

Functional composition and structural diversity enhance mangrove forest resilience in the Sundarbans

Corresponding Author: Professor Qihao Weng

This manuscript has been previously reviewed at another journal. This document only contains information relating to versions considered at Communications Earth & Environment.

This file contains all editorial decision letters in order by version, followed by all author rebuttals in order by version.

Attachments originally included by the reviewers as part of their assessment can be found at the end of this file.

Version 0:

Decision Letter:

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Dear Professor Weng,

Your manuscript titled "High Functional Distinctiveness and Structural Diversity Strengthen Mangrove Forest Resilience Against Rising Temperatures" has now been seen by 3 reviewers, whose comments are appended below. You will see that they find your work of some potential interest. However, they have raised quite substantial concerns that must be addressed. In light of these comments, we cannot accept the manuscript for publication, but would be interested in considering a revised version that fully addresses these serious concerns.

Specifically, please address the editorial thresholds as follows:

* Provide a compelling case that high functional and structural diversities enhance mangrove resilience in the Sundarbans from 2000 to 2024, including a full and robust analysis to show mangrove resilience variation and clarifications of the methods used.

We hope you will find the reviewers' comments useful as you decide how to proceed. If additional work allows you to either incorporate or refute these criticisms, we will be happy to look at a substantially revised manuscript. If you choose to take up this option, please either highlight all changes in the manuscript text file, or provide a list of the changes to the manuscript with your responses to the reviewers.

When resubmitting, please provide a point-by-point response to the reviewers' comments. Please submit your responses as a separate file, distinct from your cover letter where you can add responses to the Editors' comments that you do not want to be made available to the reviewers. Word files are preferred. We recommend that any figures, tables or graphs that are included in the response to reviewers are also included in the main article or Supplementary Information.

Please bear in mind that we will be reluctant to approach the reviewers again in the absence of substantial revisions.

If the revision process takes significantly longer than three months, we will be happy to reconsider your paper at a later date, as long as nothing similar has been accepted for publication at Communications Earth & Environment or published elsewhere in the meantime.

We are committed to providing a fair and constructive peer-review process. Please do not hesitate to contact us if you wish to discuss the revision in more detail.

Please use the following link to submit your revised manuscript, point-by-point response to the reviewers' comments with a list of your changes to the manuscript text (which should be in a separate document to any cover letter), a tracked-changes version of the manuscript (as a PDF file) and any completed checklist:

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Please do not hesitate to contact us if you have any questions or would like to discuss the required revisions further. Thank you for the opportunity to review your work.

Best regards,

Lidiane Gouvêa
External Editor
Communications Earth & Environment

Mengjie Wang
Associate Editor, Communications Earth & Environment
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REVIEWER COMMENTS:

Reviewer #1 (Remarks to the Author):

Dear authors

Ref.: Ms. No. COMMSENV-25-1428-T

The title of manuscript is sound good. However, the authors were not explained well regarding the application of structural equation model or SEM in this study. It seemed just correlation analysis rather than model for forest ecosystem resilience. SEM allows researchers to model relationships between multiple variables, including both observed and unobserved constructs, which are common in complex ecological systems.

Additionally, the authors can not justified the complex relationships among biotic and abiotic factors in simple way by using simple correlation or regression models because these factors complement each other, while SEM can be used to model how multiple biotic and abiotic factors affect forest composition, structure, and productivity, etc.

SEM can also model the impact of climate change on forest ecosystems, considering how climate change affects forest composition for example, increased tree species richness might lead to increased resilience capacity.

The authors had made many hypotheses, but this is better to simplified the hypothesis. The authors can use SEM to answer the hypothesis because SEM allows researchers to test hypothesized relationships between variables, confirming or refuting theoretical models of forest ecosystem dynamics.

My specific comments are as follows:

Title:

Better to specify the title as follows:

High Functional Distinctiveness and Structural Diversity Strengthen Resilience of Sundarbans Mangrove Forest

Abstract:

The abstract part should be reconstructed to improve this part as follows.

- 1.The general statement is to long sentences, and the authors not need to mention references in the abstract part.
- 2.Provide the result of SEM analysis in the abstract part.

3. Keywords should be corrected.

Introduction:

There were many recent publication of mangroves worldwide close related to this study. To improve the introduction part, please look and site at the more recent blue carbon studies including relation of mangrove vulnerable and blue carbon stock. For examples: (1) <https://esj-journals.onlinelibrary.wiley.com/doi/abs/10.1111/1440-1703.12374>
(2) <https://www.frontiersin.org/journals/ecology-and-evolution/articles/10.3389/fevo.2024.1420827/full>
(3) <https://www.science.org/doi/10.1126/sciadv.adk5430>
and many others.

Methods:

Please improve manuscript by adding more analysis and applying the structural equation modelling (SEM).

Results and discussion

Please elaborate results and discussion from new analysis by applying SEM.

Reviewer #2 (Remarks to the Author):

Mizanur Rahman et al., assess mangrove forest resilience in the Sundarbans located within Bangladesh. A resilience metric derived from kNDVI, which is defined as the recovery rate from disturbances based on 1 lag autocorrelation and variance, in 5-year rolling windows, over the study period 2000 – 2024. From this they categorized mangroves as stable, increasingly resilient, and decreasingly resilient, across the entirety of the Sundarbans. Mangrove forest stand structure and diversity were calculated from the national forestry inventory data, in addition to sediment profiles collated from 110 permanent plots. Environmental variables were collated from various repositories. The interaction of these different variables and their influence on the three resilience categories were assessed using structural equation modelling. The main findings of the paper were that mangroves within the Sundarbans (Bangladesh side) were associated with a decrease in resilience, especially those along the seaward fringe. Areas of mangrove that exhibited increases in resilience were located further from the shore, and were associated with larger tree species (e.g., *Heritiera fomes*), and greater species and forest structural diversity. I think that these findings are of interest to those in the mangrove and/or management fields, as the results can inform restoration/reestablishment best practices in the region, such as not planting monocultures.

However, I do have some questions and comments that need to be addressed for this manuscript to be published.

Within the title the authors highlight that “High Functional Distinctiveness and Structural Diversity Strengthen Mangrove Forest Resilience Against Rising Temperatures”, it would be good in the paper if you can define what you mean by “Functional distinctiveness” within the context of this study.

I have some points within the methodology that it would be useful to clarify. Some of this is because I think potentially all the information is there, in regard to the forest inventory, but it is not all in one place and therefore I am not sure of the types of plots or exact number of locations of these plots within the study. It would be useful to have a section briefly outlining the inventory methods and the data used from it.

Methods – Remote sensing

1. “We used the MODIS ... from October 1, 2000 to September 30, 2024.”

This is a 24-year period, not a 25-year period

Methods - Resilience

1. “Theoretical studies suggest that complex systems can reach tipping points—critical thresholds that lead to sudden and irreversible changes.”

Here is would be good to know what your different thresholds are – what is the starting condition of the mangroves in 2000?

My concern is that by just looking at trends you do not establish a baseline level of resilience status. While a loss in resilience is not a good thing, a mangrove forest in good condition losing some resilience may still be more resilient than a forest in poor condition that is potentially recovering and increasing its level of resilience (but overall resilience is still low).

2. With these baseline levels in mind, it would be good to know if any of the regions of the Sundarbans are subjected to greater levels of disturbances (e.g., cyclones) than others, as this would play a role in understanding the condition of these systems at the start of the study.

3. No large-scale disturbances are taken account within the time frame of the study, in particular cyclones, two major events are noted in the discussion. These will have impacted the mangrove systems and their potential resilience trends. I would highly recommend adding cyclone and other major known disturbances into the model, and timings of these events – do multiple events occur in one or more of the 5-year rolling trends of the kNDVI rolling mean? As a declining resilience trend in one area of the Sundarbans could be due to a quick succession of multiple disturbances, where as another area either went unscathed or only received one event and has since been able to recover.

Methods - Forest stand structure and diversity, environmental data

1. “We used ground-measured plot-level data with the number of tree species, their basal area, stem density, maximum tree diameter from the Sundarbans Forest carbon inventory 2010.”

Are you able to provide more details on the methodology of the forest carbon inventory at the start of this section. Are these the 110 permanent plots? What type of plots are they circular, square, are they clustered, and what is the area? I would also like to see on a map where all of these plots are, while they may be good for representation of different forest types are the well distributed throughout the entire study site?

2. “We used the publicly available plant trait data specific for the Sundarbans acquired in recent years. For example, plant trait data, such as leaf traits...”

I don't think these are examples, seems like you list out all traits used. It might be good to have a table here of all the different traits and how you used them within the analyses, such as structural diversity variables, etc.

3. "We averaged the leaf litter nitrogen value that were collected by three distinct seasons (monsoon, pre-monsoon, and post-monsoon periods) in the Sundarbans."

How many leaves were included in the analyses for each of the seasons? Are the seasons distinct months, if so can you identify the months with each of these season?

4. "The long-term monthly temperature and precipitation data from 1980 to 2010 were averaged for calculating mean annual temperature and precipitation."

Were data on temperature and precipitation not available for the period of the study, 2000 – 2024? There is limited overlap in some of the key variable from which you are basing much of your findings on. Especially as you are suggesting rising temperatures in the region, but you don't have the last 14-years of data for the study.

5. "We used high resolution (1 km) climatic (mean annual precipitation and temperature) from the Coupled Model Intercomparison Project Phase 6 from CHELSA (<https://chelsa-climate.org/>) maintained by the Swiss Federal Institute for Forest, Snow, and Landscape Research."

This is repeated within the methods section, can remove from line 75 onwards.

6. "By using the plot shapefile (100 plots, each plot is composed of five 10m radius circular subplots), we extracted the mean soil properties from these spatial maps."

Are these 100 plots from the forest carbon inventory – is this a typo and should be 110, or have you dropped 10 plots or is this another inventory.

Methods – Statistical analysis

1. "We assessed the trends in recovery rate λ using Kendall's τ with overlapping 5-year windows over 2001-2020"

Is this a typo, should it be 2000 – 2024? Or can you explain why there is a difference in the time periods used.

2. DBH variation (as a proxy for structural diversity)

Not sure why you used a proxy for structural diversity – from the variables you state in the methods you should be able to get structural diversity from calculating the horizontal diversity (DBH) and vertical diversity (tree height) – see LaRue et al., 2023 <https://esajournals.onlinelibrary.wiley.com/doi/10.1002/fee.2586>.

I really think that the authors need to provide the reader with a threshold resilience value, which provides a general condition status to the forest, from which the maintenance, gain, or loss of resilience can be assessed, rather than a general trend which does not take into account original status. In light of some of these methodologies issues and wondering how they will influence the outcome of any updated results, I am concluding my review with a focus on the methodology, and would ask the authors to revise the manuscript.

Reviewer #3 (Remarks to the Author):

Thank you for inviting me to review this paper. It offers valuable insights into understanding the effects of functional, structural, and taxonomic diversity, as well as environmental factors, on the resilience of mangroves to disturbances. The discussion of niche complementary effect theory is particularly beneficial for the mangrove community. I enjoyed reading this paper, which is relevant to both scientists and practitioners. Below, I have listed several major comments to help authors improve the manuscript's quality.

Title: As resilience was evaluated against historical mean temperature rather than "rising temperature," I recommend that the authors exclude "... against rising temperatures," including "... to disturbances," or keeping only "... Mangrove Resilience."

Abstract: Please don't use citations in the abstract.

Line 33: Could the authors provide the percentage of mangroves that showed reduced resilience?

Line 40: The authors didn't study if the resilience is against climate change or human activities, so I suggest rephrasing it as "resilience against disturbances."

Line 42: How can we quantify this "limited" number of other species? The term limited seems very subjective. Could the authors rephrase it?

Keywords: I don't think "Remote Sensing of Mangrove Resilience" is a keyword; maybe remote sensing, MODIS, or kNDVI would work better here.

Line 82: I am uncertain if NDVI accurately reflects species richness; could the authors provide a reference for this?

Line 178: "We investigate objective ii, instead of 2".

Figure 1: I think readers would benefit from seeing in Figure 1b the $\lambda AC1 / \lambda VAR$ map, rather than the histogram, from which the content could be presented in the text.

Figure 2: What is the time window used for this figure (Kendall's tau trend analysis)? Please specify in the caption.

