorporated into modelling frameworks without necessarily reducing the number of functional classes. For example, Lee et al. (2013) and Müller et al. (2014) successfully implemented EFTs (or closely related functional groupings) in regional climate and land–surface models, demonstrating that functional ecosystem classifications can be operationalized within model structures.

In the revised manuscript, we now note in the Discussion that simplification of the EFT scheme is *possible* when required by specific modelling applications, for instance, by clustering functionally similar EFTs. However, such simplification is not inherent to the EFT approach nor necessary for the aims of the present study. Our focus here is on evaluating the ecological validity of the full EFT classification, while model-oriented adaptations can be explored in future work depending on modelling needs, explained in Discussion (lines 432–436): "*Finally, incorporating EFTs into earth system models is challenging since these models generally use simple and small numbers of categories in a variable, and some models might not be able to run with so many (64) EFT categories. Nevertheless, some studies have successfully incorporated EFTs into earth system models (Lee et al. 2013; Müller et al. 2014). The incorporation of these types of variables (dynamic and easily accessible) into the models might be helpful in the monitoring and sustainable management of carbon reservoirs at short to medium-time scales.*"

C7 - *The study uses EVI_DMAX as a phenology metric. However, the start and end of the growing season are also informative indicators of functional timing and duration. Please clarify whether metrics such as SOS/EOS (start/end of season) were tested or considered. If not, do the authors anticipate that they could provide complementary or better information than EVI_DMAX?

R7 - Thank you for this insightful suggestion. In our classification, we used EVI_DMAX, the timing of maximum greenness, because it captures more variance than other phenological metrics, represents a broad and integrative phenological trait that is consistently detectable with 16-day MODIS data (and other satellites with lower temporal resolution). As a general marker of peak canopy activity, EVI_DMAX is less sensitive to atmospheric noise and data gaps than transitional metrics such as the start or end of the season (SOS/EOS), making it particularly suitable for regional-scale functional classifications, where robustness and comparability across biomes are essential. This reasoning is supported by previous work showing that metrics based on the annual maximum of vegetation indices (e.g., EVI_max) provide reliable proxies for peak productivity and are less sensitive to missing observations than SOS/EOS metrics (Walther et al. 2018; Tang et al. 2024). Reviews of satellite-derived phenology further emphasize that transitional metrics are often more sensitive to noise and observation gaps, especially when derived from sensors with coarser temporal resolution, such as MODIS (Cui et al. 2020; Dronova and Taddeo 2022). The use of EVI-based maximum-greenness metrics in functional classifications has also been demonstrated in recent EFT-focused studies (Liu et al. 2023; Cazorla et al. 2023).

We agree that SOS/EOS can provide complementary information on growing-season timing or duration, and we now mention in the Discussion that these metrics may offer additional insights, especially when higher-resolution sensors allow more precise detection of phenological transitions. This clarification has been added in the revised manuscript (lines 428-431) as follows: *"Similarly, additional phenological transition metrics such as the start and end of the season (SOS/EOS) may offer complementary insights into growing-season timing and duration; however, their higher sensitivity to noise and temporal gaps, particularly in 16-day MODIS time series, makes peak-greenness metrics like EVI_DMAX more robust and comparable for regional-scale functional classifications."*

Minor comments

C8 - *L66: Please clarify which method is referenced for estimating EFTs from EC measurements.

R8 - Thank you for raising this point. In the corresponding paragraph of the Introduction, we intended to describe different established approaches commonly used to evaluate ecosystem functioning (e.g., trait-based classifications, PFTs, eddy covariance flux measurements, and remote sensing), rather than to imply that a specific method already exists for estimating EFTs from EC data. EC has long been used to quantify ecosystem functioning through direct measurements of CO_2, water, and energy exchange (Baldocchi 2003; Reichstein et al. 2014; Migliavacca et al. 2021), but to our knowledge, no previous studies have used EC observations to derive EFTs. This represents a novel contribution of our work. In this study, we introduce an approach that uses EC data to characterize the seasonal dynamics of NEE at flux-tower sites (e.g., Stoy et al. 2013) and compare these observed EC-based seasonal patterns with the corresponding satellite-derived EFT seasonal patterns at each site. This allows us to directly assess how well the remote-sensing-based EFT captures ecosystem-scale carbon dynamics.

To avoid the ambiguity identified by the reviewer, we have now revised the text in the Introduction by replacing the term *"EC"* with *"this method"* in the sentence in question, making the wording clearer and preventing the unintended interpretation that a specific EC-based procedure for deriving EFTs already exists (line 66).

