Author’s Response

We would like to thank the editor and both the reviewers for their careful review and constructive suggestions, which helped in further improving the quality of the paper. We have addressed the comments and incorporated several changes in the revised manuscript in line with the comments as detailed below under each point.

Review Comments

Reviewer 1#

General Observations

The manuscript presents novel research investigating the influence of socioeconomic, biophysical, and behavioural characteristics on the spatial distribution of land management intensity. The authors have developed a global dataset of land management intensity for 2020 at a spatial resolution of 0.01°, comprising four management classes: unmanaged, very extensive, extensive, and intensive. These classes are mapped globally across cropland, pasture, and forest systems.

The study concludes that income, market access, population density, and aridity influence cropland management intensity, whereas pasture and forest systems exhibit more complex relationships. The results are further compared with global land decision-making types, demonstrating a spatial consistency of 68%. Based on this comparison, the authors conclude that land management intensity is also influenced by land-user behaviour.

The study addresses an important research gap in land system science regarding land management intensity. It also provides a foundational global dataset of land management intensities and their spatial distribution, thereby creating opportunities for further research into the socioeconomic, biophysical, and behavioural factors influencing land-use and land-change decisions. The topic is timely and highly relevant, and the resulting dataset could become an important resource for global land-system modelling and land-management policy analysis.

The study is promising, original, and likely to be of interest to a broad range of researchers, particularly because it links the socioeconomic, biophysical, and behavioural characteristics of decision-makers with land management intensity and, more broadly, with land-use change. In my opinion, the following minor revisions should be considered before the manuscript is accepted for publication in ESSD.

Response: Thank you for your nice feedback; we have incorporated your suggestions in the revised manuscript.

Comments and Suggestions

Comment 1# The study has considerable innovative potential, particularly in linking global land management intensity with socioeconomic and behavioural decision-making variables. This perspective is highly relevant to current research frontiers in land system science. However, highlighting the work's originality and explaining how the resulting global dataset and research findings would contribute to future research in land system science will strengthen the manuscript.

Response: Thanks for the feedback. We have made several changes in the abstract to highlight the suggested points precisely. However, we pick-up on the novelty and key contribution of the work in the last paragraphs of the Introduction. There, we clearly state what was missing from existing research and how our work will contribute to filling those gaps.

In the Abstract we add:

This dataset may be useful for various earth system modelling applications in land system science and environmental studies.

Introduction section already includes:

Overall, two key knowledge gaps remain. First, there is no harmonised global representation of land management intensity that consistently distinguishes management intensity levels across cropland, pasture and forest systems. Second, the extent to which observed patterns of management intensity align with underlying socioeconomic drivers and land-use decision-making behaviour remain largely unexplored. To address these gaps, we make three key contributions. First, we develop a harmonised, spatially-explicit global dataset of land management with distinct levels of management intensity across cropland, pasture, and forest systems. Second, we integrate multiple variables in a unified framework, enabling a consistent comparison of management intensity across land systems and regions. Third, we link spatial patterns of land management intensity with socioeconomic and biophysical variables and with land-use decision making types. We then develop new insights into the behavioural and socioeconomic dimensions of land systems which have not previously been analysed using a globally consistent and spatially-explicit framework.

To analyse global land management intensity and its association with explanatory variables we pose the following research questions;

1. How is land management intensity spatially distributed across cropland, pasture, and forest systems globally, and how does this distribution vary between regions, income groups, and countries?

2. To what extent are observed patterns of land management intensity associated with socioeconomic drivers such as economic development, inequality, market access, and population density, and biophysical variables (aridity index and elevation), and do these relationships differ across land-use sectors?

3. Do spatial patterns of land management intensity align with land-use decision-making types?

We address these questions by developing a harmonised, spatially-explicit global dataset of land management intensity for the year 2020 at 0.01° spatial resolution. The dataset captures cropland, pasture, and forest systems, each classified into management intensity categories of unmanaged, very extensive, extensive, and intensive, derived from multiple biophysical and management indicators. Using this dataset, we (i) analyse the global spatial distribution of land management intensity across regions, income groups and countries; (ii) quantify relationships between management intensity and important socioeconomic drivers including GDP per capita, income inequality (GINI), market access, population density, aridity index and elevation using multinomial logistic regression; and (iii) assess the correspondence between management intensity patterns and independently derived global land-use decision-making types (Malek and Verburg, 2020). These analyses provide an understanding of the drivers and behavioural influences of land management intensity at the global scale and provide a basis for integrating management intensity into a global land system analysis.