Figure 2: There are numerous conclusions regarding the spatial relationship between resilience loss and environmental settings. Could the authors provide additional base maps that illustrate these environmental settings, as well as the distribution of plots and soil and vegetation characteristics? I find this information is crucial for connecting the results with the authors' discussions and conclusions.

Table 1: Could the authors improve the caption for Table 1? What do these results represent? Are they R or R^2 , or what? The description of the level of significance should also be presented. Additionally, could the authors provide a better explanation of the differences in correlations shown in Figure 4 and Table 1? E.g. between resilience and MAP? Moreover, what is the resilience metric used here? It's not clear in the results and in the methods as well. Is it Kendall's tau? For what period?

Line 422: When authors suggest that "greater resilience" is found in "old-growth or mature stands," is there a way to illustrate this? If a map isn't available, could there be plots that show the relationship between greater resilience, vegetation, and environmental settings?

Line 434-435: Please rephrase it.

Line 442: The authors mention positive correlations but do not indicate whether these correlations are weak or strong. In both Figure 4 and Table 1, we observe several positive and negative correlations; however, these correlations are generally weak. Could the authors clarify the nature of these correlations throughout the text?

Line 489: "by climate change and human pressures."

Method and materials

Line 19: Typo of "Kernel". Please correct it. Please also check throughout the text (and supplemental material) the word "Kendall", as it was mistyped in many places.

Lines 22-39: Could the authors please provide a figure that illustrates an example of the time series, along with the smoothing process and potentially the application of the autoregressive model? Additionally, could they clarify the time window for the 1-lag autocorrelation? Is it the 16-day interval between MODIS composites?

Line 42: Please provide a clearer description of the number of plots, their sizes, and their distribution. It appears that the vegetation data was collected from a different set of plots than the soil data, and this distinction needs to be clearly stated. Could the authors include a figure that displays the spatial distribution of plots from both campaigns/projects? It would be helpful to detail the number of plots, their sizes, and the dates of data collection in the figure caption.

Lines 67 to 69: Please clearly state that the study uses pixel-based historical averages of temperature and precipitation. There is no analysis of climate change or rising temperatures, as far as I can understand. Is that correct?

Line 72: size of the plots

Until line 80: Please clearly describe how the authors harmonized the datasets in time and space (MODIS-derived resilience, Chelsea, and plot-level data).

Lines 82-85: Did the authors validate these results?

Line 92: How did the authors define the thresholds?

Line 97: "...a resilience metric" is too vague. Please describe this metric and how you harmonized it over time with other variables.

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Version 1:

Decision Letter:

**** Please ensure you delete the link to your author home page in this e-mail if you wish to forward it to your coauthors ****

Dear Professor Weng,

Please allow us to apologize again for the delay in sending this decision on your manuscript titled "Functional Composition and Structural Diversity Enhance Mangrove Forest Resilience in the Sundarbans". It has now been seen by our reviewers, whose comments appear below. In light of their advice we are delighted to say that we are happy, in principle, to publish a suitably revised version in Communications Earth & Environment.

We therefore invite you to revise your paper one last time to address the remaining concerns of our reviewers. At the same time we ask that you edit your manuscript to comply with our format requirements and to maximise the accessibility and therefore the impact of your work.

EDITORIAL REQUESTS:

Please review our specific editorial comments and requests regarding your manuscript in the attached "Editorial Requests Table".

*****Please take care to match our formatting and policy requirements. We will check revised manuscript and return manuscripts that do not comply. Such requests will lead to delays. *****

Please outline your response to each request in the right hand column. Please upload the completed table with your manuscript files as a Related Manuscript file.

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We hope to hear from you within two weeks; please let us know if you need more time.

Best regards,

Mengjie Wang

Associate Editor, Communications Earth & Environment
Consulting Editor, Communications Sustainability
Bluesky: @commsearth.nature.com; @commssustain.nature.com

REVIEWERS' COMMENTS:

Reviewer #1 (Remarks to the Author):

Dear Editor

The authors had revised and improved the manuscript following my comments and suggestions, which were complements with comments and suggestions of other reviewers. The manuscript revision was done in all parts including title, abstract, introduction, methods, and discussion. It looks well and the present form of manuscript is acceptable for publication. However, if it is possible please avoid many repetitions of citation for similar references in the text particularly in the introduction part. There were many other appropriate references can be cited rather than replication of similar citation references.

best regards
Kangkuso Analuddin
Professor in Marine Biology and Wetlands Ecology, Halu Oleo University.

Reviewer #3 (Remarks to the Author):

The authors reviewed the manuscript thoroughly. I uploaded the revised version with minor comments for improvement.

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Response to Reviews (Ref.: Ms. No. COMMSENV-25-1428-T)

Dear Reviewers,

Thank you for your thoughtful and constructive feedback on our manuscript. We sincerely appreciate the time and effort you dedicated to reviewing our manuscript. Our Manuscript has been enhanced significantly with higher clarity and rigor by your insightful suggestions and comments. We have carefully addressed each of your comments and made the necessary revisions accordingly.

Below, we outline the main changes incorporated in the revised version.

1. We detected significant perturbation using standard method at pixel level from 2000-2024. Perturbation frequency, damage, decay factor and time we develop two disturbance metrics. Additionally, we estimate the empirical recovery rate recovery rate. We also show all the step — from raw timeseries, smoothing process —at five points with cyclone flagging and resilience indicators (Fig 1).
2. We applied Quantile Threshold based resilience classification for 2001-2024, and their mean, relative to baseline year 2000. First, we used the 2000 mean kNDVI as the baseline and classified it using a quantile-based approach: Resilient (Q3) where $kNDVI > 0.49$, Moderately Resilient (Q2) where $0.39 < kNDVI \leq 0.49$, and Low Resilient (Q1) where $kNDVI \leq 0.39$. Using these thresholds, we then classified all years from 2001 to 2024 and calculated their mean resilience. We further analyzed class transitions, including gains, losses, and stable areas (Figs. 4–5, Table 1).
3. We reanalyzed the resilience indicators using 3- and 5-year rolling windows. Additionally, we employed six new structural equation models (SEMs), incorporating two resilience metrics ($\lambda AC1$ and λVAR) and three disturbance-related variables. The SEM based on perturbation frequency and λVAR performed better, showing a negative association between perturbation frequency and λVAR . Nonetheless, our original conclusion remains robust: functional composition—specifically functional identity—was the dominant driver of resilience, best represented by canopy height, followed by specific leaf area and precipitation.
4. We added study area map with vegetation type and salinity zones. We also showed the carbon inventory plots and permanent sample plots that are distributed across the ecological zones (vegetation type and salinity zones).
5. Based on these four main tasks, we have comprehensively revised the entire manuscript.

Thank you once again, for your comprehensive, thoughtful and positive feedback. Your expert commentary has been instrumental in strengthening overall impact of our manuscript to showcase the manuscripts key messages. We have carefully considered each of your suggestions and have incorporated them into the revised manuscript, which is attached with track changes as well as clean revised part with blue heightened enabled for your convenience. We believe these revisions fully address all concerns raised during the review process and have significantly improved the overall quality of the paper.

Thank you once again for your time and support.

Sincerely,

Qihao Weng (on behalf of the author team)

REVIEWER COMMENTS:

Reviewer # 1

Thank you for your valuable comments and suggestion. We have diligently addressed each of your comments in the revised version. Please see below our point-by-point responses, with your comments are shown in black and our responses in blue.

Sincerely,

Qihao Weng (on behalf of the author team)

Reviewer #1 (Remarks to the Author):

Dear authors

Ref.: Ms. No. COMMSENV-25-1428-T

The title of manuscript is sound good. However, the authors were not explained well regarding the application of structural equation model or SEM in this study. It seemed just correlation analysis rather than model for forest ecosystem resilience. SEM allows researchers to model relationships between multiple variables, including both observed and unobserved constructs, which are common in complex ecological systems.

Additionally, the authors can not justified the complex relationships among biotic and abiotic factors in simple way by using simple correlation or regression models because these factors complement each other, while SEM can be used to model how multiple biotic and abiotic factors affect forest composition, structure, and productivity, etc. SEM can also model the impact of climate change on forest ecosystems, considering how climate change affects forest composition for example, increased tree species richness might lead to increased resilience capacity.

R1.1: The authors had made many hypotheses, but this is better to simplified the hypothesis. The authors can use SEM to answer the hypothesis because SEM allows researchers to test hypothesized relationships between variables, confirming or refuting theoretical models of forest ecosystem dynamics.

Answer: Thank you for your comments. We have already applied structural equation model (Fig 6, direct association; Table 3, direct, indirect and total association). In the table 3, is the standardized beta (β) of indirect and total association predictors (exogenous variable, column) on response (Endogenous variable) and based on structural equation model (in figure 6). We have updated the table caption as well as added the direct association of all the predictors as we showed only significant paths in figure 6 in order to make it visually less complex. In our

current, version we have added perturbation frequency (to observe disturbance effect on resilience) tested it with both resilience metrics (Autocorrelation and variance-based recovery rate). Additionally, we also tested the four more SEMs with two disturbance metrics (ADI, based average drop and perturbation frequency; WDI, Weighted average drop and perturbation frequency) with both Autocorrelation and variance-based recovery rates (Table S3; please also see the relevant response to your specific comment, R1.7 and second reviewer, R2.4-2.6, for details methodology, changes in result and discussion section). In all the four models (two λ_{AC1} and 2 for λ_{VAR}), the disturbance metric has no significant association with resilience, even reduces the performance of model fit index particularly AIC and R^2 . SEM with variance-based recovery and perturbation frequency out performed all other SEMs. So, in our current version, we selected the variance-based recovery and perturbation frequency.

My specific comments are as follows:

R1.1 Title:

Better to specify the title as follows:

High Functional Distinctiveness and Structural Diversity Strengthen Resilience of Sundarbans Mangrove Forest

Answer: Thank you for your suggestion. Second (“distinctiveness”) and third reviewers (“Against rising Temperature”) also made comments on title editorial board also suggest to use “High Functional and structural diversities”. However, in our case function diversity (e.g., functional dispersion) was not the main drivers. Instead, functional composition—specifically, the functional identity of traits measured by community-weighted means—played the dominant role. Therefore, using “diversities” would misleading. Accordingly, in our current version, we have changed the title as below.

“Functional composition and Structural Diversity enhance Mangrove Forest Resilience in the Sundarbans.” L1-2

Abstract:

The abstract part should be reconstructed to improve this part as follows.

R1.2. **The general statement is too long sentences, and the authors not need to mention references in the abstract part.**

Answer: Thank you for your comment on this large sentence. We have concise the sentence as below. Regarding reference, initially we submitted it to “*Nature*” and followed their structure. We have removed the reference from abstract as it is not necessary in *Communications Earth & Environment*. Please see the change below:

“Mangrove forests offer nature-based solutions for climate change mitigation by storing atmospheric CO₂, while also supporting biodiversity, livelihoods and coastal protection. Yet, they face increasing threats from deforestation, salinity and extreme weather events.” L23-25

R1.3. **Provide the result of SEM analysis in the abstract part.**

Answer: In Nature and its sister journals, it has been prescribed to write the abstract simple language and without any technical and statistical jargons. Furthermore, the word limitation in most cases 150 words which is hard to maintain the word limit if we want to show SEM result quantitatively. So, we wrote the SEM result in abstract as verbal text. What we written in abstract in our previous and current version were based on SEM not simple correlation. Even though, as you recommend, we have mentioned the standardized beta value in abstract in our current version. Please see the result section of abstract below:

“The functional composition of maximum canopy height (MCH) was the strongest driver of mangrove forest resilience ($\beta=0.61$), followed by specific leaf area (SLA; $\beta=0.56$) and precipitation ($\beta=0.44$). Structural diversity ($\beta=0.22$), though weakly associated, mediated the positive association of species richness on resilience. Perturbation frequency had significant negative direct ($\beta=-0.29$) and total ($\beta=-0.33$) association on resilience whereas temperature exhibited only a total negative association ($\beta=-0.20$).” L31-37

R1.4. Keywords should be corrected.

Answer: Thank you for this valuable comment. We have revised the key word as below:

“Keywords: Remote Sensing, Mangrove Forest resilience, climatic effect, biodiversity, functional traits.” L42-43

Introduction:

R1.5: There were many recent publications of mangroves worldwide close related to this study. To improve the introduction part, please look and site at the more recent blue carbon studies including relation of mangrove vulnerable and blue carbon stock. For examples:

(1) <https://esj-journals.onlinelibrary.wiley.com/doi/abs/10.1111/1440-1703.12374>

(2) <https://www.frontiersin.org/journals/ecology-and-evolution/articles/10.3389/fevo.2024.1420827/full>

(3) <https://www.science.org/doi/10.1126/sciadv.adk5430>

and many others.