C9 - * L138 144: The sentence describing the naming convention is dense and complex to digest. A schematic or table showing example combinations (e.g., Ba1, Cb2, etc.) and their meaning would be helpful for unfamiliar readers.

R9 - We appreciate the reviewer's comment. Examples of EFT codes, together with their meanings, are already included in the main text (lines 209 and 222). Nevertheless, to further improve clarity, we have added a schematic table in the Supplementary Material that summarizes several examples along with their corresponding meanings (S3, Table S2). We have added a sentence to clarify this point (line 151-152).

C10 - *Caption of Fig. 1: The caption refers to squared colours, but circles appear to be used instead. Please correct for consistency.

R10 - We thank the reviewer for pointing out this inconsistency. The caption of Fig. 1 has been corrected by replacing "squared colours" with "circles" to ensure consistency with the figure.

C11 - *Concluding remarks

This study makes a valuable contribution to the growing body of literature on remote sensing of ecosystem function. The empirical validation of EFTs against eddy-covariance NEE across Europe is a significant achievement, and the comparisons to PFTs are well-executed and relevant. The manuscript would benefit from more explicit justifications for methodological choices (e.g., the number of intervals), a more nuanced discussion of scale mismatches and model usability, and an exploration of additional dimensions of ecosystem functioning.

R11 - We are grateful for the reviewer's constructive suggestions, which will strengthen our manuscript. The changes will include explicit methodological justifications, a clearer discussion of limitations, additional visualizations, and recognition of future research directions.

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RESPONSE TO COMMENTS FROM REVIEWER 2

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Reviewer: 2

Comments to the Author(s)

C1 - *General assessment: This study provides a valuable perspective on how to evaluate diversity in ecosystem functional patterns through the classification of Ecosystem Functional Types (EFTs). EFTs are surface-based classifications derived from key functional attributes of ecosystems, and here they are compared against more conventional classifications that emphasize composition and structure, such as Plant Functional Types (PFTs).

R1 - We appreciate this recognition. Our objective was precisely to examine whether classifications based on EFTs could complement or match PFT classifications, offering a dynamic characterization that could be updated annually and could be measured at the global scale. We were pleased that this comparison was considered valuable.

C2 - *The comparison is grounded on in situ measurements obtained with the eddy covariance technique, one of the most robust and reliable approaches for quantifying ecosystem-level functional processes. The analysis further benefits from the use of the highly reputable FLUXNET2015 database.

R2 - We thank the reviewer for highlighting this. These datasets are indeed essential for ensuring reliability, and we are glad that their inclusion strengthens confidence in the study.

C3 - *The methodological design is rigorous, offering a well-balanced comparison between EFTs and PFTs prior to subjecting them to discriminant analysis.

R3 - We appreciate this comment. We intended to establish the correct framework for comparing EFTs and PFTs, and we are pleased that this was recognized.

C4 -*Although results did not reveal statistically significant differences, the study successfully validates the effectiveness of EFTs in representing functional patterns at the ecosystem scale. A key advantage is that EFTs provide more dynamic insights than classifications based solely on compositional or structural traits.

R4 - We agree with this interpretation. The comparable performance of EFTs and PFTs shows that EFTs can capture functional patterns reliably. Furthermore, a key advantage is that EFTs provide more dynamic insights than classifications based solely on compositional or structural traits.

C5 - *The authors also acknowledge the limitations of EFTs, particularly regarding spatial resolution and the fact that not all EFT classes were represented in the study area. These issues are appropriately addressed in Section 4.3.

R5 - We are glad that our discussion of these limitations was found appropriate. While some classes were missing, we agree that the coverage of >70% provides robust support for our conclusions.

C6 - * Furthermore, the manuscript is well-written, demonstrating good coherence, cohesion, and flow.

R6 - We are very grateful for this positive feedback on the clarity of the manuscript.

C7 - *Concluding remarks: This work makes an important contribution to the representation of spatial functional patterns and their comparison against more conventional classification systems, validated with in situ flux measurements. The choice of the study domain is appropriate given the high density of flux tower sites. However, due to the diversity of EFTs, not all classes were represented by field observations. Nevertheless, more than 70% of the spatial coverage of EFTs was captured within the study area.

R7 - We thank the reviewer for acknowledging this. We are pleased that the coverage achieved is considered sufficient.

C8 - *Overall, I consider this manuscript to be in a publishable form as it stands.

R8 - We sincerely thank the reviewer for this positive conclusion.

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