In the Discussion section we add:

The dataset presented here provides a robust baseline of current global land management patterns. It can support the initialisation, parameterisation and validation of land-use models, enabling a better representation of spatial heterogeneity in management practices. In addition, the study can be useful in the assessment of policy-oriented analyses for example land-based climate mitigation strategies – assessing trade-offs between ecosystem service provision and environmental impacts.

Comment 2# The following sentence in the first paragraph of the abstract should be revised for clarity and grammatical accuracy: "However, there are limitations in data and in the systematic understanding of management intensity and how it is shaped by socioeconomic and biophysical factors and human behaviour."

Response: Thank you for highlighting this. We have revised the sentence for clarity and grammatical accuracy. It now reads as "However, persistent data limitations prevent systematic understanding of management intensity and its dependencies on behavioural, socioeconomic and biophysical factors."

Comment 3# The authors should briefly explain how the newly developed global land management intensity dataset addresses the limitations or gaps in existing datasets. This discussion may be included in either the Introduction or the Discussion section.

Response: Thank you for the comment. We include the explanation on how we have addressed the research gaps in the last paragraphs in the Introduction as below. We now also highlight this in the Discussion section.

Introduction (already included)

To address these gaps, we make three key contributions. First, we develop a harmonised, spatially-explicit global dataset of land management with distinct levels of management intensity across cropland, pasture, and forest systems. Second, we integrate multiple variables in a unified framework, enabling a consistent comparison of management intensity across land systems and regions. Third, we link spatial patterns of land management intensity with socioeconomic and biophysical variables and with land-use decision making types. We then develop new insights into the behavioural and socioeconomic dimensions of land systems which have not previously been analysed using a globally consistent and spatially-explicit framework.

To analyse global land management intensity and its association with explanatory variables we pose the following research questions;

1. How is land management intensity spatially distributed across cropland, pasture, and forest systems globally, and how does this distribution vary between regions, income groups, and countries?

2. To what extent are observed patterns of land management intensity associated with socioeconomic drivers such as economic development, inequality, market access, and population density, and biophysical variables (aridity index and elevation), and do these relationships differ across land-use sectors?

3. Do spatial patterns of land management intensity align with land-use decision-making types?

We address these questions by developing a harmonised, spatially-explicit global dataset of land management intensity for the year 2020 at 0.01° spatial resolution. The dataset captures cropland, pasture, and forest systems, each classified into management intensity categories of unmanaged, very extensive, extensive, and intensive, derived from multiple biophysical and management indicators. Using this dataset, we (i) analyse the global spatial distribution of land management intensity across regions, income groups and countries; (ii) quantify relationships between management intensity and important socioeconomic drivers including GDP per capita, income inequality (GINI), market access, population density, aridity index and elevation using multinomial logistic regression; and (iii) assess the correspondence between management intensity patterns and independently derived global land-use decision-making types (Malek and Verburg, 2020). These analyses provide an understanding of the drivers and behavioural influences of land management intensity at the global scale and provide a basis for integrating management intensity into a global land system analysis.

In the Discussion section we add:

We provide a global harmonised land management dataset including all major land-use/cover types across cropland, pasture, forest, photovoltaics, unmanaged land and urban sectors, along with management intensity information for agriculture and forest sectors. Until now, no such consistent dataset has been available globally to allow analysis of the statistical relationships between land management and underlying variables relating to income, accessibility, biophysical conditions and demography, among others.

Comment 4# The influence of the biophysical and behavioural characteristics of decision-makers on land management intensity may be discussed more explicitly in the Results and Discussion sections.

Response: Thanks for the comment. We have discussed the associations of biophysical and behavioural decision-makers on land management intensity in the Discussion section.

In the Discussion section we add:

The relationships between management intensity and socioeconomic and biophysical variables are sector dependent and also non-linear. Nonetheless, a fairly good match (68) between our land management intensity dataset and the decision-making types of Malek and Verburg (2020) indicates an association between the spatial distribution of management intensity and the behavioural aspects of land management decisions.

Comment 5# Several input datasets with different spatial resolutions were used to produce the harmonised global land management intensity dataset. The Discussion section should therefore include a brief statement of the potential uncertainties associated with the harmonisation process.

Response: Thanks for the comment. We have a dedicated section about limitations and uncertainties and now also discuss resampling limitations while harmonising the dataset in this section.