Answer: We agreed with you. In this current version, we have referred those excellent recent blue carbon studies. We have also included several sentences that are relevant to previous studies on cyclone induced mangrove damage, mangrove condition change and risk, and empirical recovery. By doing so, we also mentioned how our study can improve our understanding on how mangrove recovery, what are roles of different dimension of biodiversity.

Mangrove forests provide a wide range of ecosystem services, including the support of livelihoods of coastal communities, the protection of lives and properties from tropical cyclones and tidal surges (valued at more than \$US 65 billion annually), the provision of habitat

for biodiversity and high carbon sequestration and storage rates(Analuddin et al., 2023, 2024; Bourgeois et al., 2024; Donato et al., 2011; Rahman, Zimmer, et al., 2021). With these invaluable ecosystem services, mangrove forests can serve as nature-based solutions for climate change mitigation and adaptation(Analuddin et al., 2023, 2024; Bourgeois et al., 2024; Macreadie et al., 2019; Rahman, Zimmer, et al., 2021; Rovai et al., 2018). Despite these benefits, mangrove forests face multiple threats including land cover-change, rising temperatures, sea level-rise, disrupted freshwater flows, increasing salinity and more frequent cyclones and other extreme events(Analuddin et al., 2024; Bourgeois et al., 2024; Goldberg et al., 2020; Lagomasino et al., 2021). These stressors collectively contribute to the degradation of mangrove habitats, affecting species richness, composition and abundance, as well as diversity and composition of functional traits, thus, plant ecophysiological processes, physicochemical processes in sediments and blue carbon stocks both in the biomass and the sediment(Analuddin et al., 2023, 2024; Bourgeois et al., 2024; Rahman, Zimmer, et al., 2021). Such changes potentially undermine the resilience of mangrove forests—their capacity to recover from disturbances(Boulton et al., 2022; Forzieri et al., 2022)—thereby restricting their ability to provide multiple ecosystem services sustainably under changing environmental and climatic conditions. L48-62

Cyclone impacts (Mandal & Hosaka, 2020; Mohammed et al., 2024; Mondal et al., 2022; Sharma et al., 2022; Yang et al., 2024), associated risks(Mo et al., 2023), driver of dieback(Asbridge et al., 2019) and empirical recovery rates(Lagomasino et al., 2021) in mangrove forests have been documented across various regions and globally. Most existing studies focus on historical cyclone damage assessments using MODIS- and Landsat imagery-derived vegetation indices with thresholding, machine learning and deep learning approaches, or case studies of individual cyclone events(Asbridge et al., 2019; Lagomasino et al., 2021; Mandal & Hosaka, 2020; Mo et al., 2023; Mohammed et al., 2024; Sharma et al., 2022; Yang et al., 2024). However, most previous studies have concentrated on tracking mangrove forest condition and empirical recovery and future risk, while paying less attention to understanding how mangrove forest recover, what drives their post-disturbance recovery, or which role multidimensional diversity plays in shaping their recovery. L126-135

Methods:

R1.6: Please improve manuscript by adding more analysis and applying the structural equation modelling (SEM).

Answer: Thank for your comments. We have investigated more SEMs in our current version. Please see our explanation to your first general comment.

Results and discussion

R1.7 Please elaborate results and discussion from new analysis by applying SEM.

Answer: Please see the response to R1.1. Based on the new SEM analysis, we have updated both methods (L173, -L188), result (L346-L408, also see, Fig. 6 and Table 2 L430-438), and discussion (L454-464, L493-568.). Please see some of the major changes, below.

Result: (L346-L408, also see, Fig. 6 and Table 2 L430-438)

Drivers and mechanisms of mangrove forest resilience

Using the perturbation frequency and the two-disturbance metrics along with climatic, physicochemical sediment properties and taxonomic, structural and trait diversity, we developed six structural equation models (SEM): 3 for λ_{AC1} and 3 for λ_{VAR} (by adding separately three disturbance-related variables). Based on the fit indices (Chi Square = 2.464, $p = 0.292$, Goodness of Fit Index of 0.999, Comparative Fit Index of 0.999 and a standardized root mean square residual of 0.009), our fitted SEM models did not show any significant deviation from our dataset (Fig. 6; Table S3). However, according to the Akaike Information Criterion (AIC) and the Co-efficient of determination (R^2), SEM λ_{VAR} exhibited (AIC= 3776.63 and $R^2= 0.49$) a better performance than λ_{AC1} (AIC= 3786.92 and $R^2= 0.44$) with disturbances as perturbation frequency. Thus, we report the variance-based SEM. The model fitted well with 14 predictors, including mean annual temperature (hereafter, temperature), total annual precipitation (hereafter, precipitation), sediment salinity, sediment pH, sediment concentrations of sulfide, phosphorus and iron, sediment texture (silt content), perturbation frequency (count of perturbations), species richness, structural diversity, functional compositions of maximum canopy height and specific leaf area and the functional diversity of succulence (other functional traits had a variance inflation factor over 10; Supplementary Table 1-2xx).

Biotic and abiotic variables displayed distinct types of associations with resilience, biotic variables exerting the dominant role (Fig. 6). For instance, perturbation frequency exhibited a significant negative association with resilience ($\beta = -0.29$, $P < 0.05$; Fig. 6, Table 2), whereas neither precipitation nor temperature demonstrated any significant direct association ($P > 0.05$; Table 2). Both sediment pH and phosphorus content had direct significant negative association with resilience ($P < 0.05$, Table 2). However, sediment salinity and the sediment contents of iron and sulfide did not have any significant direct association (Table 2).

Structural diversity showed significant positive direct association with resilience, while species richness and functional diversity did not exhibit any significant direct association (Fig. 6; Table 2). The functional compositions of maximum canopy height ($\beta = 0.62$, $P < 0.05$; Fig. 6, Table 2) and specific leaf area height ($\beta = 0.62$, $P < 0.05$; Fig. 6, Table 1) showed a strong significant positive association with resilience. Thus, functional composition diversity metrics were the dominant driver of mangrove forest resilience in the Sundarbans. We did not find any direct association of sediment salinity with resilience ($P > 0.05$). However, we observed an indirect weaker negative association of sediment salinity with resilience through species richness to structural diversity pathways ($\beta = -0.25$; $P < 0.05$; Fig. 6).

Species richness showed a significant positive association with structural diversity ($\beta = 0.35$; $P < 0.05$; Fig. 6). Consequently, through this specific pathway, species richness showed significant weaker positive associations with resilience ($\beta = 0.08$; $P > 0.05$; Fig. 6; Table 2). However, the total indirect and total association of species richness with resilience was not significant ($P > 0.05$; Table 2). While the total association of functional diversity on resilience was negative and weaker ($\beta = -0.22$, $P < 0.05$; Fig. Table 2). Although precipitation showed no direct association with resilience, it exhibited an indirect association with resilience through specific functional trait pathways. Notably, precipitation showed an indirect positive association through the functional composition of maximum canopy height path ($\beta = 0.34$, $P < 0.05$; Fig. 6, Table 2). Conversely, precipitation also showed an indirect negative association with resilience through the specific pathway of the functional composition of specific leaf area ($\beta = -0.22$, $P < 0.05$; Fig. 6). However, the positive association through canopy height was higher than the negative association through specific leaf area ($\beta = 0.12$; Fig. 6). Precipitation

also showed a negative association with resilience through the sediment salinity to functional composition of maximum canopy height pathway (Table 2). More importantly, precipitation also showed a positive indirect association with resilience through reducing the perturbation frequency which was weakly negatively related to resilience ($\beta = 0.10$, $P < 0.05$; Fig 6 and Table 2). These indirect positive and negative associations, combined with weaker positive direct association, resulted in the moderate total positive association of precipitation with resilience ($\beta = 0.44$, $P < 0.05$; Fig. 6; Table 2). Temperature exhibited an indirect negative association with resilience through functional composition of maximum canopy height ($\beta = -0.40$, $P < 0.05$; Fig. 6; Table 2) and through the sediment salinity to species richness to structural diversity pathway (Fig. 6; Table 2). Conversely, temperature also showed an indirect positive association with resilience through the functional composition of specific leaf area ($\beta = 0.33$, $P < 0.05$; Fig. 6; Table 2). However, the total association of temperature with resilience was negative ($\beta = -0.20$, $P < 0.05$; Table 2). The total association of perturbation frequency with resilience was significant and negative ($\beta = -0.29$, $P < 0.05$; Table 2). Although we observed strong positive direct association of the functional compositions of both maximum canopy height and specific leaf area with resilience, the total association of the functional composition of maximum canopy height ($\beta = 0.61$, $P < 0.05$; Table 2) outperformed that of specific leaf area ($\beta = 0.56$, $P < 0.05$; Table 2).

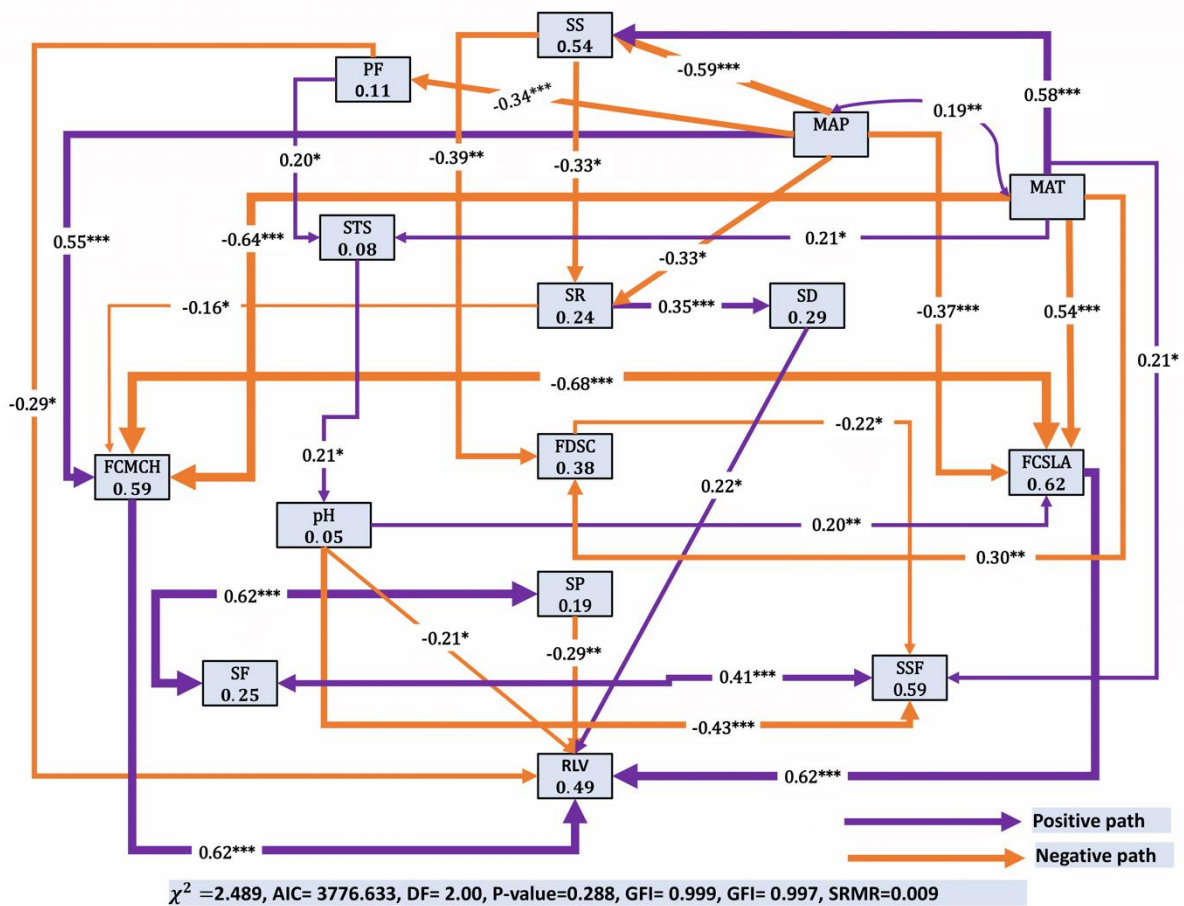


Fig 6. Structural Equation Model illustrating the mechanisms connecting biodiversity measures, abiotic factors and resilience (λ_{VAR}). Hypothesized paths with asterisks (***: $P < 0.001$, **: $P < 0.01$, *: $P < 0.05$) indicate significant associations between variables; non-

significant associations ($P > 0.05$) are not shown for the sake of clarity (please see Table 2). The non-significant χ^2 (Chi-Square) of 2.489 ($P = 0.288$), with a goodness of fit index (GFI) of 0.997, with a comparative fit index (CFI) of 0.999 and a standardized root mean square residual of 0.009 suggests no significant deviation from the model and datasets at 2 degrees of freedom. Orange lines indicate negative associations, while purple lines indicate positive associations between covariables. Numbers on the arrows show the standardized associations of predictors with dependent variables. R^2 Coefficient of Determination within the endogenous variables represent their explained variance by all predictors. *MAP* mean annual precipitation, *MAT* mean annual temperature, *SS* sediment salinity, *SR* Species richness, *FCMCH* functional composition of maximum canopy height, *SD* Structural diversity (variation of diameter at breast height), *FCSLA* functional composition of specific leaf area, *FDLS* functional diversity leaf succulence, *P* sediment phosphorus concentration, *SF* sediment iron concentration, *SSF* sediment sulfide concentration, *pH* sediment pH level, *STS* sediment texture silt, *PF* perturbation frequency.

Discussion:

With SEM analysis, we found that mangrove forest resilience in the Sundarbans is primarily driven by the functional composition of maximum canopy height (MCH) and specific leaf area (SLA), while structural diversity and species richness play minor roles (hypothesizes H2). Mean annual precipitation was the dominant abiotic driver of resilience, mainly mediated by MCH and SLA, whereas perturbation frequency and sediment phosphorus content showed negative associations (hypothesizes H1 and partly H3). Thus, mangrove forest resilience in the Sundarbans is shaped by a dynamic interplay of functional trait dominance, structural complexity and precipitation. These findings highlight the urgent need to integrate trait-based approaches and disturbance regimes into conservation and (re-)establishment strategies under changing environmental conditions. L454-464

Mangrove forest resilience or recovery from disturbances in the Sundarbans is strongly driven by the functional composition of whole-plant traits and the leaf economic spectrum. Our findings reveal that the functional composition of MCH and SLA qualify as the strongest biotic predictors of mangrove forest resilience in the Sundarbans. This result suggests that the selection effect theory (Finegan et al., 2015; Tilman et al., 2009)—dominant species with their key functional traits drive ecosystem process—is primarily governing mangrove forest resilience in the Sundarbans. Mangrove stands with tall-growing species capitalize on vertical light gradients (Finegan et al., 2015), enabling rapid canopy reformation and biomass accumulation after disturbances. Concurrently, high SLA—reflecting an acquisitive leaf strategy along the leaf economic spectrum (Wright et al., 2004)—supports faster photosynthesis, nutrient turnover and growth rates (Finegan et al., 2015). Together, these traits synergistically accelerate post-disturbance recovery, reinforcing the critical role of functional trait composition for mangrove forest resilience, similar to other ecosystem process and properties (Finegan et al., 2015) (e.g., biomass, productivity and carbon storage).

Studies in mangrove and terrestrial ecosystems, consistently link species diversity and structural diversity (variation in DBH and tree height) to key ecosystem properties and processes, such as productivity, aboveground biomass, carbon storages, and these descriptors of community composition can also promote ecosystem resilience (Dănescu et al., 2016; Godlee et al., 2021; Rahman, Kundu, et al., 2021; Rahman, Zimmer, et al., 2021). Our findings of a direct positive association of structural diversity with resilience, and an indirect positive association of species richness through increasing structural diversity, aligns with this growing body of work, indicating the minor relevance of a niche complementarity effect (Finegan et al.,

2015; Tilman et al., 1997) on mangrove forest resilience. Forest stands with high DBH variation reflect both horizontal and vertical heterogeneity (Ali, 2019; Dănescu et al., 2016; Messier et al., 2013), characterized by the spatial co-existence of trees with different sizes and growth forms. This complexity promotes niche partitioning, reduces competitive exclusion, and enhances microhabitat diversity, leading to more efficient light capture and resource use (Onoda et al., 2014). In this way, structural diversity buffers mangrove forests against disturbance and enhances their recovery potential. Additionally, species-rich forest stands with high structural diversity may prevent catastrophic canopy collapse during "super cyclones". For example, if dominant tall trees are damaged, smaller or intermediate-sized individuals maintain partial canopy cover, stabilize sediments through diverse rooting architectures and facilitate faster regrowth (D. M. Alongi, 2008; Krauss & Osland, 2020). Thus, while functional trait composition primarily drives post-disturbance recovery in the Sundarbans, species diversity enhances resilience by promoting structural heterogeneity, increasing the range of growth forms and life-history strategies and fostering functional redundancy (Finegan et al., 2015; Messier et al., 2013; Tilman et al., 2009).

The rapid change in global temperatures is causing more frequent extreme weather events, such as tropical cyclones, as well as rising sea levels and, in conjunction with changing precipitation patterns, fluctuating salinity levels, which could influence the resilience of mangrove forests (D. Alongi, 2018; Kirwan & Megonigal, 2013; Loucks et al., 2010). The moderate total positive association of mean annual precipitation with resilience highlights their pivotal role in mangrove forest resilience. Our SEM analysis also showed how precipitation patterns exerted this positive influence mainly through three different pathways: functional composition of MCH, salinity and perturbation frequency. Higher rainfall plays a crucial role in alleviating water stress, increasing freshwater flow and diluting porewater salinity, which, in turn, reduces the energetic cost of osmoregulation and improves overall physiological performance. This allows mangrove trees to allocate more energy into vertical growth (D. M. Alongi, 2008; Ball, 1988; Krauss & Osland, 2020). Moreover, consistent precipitation helps maintain a hydrological balance and stabilizes sediment conditions (Krauss & Osland, 2020). In this way, rainfall can support enhanced growth capacity of dominant tall species and likely contributes to faster post-disturbance recovery, reinforcing the mass-ratio effect observed in our study.

Our results on the negative direct, indirect and total associations of perturbation frequency (PF), suggest that mangrove forest stands exposed to frequent cyclones, tidal surges and anthropogenic pressures exhibit lower resilience. Severe cyclones typically cause direct physical damage of mangrove trees, including canopy top breakage, uprooting and defoliation^{9,18,19,22,57}. Indirectly, these disturbances alter biogeochemical processes by creating hypersaline condition, increasing the sediment silt content, and elevating sediment pH—all of which are detrimental to mangrove health, productivity and, ultimately, mangrove forest resilience (Krauss & Osland, 2020; Lagomasino et al., 2021; Mo et al., 2023). Increased salinity can render nutrients inaccessible to plant roots or force plants to spend more energy in coping with osmotic stress, thereby weakening their physiological performance (D. M. Alongi, 2008; Ball, 1988; Krauss & Osland, 2020). On the other hand, increased sediment pH, resulting from silt accumulation (Fig. 6) and reduced tidal flushing, can further reduce the availability of essential micronutrients, such as iron and manganese (Krauss & Osland, 2020). This alteration in physicochemical mangrove sediment properties disrupts microbial activity that is critical for nutrient-cycling and organic matter decay, compounding the stress on mangrove ecosystems and diminishing their capacity to recover from disturbance (Pradisty et al., 2021; Quadros et al., 2019).

Phosphorus, although a key essential nutrient for mangroves, playing a crucial role in photosynthesis, growth and sediment microbial activity (Ball, 1988; Krauss & Osland, 2020), can become ecologically disruptive when present in excessive amount. The direct negative association of the sediment phosphorus content with resilience suggests that excessive phosphorus-enrichment in mangrove forest sediments may disrupt the nutrient stoichiometric balance and interfere with microbial processes (Ball, 1988; Krauss & Osland, 2020). In mangrove forest sediments, a balanced ratio of carbon (C), nitrogen (N) and phosphorus (P) is essential for sustaining microbial metabolic processes and ecological interactions. This stoichiometric balance supports efficient microbial activity, organic matter decay and nutrient-cycling (Ball, 1988; Pradisty et al., 2021; Quadros et al., 2019), all of which are critical for mangrove forest health and resilience. High phosphorus levels can skew this ratio, leading to disproportionate growth of microbes that rapidly decay organic matter (Ball, 1988; Krauss & Osland, 2020) which, in turn, accelerates microbial respiration, depleting oxygen in the sediment and creating hypoxic conditions (Krauss & Osland, 2020). Under low oxygen availability, nutrient-cycling is impaired, and root respiration is restricted, ultimately weakening mangrove health and reducing ecosystem resilience.

Reviewer # 2

Thank you for your insightful suggestions and comments. We have carefully and thoroughly followed all your valuable suggestions and comments in our revision. We present below a point to point response with reviewer comments in Black and our corresponding responses in blue.

Sincerely,

Qihao Weng (on behalf of the author team)

Reviewer #2 (Remarks to the Author):

Mizanur Rahman et al., assess mangrove forest resilience in the Sundarbans located within Bangladesh. A resilience metric derived from kNDVI, which is defined as the recovery rate from disturbances based on 1 lag autocorrelation and variance, in 5-year rolling windows, over the study period 2000 – 2024. From this they categorized mangroves as stable, increasingly resilient, and decreasingly resilient, across the entirety of the Sundarbans. Mangrove forest stand structure and diversity were calculated from the national forestry inventory data, in addition to sediment profiles collated from 110 permanent plots. Environmental variables were collated from various repositories. The interaction of these different variables and their influence on the three resilience categories were assessed using structural equation modelling. The main findings of the paper were that mangroves within the Sundarbans (Bangladesh side) were associated with a decrease in resilience, especially those along the seaward fringe. Areas of mangrove that exhibited increases in resilience were located further from the shore, and were associated with larger tree species (e.g., *Heritiera fomes*), and greater species and forest structural diversity. I think that these findings are of interest to those in the mangrove and/or management fields, as the results can inform

restoration/reestablishment best practices in the region, such as not planting monocultures. However, I do have some questions and comments that need to be addressed for this manuscript to be published.

R2.1 Within the title the authors highlight that “High Functional Distinctiveness and Structural Diversity Strengthen Mangrove Forest Resilience Against Rising Temperatures”, it would be good in the paper if you can define what you mean by “Functional distinctiveness” within the context of this study.

Answer: Thank you for your comments on title. Please see the details explanation in our first reviewer’s response section (R1.1). We have revised the title as below.

“Functional composition and Structural Diversity enhance Mangrove Forest Resilience in the Sundarbans.” L1-2.

R2.2 I have some points within the methodology that it would be useful to clarify. Some of this is because I think potentially all the information is there, in regard to the forest inventory, but it is not all in one place and therefore I am not sure of the types of plots or exact number of locations of these plots within the study. It would be useful to have a section briefly outlining the inventory methods and the data used from it.

Answer: Thank you for your concern. The plot type was cluster. Each plot consists of five circular subplots. We have added a figure in method with plots location (both solid sampling plots-permanent sample plots and forest carbon inventory plots why vegetation types (Method; Fig. S7; Response to R3.20). In the method we have also added a description on the field plots.

“A total of 150 plots were surveyed from 5 December 2009 to 30 May 2010¹². Each plot consisted of five 10-meter radius nested subplots. From the central subplot, the other four subplots were 50m (Fig. S7) away towards four-cardinal directions¹². In our current study we 100 plots the remaining 50 plots have either fully under water or subplot with waterbody more than 20% due to presence of small canal or on the bank of the river or big canal ^{12,13}.” (Mthod, L104-109)

“We extrapolated the soil physiochemical properties (sediment phosphorus (P), sediment ammonium (NH₄), sediment potassium (K) and sediment sulphide) using field data that was collected by Saker et al.(2021) from 110 permanent sample plots (each plot size 120 × 20 m) in the Sundarbans, during January – June 2014.” L37-141

Methods – Remote sensing

R2.3. “We used the MODIS ... from October 1, 2000 to September 30, 2024.”

This is a 24-year period, not a 25-year period

Answer: Yes, you are right. In our current version we, added full coverage from 18 February 2000 to 31 December 2024 and revised the results. So, the now it is 25 years period. Please see the relevant revisions that we made in the method below.