It now reads as:

Limitations and uncertainties

The dataset developed here represents a spatially harmonised approximation of global land management conditions around 2020. Absolute thresholds were used to classify management intensity, which may not fully capture regional differences and all locally relevant management practices. Using this approach does, however, enable a consistent global comparison of management intensity patterns, essential for assessing patterns and relationships. The dataset integrates multiple inputs with different spatial resolutions, temporal coverages, and methodological assumptions. Several crop and pasture management indicators originally available at coarse resolutions were resampled to the 0.01° grid. This approach preserves finer land-use classes, but inevitably retains underlying uncertainties associated with the coarse data. Resampling methods are limited when approximating class assignment, we have tried to minimize this limitation by applying the most suitable methods in individual cases. These are particularly pertinent to pasture classes, where data are not only of coarse spatial and temporal resolution but also more uncertain than equivalent datasets for other land cover classes (Harrison et al., 2025). Some datasets were derived from slightly earlier time periods than 2020 and may therefore not fully represent recent changes. Missing fertiliser values were conservatively treated as absence of fertiliser input and therefore assigned to the very extensive management class. This approach avoids artificially inflating intensive management for a relatively small number of grid-cells, but it may lead to some underestimation of management intensity where fertiliser was unrecorded rather than unused. However, this limitation reflects a broader challenge in global land system science, where key processes cannot be directly measured but instead need to be approximated using the best-available data.

Comment 6# The systematic sensitivity analysis undertaken to assess uncertainties in the spatial distribution of land management intensity resulting from the thresholds used to define the management classes is appreciated. A brief discussion of the remaining uncertainties associated with the selected thresholds would further strengthen the manuscript.

Response: Thanks for the comment, we now add a few lines in the Limitations and uncertainties section as below:

The dataset developed here represents a spatially harmonised approximation of global land management conditions around 2020. Absolute thresholds were used to classify management intensity, which may not fully capture regional differences and all locally relevant management practices.

Comment 7# Remove the dash in line 305 on page 12.

Response: Thanks for noticing this. We have now corrected this in the revised version.

Comment 8# The Limitations section should be concise and focused on the most important limitations of the study.

Response: Now we shorten the Limitations section to include only the most important points. The limitation section now reads as:

Limitations and uncertainties

The dataset developed here represents a spatially harmonised approximation of global land management conditions around 2020. Absolute thresholds were used to classify management intensity, which may not fully capture regional differences and all locally relevant management practices. Using this approach does, however, enable a consistent global comparison of management intensity patterns, essential for assessing patterns and relationships. The dataset integrates multiple inputs with different spatial resolutions, temporal coverages, and methodological assumptions. Several crop and pasture management indicators originally available at coarse resolutions were resampled to the 0.01° grid. This approach preserves finer land-use classes, but inevitably retains underlying uncertainties associated with the coarse data. Resampling methods are limited when approximating class assignment, we have tried to minimize this limitation by applying the most suitable methods in individual cases. These are particularly pertinent to pasture classes, where data are not only of coarse spatial and temporal resolution but also more uncertain than equivalent datasets for other land cover classes (Harrison et al., 2025). Some datasets were derived from slightly earlier time periods than 2020 and may therefore not fully represent recent changes. Missing fertiliser values were conservatively treated as absence of fertiliser input and therefore assigned to the very extensive management class. This approach avoids artificially inflating intensive management for a relatively small number of grid-cells, but it may lead to some underestimation of management intensity where fertiliser was unrecorded rather than unused. However, this limitation reflects a broader challenge in global land system science, where key processes cannot be directly measured but instead need to be approximated using the best-available data.

Comment 9# The citation style should be consistent throughout the manuscript. For example, multiple references should be listed consistently in either ascending or descending chronological order, in accordance with the journal's guidelines.

Response: Thanks for the comment. We have now arranged the citation in an order throughout.

Comment 10# The manuscript contains a very few grammatical errors and unclear sentences. Minor language editing is required to improve its overall readability and clarity.

Response: Thanks for the comment. We have read the manuscript thoroughly and improved any linguistic errors if there were any.

Recommendation

The study addresses an important research gap in land system science by examining how land management intensity is influenced by decision-makers' socioeconomic, biophysical, and behavioural characteristics. It also provides a potentially valuable global dataset that may support further research in land-system modelling, land-use change, and land-management policy analysis.

The manuscript currently requires only minor improvements, mainly related to language and grammatical editing, clearer presentation of the originality of the work, and a stronger explanation of how the present findings and dataset may support future research. These issues can be adequately addressed in a revised manuscript.

Therefore, I recommend a Minor Revision before the manuscript is considered for publication.

Response: Thank you for your recommendation!

Reviewer 2#

In this study the authors develop a harmonized global dataset of land management intensity for 2020 at 0.01 ° spatial resolution, distinguishing unmanaged, very extensive, extensive, and intensive management across cropland, pasture, and forest systems. They also link the spatial patterns of land management intensity with socioeconomic and biophysical variables and with land-use decision making types. The developed dataset and the conducted analysis can facilitate the global land system analysis and understanding of the drivers and behavioural influences of land management intensity.