“We used the MODIS (Moderate Resolution Imaging Spectroradiometer) 16 days composite Normalized Difference Vegetation Index (NDVI) dataset (products MOD13Q1 (250 m) product, from February, 2000 to December, 2024. We ensured high-quality pixels in our analysis by using the quality assurance band of QC_250m to exclude pixels affected by cloud cover, cloud shadows, and relevant atmospheric effects. For getting stable forest, we intersected between 2000 and 2024 MODIS annual tree cover percentage (>2). As we used MODIS 250m resolution pixel adjacent or over small rivers or canals usually mixed pixel with reflectance comes from vegetation and waterbody. To remove those pixels from our analysis, we further intersected Landsat of 2000 and 2024 after masking waterbody using a Modified Normalized Water Index with a threshold of 0.3(Xu, 2006).” (Method; L4-13)

Methods – Resilience

R2.4. “Theoretical studies suggest that complex systems can reach tipping points—critical thresholds that lead to sudden and irreversible changes.”

Here is would be good to know what **your different thresholds are** – what is the starting **condition of the mangroves in 2000**? My concern is that by just looking at trends you do not establish a **baseline level of resilience status**. While a loss in resilience is not a good thing, a mangrove forest in good condition losing some resilience may still be more resilient that a forest in poor condition that is potentially recovering and increasing its level of resilience (but overall resilience is still low).

Answer: Thank you for this most insightful comment. In our revised version, we first use 2000 mean kNDVI as baseline, classify it by using quantile-based approach where (Resilient (Q3) where $kNDVI > 0.49$, Moderate Resilient (Q2) where $0.39 < kNDVI \leq 0.49$, and Low Resilient (Q1) where $kNDVI \leq 0.39$. Using this threshold, we then classify, all the years from 2001-2024 and their mean. Then we calculated the class transition and gain, loss, and stable (Figs, 4-5, Table 1-2). Please see the text in method and result based on this analysis.

Change in Method:

Baseline and forest condition change

We empirically observed the vegetation dynamics from 2000 to 2024, using mean kNDVI relative to the baseline condition in 2000. By leveraging quantiles (Q1, Q2, and Q3), we classified mangrove health into three categories: quantile threshold-based approach (Resilient

(Q3) where $kNDVI > 0.49$, Moderate Resilient (Q2) where $0.39 < kNDVI \leq 0.49$, and Low Resilient (Q1) where $kNDVI \leq 0.39$, based on the raw mean $kNDVI$ of the year 2000), relative to initial year of the study 2000 as baseline. Using this quantile thresholding approach, we classify the annual mean $kNDVI$ from 2000-2024, average from 2001-2024, five-year rolling mean for each year from 2002-2022 and their mean (Fig. 5). By using this classified $kNDVI$ distribution relative to baseline, we assessed class transition and developed maps of stable, gain, and loss in mangrove health from 2001 to 2024 and mean of 2001-2024, five-year rolling mean for each year from 2002-2022 and their mean (Fig. 6, Table 1-2).

Change in Results: (L273-306; L314-344)

To observe the resilience status we followed two methods: quantile threshold-based approach (Weakly Resilient (red; Q1: $kNDVI \leq 0.39$), Moderately Resilient (yellow; Q2 $0.39 < kNDVI \leq 0.49$) and Resilient (green; Q3: $kNDVI > 0.49$), relative to the initial status of 2000 as baseline) and Kendall's tau rank correlation, utilizing three-years, five-years, and seven-years overlapping windows with one-year shifts (see method; Fig. 5, Fig. S5-6). This analysis is crucial for understanding how resilience in mangrove stands changed over time and for identifying areas at risk (Fig. 4-5). The spatiotemporal maps of resilience class show that over the past 25 years, a significant number of forest stands had shifted in their resilience classes from their baseline years and with cyclone severity, mostly towards moderate resilience (Fig. 4, Table 1). For example, from 2007-2009 (cyclones Sidr, Rashmi and Aila), an area of 820.97, 732.54 and 1,138.74 km², respectively, shifted from resilient to moderately resilient, whereas areas of 356.89, 784.68 and 945.04 km², respectively, shifted from moderately resilient to weakly resilient (Table 1). When we considered resilient status maps relative to the baseline year 2000, we found that the lowest resilience loss occurred in 2022 (Fig. 4, Table 1), while maximum resilience loss was recorded in 2009 (2110.52 km²; Fig. 4, Table 1). Significant losses were also observed in 2007 (1189.21, km²), coinciding with Cyclone Sidr on 7 December 2007, and in 2008 (2056.79 km²; Fig. 4, Table 1). The average resilience loss from 2001-2024 was 606.83 km², based on average $kNDVI$ (Fig. 5, Table 1). Notably, in 2004 and in the years after 2009-2012, more than 1000 km² of mangrove forests exhibited reduced resilience every year relative to the baselines of 2000 (Table S1). The Kendall's tau values for other window sizes (3, 5 and 7 years), which were assessed to investigate the robustness of our resilience assessment, are provided as supplementary materials (Fig. 5; Figs. S5–S6). Our analysis revealed that 61.4% (4030.88 km²) of the studied areas show non-significant Kendall's tau values, suggesting stable conditions. Conversely, 23.6% (988.81km²) of mangrove stands exhibited negative Kendall's tau ($p < 0.05$), indicating increased resilience (Fig. 5). However, 15.1% (988.81km²) of the areas displayed significant positive Kendall's tau values, indicating resilience loss (Fig. 5). The other two windows of trend analysis also exhibited similar spatial patterns of resilience trends, with slight variations in the percentage and area coverage under neutral, resilience gain and resilience loss categories (Figs. S5–S6). Trend-based resilience analysis depicted a steep resilience decrease from the central to western regions and near terrestrial or northern boundaries, along the coastline. However, the southeastern part of the Sundarbans (southern part of Chandpai and Sharonkhola range) exhibited lower resilience losses (Fig 4). L273-306

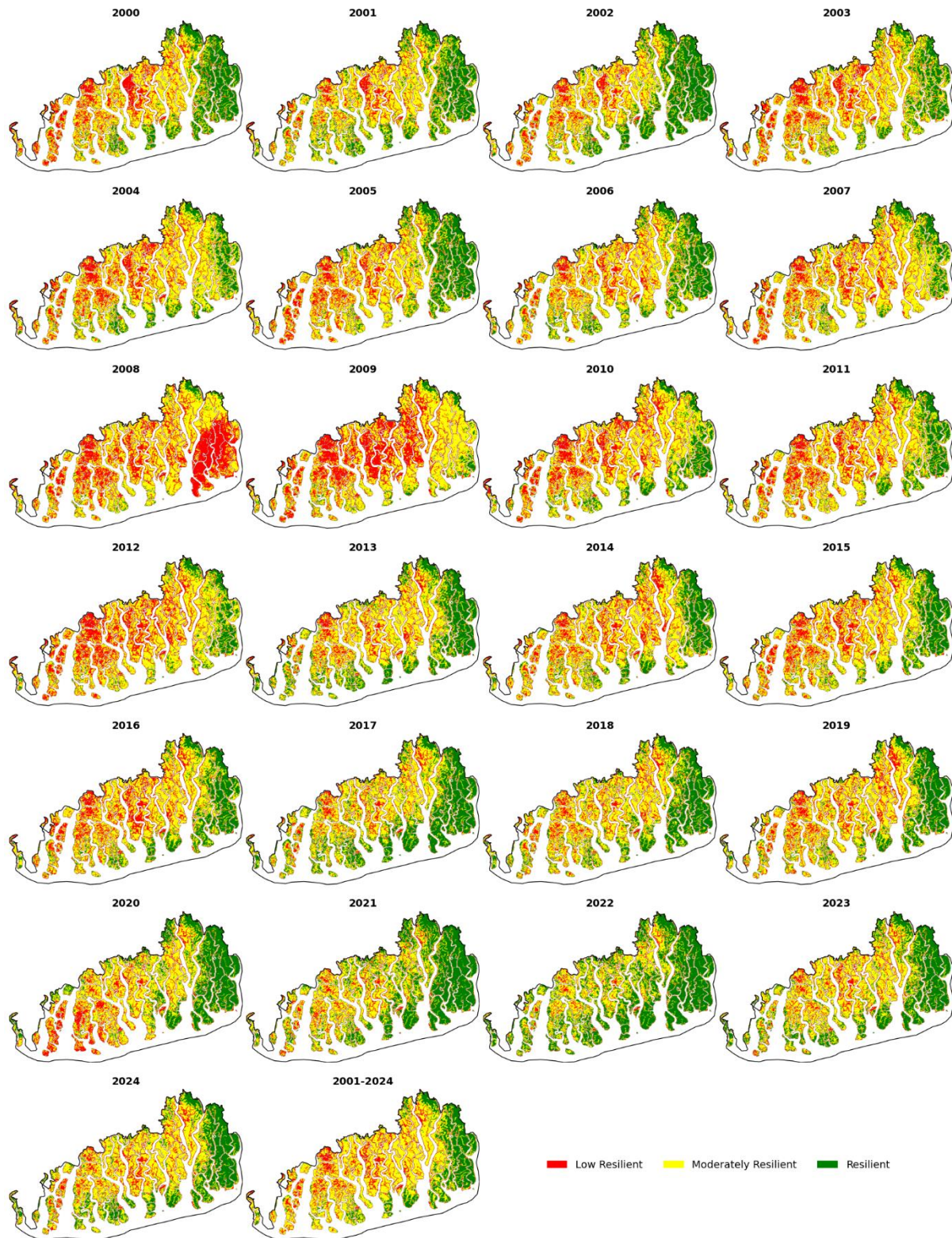


Figure 4: Threshold-Based Vegetation Resilience Classification (2000–2024). Maps categorize vegetation into three resilience classes relative to the baseline (2000) quantile approach: Weakly Resilient (red; Q1: $kNDVI \leq 0.39$), Moderately Resilient (yellow; Q2 $0.39 < kNDVI \leq 0.49$) and Resilient (green; Q3: $kNDVI > 0.49$). Individual years (2000–2024) are shown with bold titles while the bottom-right map depicts spatial patterns of the three-class mean of 2001–2024 and relative to 2000. The black boundary outlines the Sundarbans region.

Table 1. Summary of resilient class transition, total gain and loss from 2001-2024 (annual and mean) relative to baseline year 2000. *R1* Weakly Resilient (red; Q1: kNDVI $\leq$ 0.39), *R2* = Moderately Resilient (yellow; Q2 $0.39 < \text{kNDVI} \leq 0.49$), and *R3* = Resilient (green; Q3: kNDVI > 0.49). These resilience classes are based on the quantile threshold baseline year (2000).

Year	R1 to R2	R1 to R3	R2 to R3	Total Gain	R3 to R2	R3 to R1	R2 to R1	Total Loss	Stable
2001	445.28	11.61	416.74	873.63	281.62	2.49	116.12	400.23	4380.41
2002	424.39	6.01	607.11	1037.51	124.11	2.17	121.47	247.75	4368.4
2003	269.35	6.02	178.37	453.74	592.06	4.93	337.09	934.08	4265.53
2004	275.09	5.96	179.42	460.47	754.64	4.92	336.35	1095.91	4097.34
2005	317.07	3.08	334.86	655.01	324.05	5.69	269.94	599.68	4398.54
2006	396.17	8.89	300.3	705.36	402.76	3.57	205.55	611.88	4336.42
2007	291.43	4.12	145.24	440.79	820.97	11.35	356.89	1189.21	4023.79
2008	211.56	3.25	58.5	273.31	732.54	539.56	784.68	2056.78	3322.86
2009	149.48	5.15	81.99	236.62	1138.74	26.74	945.04	2110.52	3304.63
2010	261.64	9.22	173.44	444.3	753.54	10.05	463.76	1227.35	3981.14
2011	265.55	6.88	168.99	441.42	642.49	11.64	422.49	1076.62	4132.86
2012	212.83	4.66	91.62	309.11	825.01	15.09	610.98	1451.08	3892.27
2013	470.94	31.33	424.74	927.01	336.25	6.49	203.72	546.46	4179.7
2014	369.59	10.23	227.75	607.57	537.82	11.04	342.76	891.62	4154.62
2015	334.4	10.4	209.03	553.83	505.19	8.51	347.7	861.4	4236.87
2016	324.81	10.02	246.47	581.3	489.38	13.85	394.26	897.49	4170.15
2017	573.48	42	711.98	1327.46	242.79	6.17	147.1	396.06	3927.33
2018	504.1	25.94	477.86	1007.9	312.57	8.5	214.61	535.68	4106.51
2019	428.87	16.17	319.55	764.59	397.57	13.7	332.36	743.63	4140.07
2020	514.82	29.06	573.79	1117.67	278.16	27.87	344.43	650.46	3881.75
2021	637.09	42.43	1007.98	1687.5	127.38	10.35	136.14	273.87	3686.49
2022	739.56	98.62	1330.63	2168.81	82.62	7.09	78.61	168.32	3313.72
2023	561.05	47	615.93	1223.98	251.8	11.64	187.34	450.78	3971.95
2024	547.21	31.33	482.4	1060.94	340.06	16.02	233.17	589.25	3997.51
Mean	379.11	1.03	160.43	540.57	430.18	4.55	172.09	606.82	4508.17

Table 2. Summary of, mean resilient class transition and total gain and loss from 2002-2022 (five-years rolling mean and mean) relative to 2000. *R1* Weakly Resilient (red; Q1: kNDVI $\leq$ 0.39), *R2* = Moderately Resilient (yellow; Q2 0.39 < kNDVI $\leq$ 0.49), and *R3* = Resilient (green; Q3: kNDVI > 0.49). These resilience classes are based on the quantile threshold baseline year 2000.

Year (Rolling to)	R1 to R2	R1 to R3	R2 to R3	Total Gain	R3 to R2	R3 to R1	R2 to R1	Total Loss	Stable
2002	283.13	0.27	156.18	439.58	284.14	1.14	113.22	398.49	4817.5
2003	323.28	1.14	200.04	524.45	317.15	1.84	143.66	462.65	4668.46
2004	310.4	1.3	181.37	493.07	348.55	2	166.59	517.14	4645.36
2005	283.76	0.92	114.42	399.1	559.23	2.65	214.93	776.82	4479.65
2006	267.16	0.65	80.28	348.09	939.17	4.82	272.81	1216.8	4090.68
2007	231.88	0.87	62.89	295.63	1039.59	6.65	353.51	1399.75	3960.18
2008	226.24	0.98	60.97	288.18	1100.21	9.78	405.99	1515.98	3851.4
2009	199.53	1.14	47.05	247.71	1142.23	13.56	472.5	1628.29	3779.57
2010	186.68	1.3	44.34	232.33	1144.07	13.46	533.13	1690.66	3732.58
2011	243.48	2.39	91.95	337.81	769.64	7.35	403.14	1180.13	4137.62
2012	296.78	3.03	125.96	425.78	596.09	6.98	308.69	911.76	4318.03
2013	313.13	3.74	134.49	451.35	546.95	6.33	292.96	846.24	4357.97
2014	324.75	3.79	144.52	473.06	518.73	5.74	288.5	812.97	4369.48
2015	406.7	6.44	233.57	646.7	398.42	4.76	205.29	608.48	4400.33
2016	414.33	6.11	240.71	661.15	390.61	5.36	207.24	603.21	4390.93
2017	430.71	7.46	267.05	705.22	355.89	6.39	207.26	569.53	4380.44
2018	474.65	8.43	324.16	807.24	317.62	7.69	188.46	513.77	4334.4
2019	547.23	11.94	455.7	1014.86	244.08	7.58	147.62	399.28	4241.15
2020	598.39	15.77	548.28	1162.44	203.66	7.8	130.56	342.02	4151.11
2021	616.78	17.56	570.39	1204.72	197.41	8.4	125.1	330.91	4119.88
2022	644.92	19.34	618.92	1283.18	182.16	8.94	114.94	306.04	4066.18
Mean	351.66	0.92	135.94	488.52	482.03	4.39	192.24	678.66	4488.38



Fig 5. Annual, mean and rolling mean resilient status from 2000-2024, based on the class transition total gain and loss relative to 2000. *R1* = Weakly Resilient (red; Q1: $kNDVI \leq 0.39$), *R2* = Moderately Resilient (yellow; Q2 $0.39 < kNDVI \leq 0.49$), and *R3* = Resilient (green; Q3: $kNDVI > 0.49$). These resilience classes are based on the quantile threshold baseline year (2000). The five-years rolling mean was quantified for 2002-2022: as our study period covers

2000–2024, we were unable to apply a full 5-years rolling window for the boundary years 2000, 2001, 2023 and 2024 due to insufficient adjacent data. L304-344

Change in discussion: L441-454, L468-491

Mangrove ecosystems worldwide are experiencing frequent external pressures—such as warming, rising sea levels, changing precipitation patterns or fluctuating salinity levels—that could affect the resilience of mangrove forests against disturbances, such as tropical cyclones or stressors such as salinity (D. Alongi, 2018; Kirwan & Megonigal, 2013; Mo et al., 2023). In this study, we assessed mangrove resilience against disturbance in the Sundarbans using years of 25 years of MODIS kNDVI data, applying empirical quantile-based thresholding and theoretical recovery rates (λ_{AC1} and λ_{VAR}) alongside biotic and abiotic drivers. Resilience varied spatially and temporally, with the lowest values in seaward zones (from Satkhira to Sharankhola, Bangladesh) and higher resilience near the northern boundary—although Indian Sundarbans mangrove stands showed lower resilience than their Bangladeshi counterparts (Fig. 3; as indicated by red color gradients). Quantiles-based thresholding and a rolling window-based trend analysis revealed significant resilience loss over time, potentially upon increasing environmental pressure, across 11% (607 km²) and 15% (989 km²) of the region, respectively, with a peak decline in 2009 (37%, or 2110 km²) following three consecutive cyclones (Sidr, Rashmi, and Aila). L441-454

For example, southeastern, northern and southwestern areas showed higher recovery rates than the seaward zones (from Satkhira to Sharankhola) in Bangladesh. The northern boundary typically experiences cyclones with lesser intensity, particularly in the Khulna and Chandpai Range, as these regions are located 75-90 km inland off the coastline. Forests in these boundary regions are highly diverse stands with a mixture of fast-growing (*Avicennia officinalis*, *Excoecaria agallocha*), and slow-growing (*Heritiera fomes*, *Bruguiera sexangular*, *Xylocarpus mekongensis*) species (Rahman et al., 2019b; Simard et al., 2019). These species are characterized by great height, with *Excoecaria agallocha* in the northern boundary area developing greater canopy height than those in the seaward and western forest stand typically associated with higher salinity levels^{18,42}. Additionally, southeastern and northern boundary regions receive more freshwater from the Passur and Baleshwar rivers than the western and central parts of the Sundarbans⁴⁹. One notable exception is the low-resilience hotspot located between the southeastern Chandpai range and the Sharankhola range along both the east and west sides of the Shala River (dark red, Fig 3a; light blue, Fig 3b). Despite receiving more freshwater input than the southern and central western zones of the Sundarbans, being dominated by *H. fomes* and *E. agallocha* with greater canopy height and exposed to moderate perturbation frequency, the area unexpectedly exhibits low resilience. The likely reason is exposure to severe cyclones along their central track—most notably Sidr—followed by successive moderate cyclones (Rashmi, Aila, Mora, Bulbul, Amphan; Fig. 2a and 2b). The spatial map of resilience classes (2007-2013) further reveals that it took six years for these regions to regain its baseline resilient class, similar to 2000, underscoring the long-lasting impact of extreme events like Sidr and the compounded stress from tropical cyclones in the lower upstream reaches compared to the Passur and Baleshwar rivers. L468-491

R2.5. With these baseline levels in mind, it would be good to know if any of the regions of the Sundarbans are subjected to greater levels of disturbances (e.g., cyclones) than others, as this would play a role in understanding the condition of these systems at the start of the study.

Answer: Thank you for this suggestion which added a significant strength of our manuscript. Using a well established perturbation detection methods (Smith and Boers, 20022, 2023, published in *Nature climate Change* and *Nature Ecology & Evolution*), we detected perturbation frequency per pixel during 2000-2024, along with cyclone flagged, empirical recovery rate, two disturbance metrics. We also added an example whole process at five points (as recommended by reviewer 3; R3.19), Please see detail below that we added in the method section.

Change in Method: L27-51

Perturbation detection, disturbance metric, recovery rate

We detected perturbation in the residual time series using a moving window approach (Smith et al., 2022). We employed window size 24 (12 month). We use two thresholds: a strict (Smith et al., 2022) (99th percentile) and a less strict threshold (95th percentile). Furthermore, the method may flag non-significant fluctuations, especially in time series lacking strong disturbances. To mitigate this, a minimum amplitude threshold is applied: the raw time series must decrease by at least 0.01 to qualify as a valid perturbation⁶. Further, we employed a Savitsky-Golay filter with 7-point window to reduce high-frequency noise in the resultant derivative time series (Savitzky & Golay, 1964; Smith et al., 2022).

To assess the significant recovery in order to confirm that the system has not turned into an alternative state rather returned to its original state, we performed a two-sample Kolmogorov–Smirnov test ($P < 0.05$) following a dynamic baseline mean of residual kNDVI, one year before from the date of perturbation detection⁸ to subsequent five-year post perturbation. For each valid perturbation, we then find a local minimum in the residual time series with 4-month window to account a potential lag in detection and fit exponential equation for recovery rate assessment. For pixel with multiple perturbation, we took the average recovery rate (Smith et al., 2022). We also added the potential cyclones with 90 days window (Table S6), there were 34 cyclones formed in the bay of Bengal from 2000 to 2024. With the total valid perturbation counts, we develop three disturbance metrics based on average drop, weighted average drop (combine count, decay factor and severity) and baseline-normalized weighted disturbance index (consider baseline vegetation condition; Eq1-3). In all the three disturbances, a higher value indicates higher disturbance.

$$\text{Average drop disturbance index (ADI)} = \text{perturbation count} \times \text{average drop} \quad (2)$$

$$\text{Weighted Disturbance index (WDI)} = \text{perturbation count} \times \text{weighted average drop} \quad (3)$$

Where, Average drop is the mean drop magnitude across all the valid perturbations

$$\text{Weighted drop} = \frac{\sum(\text{drop}_i \times \text{weight}_i)}{\sum \text{weight}_i} \quad \text{with weight} = e^{-\frac{t_i}{365} \times \frac{\text{drop}_i}{\text{maximum drop}}}$$

Change in result: L198-259

Perturbation count and disturbance index

We estimated the perturbation frequency using residual kNDVI after removing long-term and seasonal trend (see the example along with resilience indicators and empirical recovery rate at five locations in Fig. 1a-f, Fig. S1-4) which showed that every location across the Sundarbans experienced at least one significant perturbation in the past 25 years (Fig. 2a). A high number of perturbations spanned sparsely across the Sundarbans with more homogeneous patches were observed in the seaward zone of Khulna range, northern boundary, and northeastern boundary

and central part of Sundarbans. Interestingly, the forest stands between southeastern zone of Chandpai and northwestern zone of Sharankhola range (blue coloured homogeneous patches, Fig. 2a) had 1-2, perturbations. However, those forest stands, the disturbance indices (Disturbance Index-AD and Disturbance Index-WAD; Fig. 2b-c, see method), revealing similar intensity of damage where the perturbation count more than 4 (Fig. 2a-c).