Here are some comments regarding the methodology.

Comment 1# 2.2 Mapping crop types and management intensity onto agriculture land

It is not clear how to identify rainfed areas, and how to differentiate rainfed and irrigation areas.

Response: Thanks for the suggestion, we now add explanation on how irrigation and rainfed were determined and combined with the land management dataset.

The irrigation dataset at 0.05° resolution (Mehta et al., 2024) was also used to distinguish intensive management with and without irrigation. The information on irrigation presence and absence was first extracted to generate a spatial binary map, the grid cells with an availability of irrigation being assigned value 1, while those without irrigation were assigned value 0. This irrigated and rainfed information was then combined with the intensive class of the N fertiliser application map, prepared in an earlier step, in order to divide the intensive management class into two; intensive irrigated and intensive rainfed.

Comment 2# 2.3 Mapping Pasture Management Intensity

Pasture management intensity was classified into three intensity categories based on the N application rates: very extensive (< 50 kg N ha-1 yr-1), extensive (50-100 kg N ha-1 yr-1), and intensive (≥ 100 kg N ha-1 yr-1). The authors need to justify these thresholds. Although a sensitivity analysis of a range of thresholds is provided, it is still necessary to explain how to determine the thresholds and why such values are selected.

The unit: superscript is necessary for “-1”.

Response: Thanks for the comment. We have now added a sentence explaining the reasoning and supported with a reference. Nitrogen application rates were classified into three classes of intensity based on the relevance of their application for agriculture as also described by Kleijn et. (2009): very extensive (< 50 kg N ha^{-1} yr^{-1}), extensive (50-100 kg N ha^{-1} yr^{-1}), and intensive (≥ 100 kg N ha^{-1} yr^{-1}) (Overmars et al., 2014, Dou et al., 2021).

Thanks for noticing this, we’ve corrected this in the unit.

Comment 3# 2.5: Photovoltaic (PV) Farm Mapping

PV cell allocation was restricted to non-water, non-urban, and non-forest areas and allocated by ranking candidate cells by descending PV fraction and allocating PV cells until the total PV area was achieved using latitude-adjusted cell areas. According to previous research, a large number of PV farms are located in water, urban, and forest areas. The assumption of non-water, non-urban, and non-forest areas is not valid and may produce a large uncertainty for this step.

How PV farm mapping contributes to the production of land management intensity dataset is not clearly explained. It seems that the definition of land management intensity does not involve the factor of PV farms.

Response: The study focusses on ground mounted solar PV farms (which we have now highlighted), therefore we don’t consider water and urban areas while placing solar PV (these are also relatively very small areas with limited influence on the output in comparison with cropland and rangeland in the year 2020). While accounting for potential PV locations, we considered tree crops but natural forests were excluded to remain consistent with the PV allocation assumptions in the previous dataset and to avoid crude assumptions about forest land conversion.

We aimed to develop a consistent land-use/cover dataset with classes of direct land competition along with land management intensity, and PV is included primarily to represent competition given its consistently increasing deployment.

Comment 4# Multinomial logistic regression model

It is not clear how the model was trained. How many samples were used to train the model? How were the samples collected? Did the authors use cross-validation to evaluate the model performance?

It would also be helpful to understand the model performance by adding other commonly used metrics for binary classification, such as AUC, F1-score, recall, and precision.

Response: Thank you for the comment. In our study, multinomial logistic regression was used primarily as an explanatory model to examine relationships between management intensity and socioeconomic and biophysical variables. We've not used it as a predictive classification model, and therefore, the model was not trained using a separate training sample. In fact, all grid cells containing valid management intensity and explanatory variable data were included in the respective global and world income regions regressions. We have now clarified this distinction and the purpose of the regression in the revised manuscript.

To understand the robustness of the estimated relationships, we performed spatial thinning at 0.10°, 0.25° and 0.50°, in which the regressions were repeated using progressively coarser spatial samples. Most marginal-effect relationships retained their direction under progressively coarser sampling, although the magnitude of some effects varied and selected pasture and forest relationships were more sensitive to thinning (Figs. A8-A10; Table A6).

AUC, F1-score, precision and recall are primarily measures of predictive classification performance. Because our main aim was to understand how the variables are associated with management intensity, and not to maximise classification accuracy, these metrics were not the primary focus of the regression analysis. We have now clarified this distinction and the purpose of the regression in the revised manuscript.