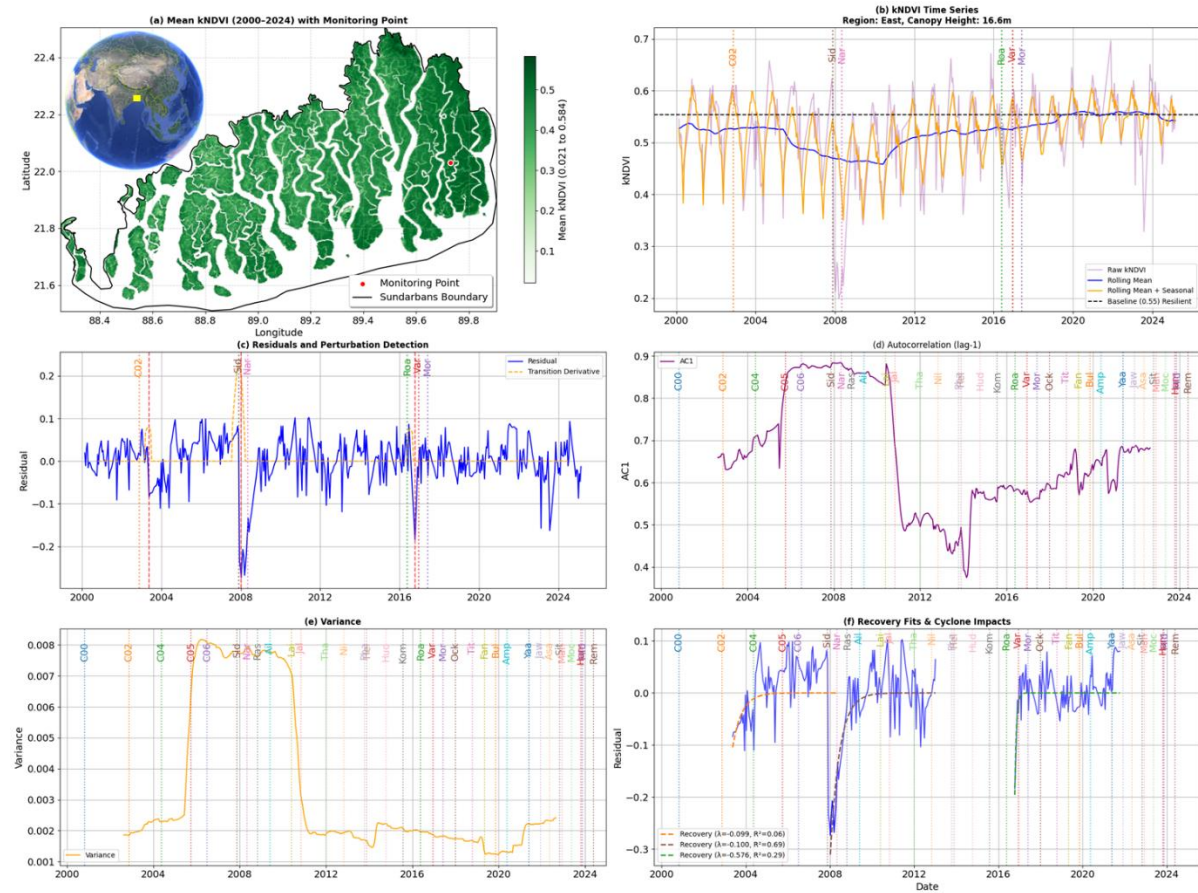


Fig. 1 Vegetation dynamics and resilience indicators in the Sundarbans. (a) Long-term Mean NDVI (2000–2020) in the Sundarbans with monitoring points and boundary; (b) kNDVI time series of particular monitoring sites in the eastern region, showing raw and smoothed kNDVI values, with cyclone impact periods marked; (c) Perturbation detection through 12-months moving windows and 95% thresholding on residual time series, highlighting perturbation periods; (d) Temporal 1-lag autocorrelation of residual kNDVI, signalling the resilience loss or critical slowing down; (e) Variance in residuals captures fluctuations in time series kNDVI with detected perturbations flagged, showcasing critical slowing down; (f) Empirical post-disturbance recovery rate trajectories from local minima, following cyclone impacts, indicating vegetation response and resilience over time. The yellow block in the Google Earth (a) showing the position Sundarbans in the Globe. C00 (Unnamed), C02 (Unnamed), C04 (Unnamed), C05 (Unnamed), C06 (Unnamed), Sid Sidr, Nar Nargis, Ras Rashmi, Ail Aila, Lai Laila, Jal Jal, Tha Thane, Nil Nilam, Pha Phailin, Hel Helen, Hud Hudhud, Kom Komen, Roa Roanu, Var Vardah, Mor Mora, Ock Ockhi, Tit Titli, Fan Fani, Bul Bulbul, Amp Amphan, Yaa Yaas, Jaw Jawad, Asa Asani, Sit Sitrang, Man Mandous, Moc Mocha, Ham Hamoon, Mid Midhili, Rem Remal.

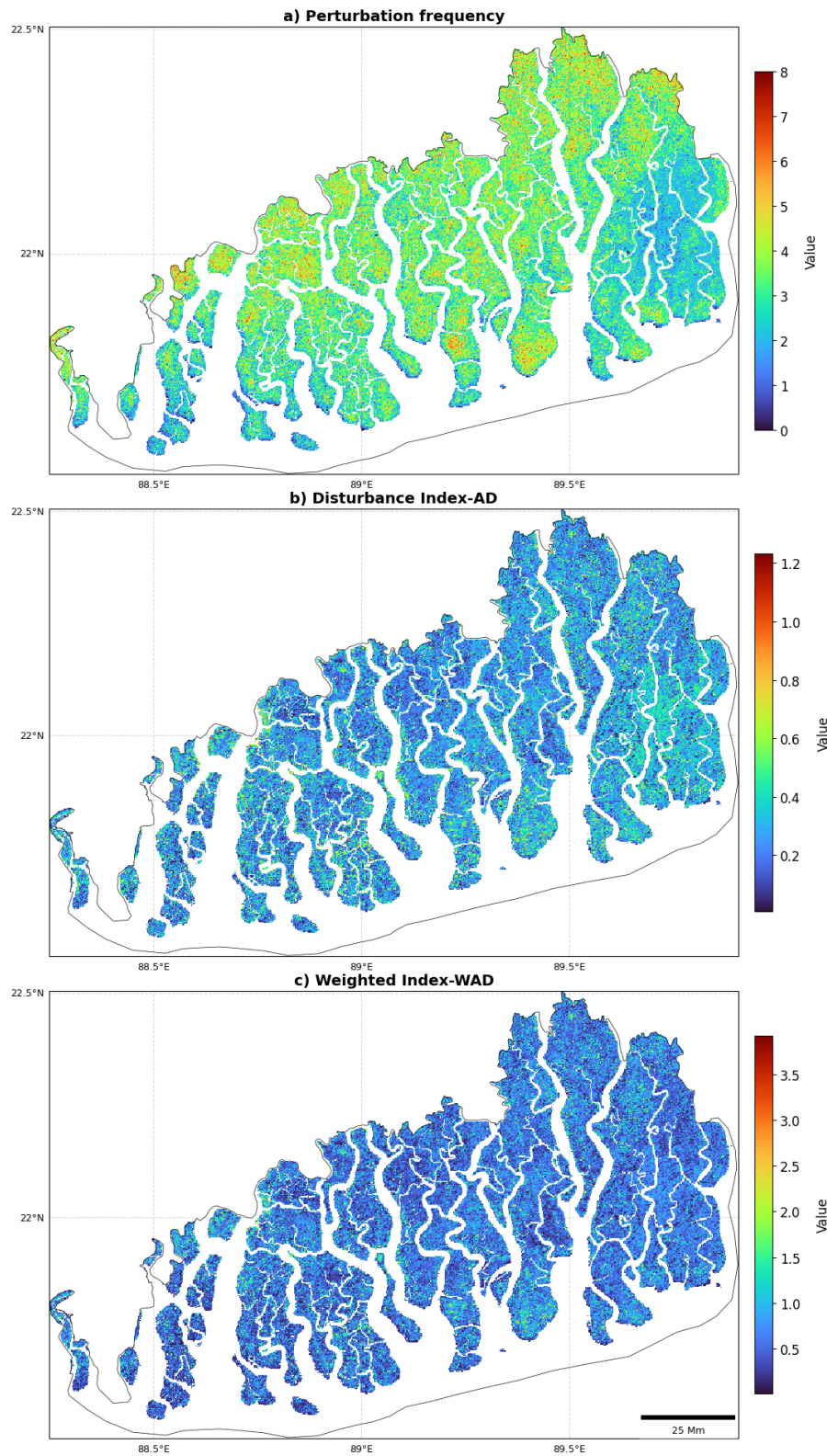


Fig. 2. Spatial pattern of mangrove forest perturbation frequency and damage severity in the Sundarbans. (a) Perturbation frequency map showing the number of disturbance events, with warmer colours (yellow to red) indicating higher frequency; (b) Disturbance Index (AD) -based on the average drop- showing the intensity of disturbance, where red areas represent higher disturbance levels and blue areas indicate lower disturbance; (c) Weighted Index (WAD) – based on weighted average drop, decay factor and time-reflecting cumulative disturbance

impact, with red indicating higher weighted values and blue indicating lower values. White lines denote water channels and geographic boundaries. The consistent layout across all panels allows for comparative analysis of disturbance patterns and resilience gradients within the region.

Change in discussion:

The likely reason is exposure to severe cyclones along their central track—most notably Sidr—followed by successive moderate cyclones (Rashmi, Aila, Mora, Bulbul, Amphan; Fig. 2a and 2b). The spatial map of resilience classes (2007-2013) further reveals that it took six years for these regions to regain its baseline resilient class, similar to 2000, underscoring the long-lasting impact of extreme events like Sidr and the compounded stress from tropical cyclones in the lower upstream reaches compared to the Passur and Baleshwar rivers. L485-491

Our results on the negative direct, indirect and total associations of perturbation frequency (PF), suggest that mangrove forest stands exposed to frequent cyclones, tidal surges and anthropogenic pressures exhibit lower resilience. Severe cyclones typically cause direct physical damage of mangrove trees, including canopy top breakage, uprooting and defoliation^{9,18,19,22,57}. Indirectly, these disturbances alter biogeochemical processes by creating hypersaline condition, increasing the sediment silt content, and elevating sediment pH—all of which are detrimental to mangrove health, productivity and, ultimately, mangrove forest resilience(Krauss & Osland, 2020; Lagomasino et al., 2021; Mo et al., 2023). Increased salinity can render nutrients inaccessible to plant roots or force plants to spend more energy in coping with osmotic stress, thereby weakening their physiological performance(D. M. Alongi, 2008; Ball, 1988; Krauss & Osland, 2020). On the other hand, increased sediment pH, resulting from silt accumulation (Fig. 6) and reduced tidal flushing, can further reduce the availability of essential micronutrients, such as iron and manganese(Krauss & Osland, 2020). This alteration in physicochemical mangrove sediment properties disrupts microbial activity that is critical for nutrient-cycling and organic matter decay, compounding the stress on mangrove ecosystems and diminishing their capacity to recover from disturbance(Pradisty et al., 2021; Quadros et al., 2019). L540-554

R2.6. No large-scale disturbances are taken account within the time frame of the study, in particular cyclones, two major events are noted in the discussion. These will have impacted **the mangrove systems and their potential resilience trends**. I would highly recommend adding cyclone and other major known disturbances into the model, and timings of these events – do multiple events occur in one or more of the 5-year rolling trends of the kNDVI rolling mean? As a declining resilience trend in one area of the Sundarbans could be due to a quick succession of multiple disturbances, where as another area either went unscathed or only received one event and has since been able to recover.

Answer: Thank for this more than important comment. We have detected perturbation at pixel basis. Please see our response to previous comment #R2.5 for relevant change in method, result and discussion. Using the perturbation frequency, and the two-disturbance metrics along with to climatic, soil physical and chemical properties including macro nutrient, and taxonomic, structural, and trait diversity, we developed six SEMs: 3 for λ_{AC1} and 3 for λ_{VAR} (adding separately for three disturbance related variable separately). Interestingly, we have found significant direct and total association of perturbation frequency with resilience. Please also

see our response to first reviewer comment # R1.7, for the changes we have made in results and discussion.

Methods - Forest stand structure and diversity, environmental data

R2.7. “We used ground-measured plot-level data with the number of tree species, their basal area, stem density, maximum tree diameter from the Sundarbans Forest carbon inventory 2010.”

Are you able to provide more details on the methodology of the forest carbon inventory at the start of this section. Are these the 110 permanent plots? What type of plots are they circular, square, are they clustered, and what is the area? I would also like to see on a MAP where all of these plots are, while they may be good for representation of different forest types are the well distributed throughout the entire study site?

Answer: Thank you for your comments and suggestion on inventory plots. We have revised them accordingly to your suggestion. Please see the added text and figure in method below.

We extrapolated the soil physiochemical properties (sediment phosphorus (P), sediment ammonium (NH₄), sediment potassium (K) and sediment sulphide) using field data that was collected by Saker et al.(2021) from 110 permanent sample plots (each plot size 120 × 20 m; Fig. S7) in the Sundarbans, during January – June 2014. (Method; L137-141)

By using the temporary carbon plot shapefile (100 plots, each plot is composed of five 10m radius circular subplots), we extracted the mean soil properties from these spatial maps that were extrapolated from 110 permanent plots (Fig. S7), MODIS derived resilience and Chelsha climatic data (Rahman et al., 2019a, 2015). We used Google Earth Engine's, reduceRegions() function applies ee.Reducer.mean() with a scale of 30 meters to summarize data within each plot geometry (Gorelick et al., 2017). (Method; L143-148)

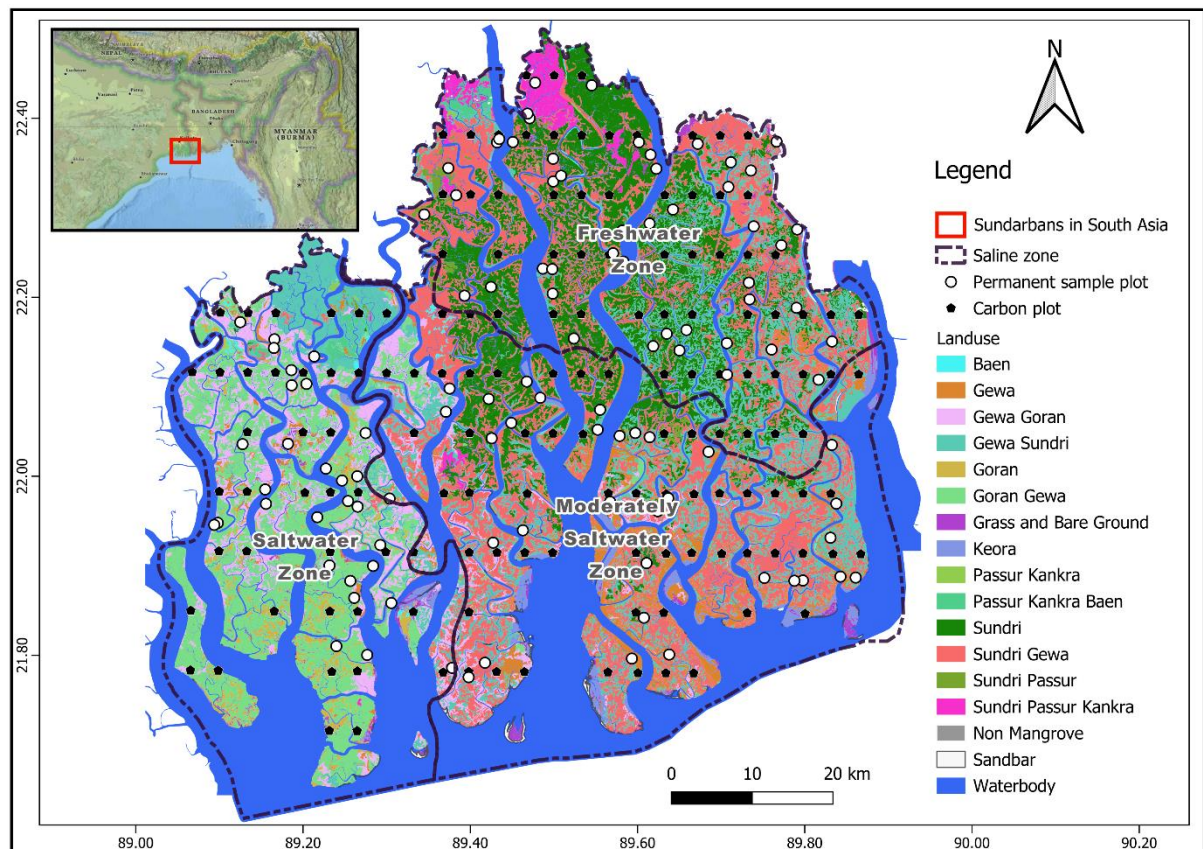


Fig S7. Sundarbans Reserved Forest vegetation with salinity zone, carbon plot and permanent sample plots. Sediment properties were taken from Sarkar et al. 2016, which were surveyed during January – June 2014 at 110 Permanent Sample Plots (white circle) distributed across different vegetation type in Sundarbans. Forest carbon inventory plots (155 plots, five were under water; Black pentagon) also spread across different vegetation types, were collected from Bangladesh Forest Department. The scientific name of species that were shown in the legend as local, are as Sundri, *Heritiera fomes*; Passur, *Xylocarpus mekongensis*; Geowa, *Excoecaria agallocha*; Been, *Avicennia officinalis*, or *A. alba* or *marina*; Goran, *Ceriops decandra*; Keora, *Sonneratia apetala*; Dhundul, *Acanthus ilicifolius* Golpata, *Nypa fruticans* or *Xylocarpus granatum*; Kankra *Bruguiera gymnorhiza* or *B. sexangular*. Map produced in Quantum Geographic Information System (Version 3.40). Open-Source Geospatial Foundation. <https://qgis.org>. Source of Landuse is Centre for Environmental and Geographic Information Services, Bangladesh. The inset image source is Food and Agricultural Organization.

R2.8. “We used the publicly available plant trait data specific for the Sundarbans acquired in recent years. For example, plant trait data, such as leaf traits...”

I don't think these are examples, seems like you list out all traits used. It might be good to have a table here of all the different traits and how you used them within the analyses, such as structural diversity variables, etc.

Answer: We agreed. We have revised the sentence as below.

The seven functional traits that were used in this study (Table S5) belong to three categories: leaf traits (specific leaf area, leaf litter nitrogen, leaf dry matter content, leaf photosynthesis

rate and leaf succulence), stem traits (wood density) and whole plant traits (maximum canopy height) (Quadros & Zimmer, 2017; Rahman, Zimmer, et al., 2021; Sarker et al., 2021; Yakub et al., 1972). (Method, L110-113)

R2.9. “We averaged the leaf litter nitrogen value that were collected by three distinct seasons (monsoon, pre-monsoon, and post-monsoon periods) in the Sundarbans.”

How many leaves were included in the analyses for each of the seasons? Are the seasons distinct months, if so can you identify the months with each of these season?

Answer: Thank you for your comment. For each species (34 species), 30 leaves were collected in the beginning of each season (Chanda et al., 2015). In Sundarbans, the three seasons are pre-monsoon (February to May), monsoon (Jun to September), and post-monsoon periods (October to January). We have revised the text as below:

We averaged the leaf litter nitrogen value that were collected by three distinct seasons pre-monsoon (February to May), monsoon (Jun to September), and post-monsoon periods (October to January) in the Sundarbans(Chanda et al., 2015; Rahman et al., 2015). (Method, L113-115)

R2.10. “The long-term monthly temperature and precipitation data from 1980 to 2010 were averaged for calculating mean annual temperature and precipitation.”

Were data on temperature and precipitation not available for the period of the study, 2000 – 2024?

There is limited overlap in some of the key variable from which you are basing much of your findings on. Especially as you are suggesting rising temperatures in the region, but you don’t have the last 14-years of data for the study.

Answer: Thank you for your comment. We have added the temperature after 2010. Please see the change we have made in the method section.

The long-term monthly temperature and precipitation data from 1980 to 2010 and 2011 to 2040, were averaged at pixel based for calculating mean annual temperature (yearly average) and precipitation (yearly total). (Method, L133-136)

R2.11. “We used high resolution (1 km) climatic (mean annual precipitation and temperature) from the Coupled Model Intercomparison Project Phase 6 from CHELSA (<https://chelsa-climate.org/>) maintained by the Swiss Federal Institute for Forest, Snow, and Landscape Research.”

This is repeated within the methods section, can remove from line 75 onwards.

Answer: Thank you. We have removed it.

R2.12. “By using the plot shapefile (100 plots, each plot is composed of five 10m radius circular subplots), we extracted the mean soil properties from these spatial MAPs.”

Are these 100 plots from the forest carbon inventory – is this a typo and should be 110, or have you dropped 10 plots or is this another inventory.

Answer: Please our response R2.2, R2.7, we have already addressed relevant comments and also added new figure in the method section. Please also see below we have revised the section in the method.

Methods – Statistical analysis

R2.13. “We assessed the trends in recovery rate λ using Kendall’s τ with overlapping 5-year windows over 2001-2020”

Is this a typo, should it be 2000 – 2024? Or can you explain why there is a difference in the time periods used.

Answer: Thank for the comment. It would be from 2002-2022, for five-year window. Please see the explanation below that we have revised in our current version.

“We assessed the trends in recovery rate λ using Kendall’s τ with overlapping 5-year windows spanning the period 2002-2022. For example, the window for year 2002 included data from 2000–2004, for 2003 from 2001–2005, and so on, up to 2022, which used data from 2020–2024. As our study period covers 2000–2024, we were unable to apply a full 5-year rolling window for the boundary years 2000, 2001, 2023, and 2024 due to insufficient adjacent data. (Method, L151-156)

R2.14. DBH variation (as a proxy for structural diversity)
Not sure why you used a proxy for structural diversity – from the variables you state in the methods you should be able to get structural diversity from calculating the horizontal diversity (DBH) and vertical diversity (tree height) – see LaRue et al., 2023 <https://esajournals.onlinelibrary.wiley.com/doi/10.1002/fee.2586>.

Answer: We have revised the section in the method. We Please see below.

“With these seven functional trait-based diversity metrics, three disturbance-related variables (Perturbation frequency, Average drop disturbance index (ADI) Weighted Average drop disturbance Index (WDI)) two recovery rate (λ_{ACI} and 2 for λ_{VAR}), species richness as a measure of taxonomic diversity), co-efficient of variation of DBH as a measure of structural diversity (Ali et al., 2016, 2019; Ali & Mattsson, 2017), and eight environmental covariates— sediment sulfide, sediment phosphorus, sediment iron concentration, sediment pH, sediment

texture silt precipitation, temperature and sediment salinity— we conducted six SEMs analysis (Table S3).” (Method, L186-194).

R2.15 I really think that the authors need to provide the reader with a threshold resilience value, which provides a general condition status to the forest, from which the maintenance, gain, or loss of resilience can be assessed, rather than a general trend which does not take into account original status. In light of some of these methodologies issues and wondering how they will influence the outcome of any updated results, I am concluding my review with a focus on the methodology, and would ask the authors to revise the manuscript.

Answer: Thank you for your valuable comments. It has enhanced our manuscript significant. We think, we have addressed all of your comments (Please see the comments, R1.7, R2.2-2.26, for details for specific responses and changes we have made in introduction, method, result, and in discussion). We are now looking for your feedback on our revised version.

Reviewer 3

We sincerely appreciate your thoughtful suggestion and comments. We have taken great care to reflect them in our current version. Below, we are happy to present a detailed point -by-point responses, where the reviewer comments were appeared as black and our responses are highlighted as blue.

Sincerely yours,

Qihao Weng (On behalf of the author team)

Reviewer #3 (Remarks to the Author):

Thank you for inviting me to review this paper. It offers valuable insights into understanding the effects of functional, structural, and taxonomic diversity, as well as environmental factors, on the resilience of mangroves to disturbances. The discussion of niche complementary effect theory is particularly beneficial for the mangrove community. I enjoyed reading this paper, which is relevant to both scientists and practitioners. Below, I have listed several major comments to help authors improve the manuscript's quality.

R3.1 : Title: As resilience was evaluated against historical mean temperature rather than "rising temperature," I recommend that the authors exclude "... against rising temperatures," including "... to disturbances," or keeping only "... Mangrove Resilience."

Answer: Thank you for your comments on title. Based on your, first and second reviewer comments as well as editorial board’s suggestion, we have revised our title as below. Please see the details explanation in our first reviewer’s response section (R1.1).

“Functional composition and Structural Diversity enhance Mangrove Forests Resilience in the Sundarbans.” L1-2

R3.2 Abstract: Please don't use citations in the abstract.

Answer: We have removed the citation from abstract.

R3.3 Line 33: Could the authors provide the percentage of mangroves that showed reduced resilience?

Answer: Thank you for suggestion. In our current version, we have revised it as below.

Approximately 610 to 990 km² (~10-15% of the total Sundarbans area) of mangrove forests exhibited declining resilience. L30-31

R3.4 Line 40: The authors didn't study if the resilience is against climate change or human activities, so I suggest rephrasing it as "resilience against disturbances."

Answer: Thank you for suggestion and we agreed. We have replaced "Climate Change with "Disturbances" (please see below)

"Based on these findings, we hold that for enhancing mangrove forest resilience against disturbances and stressors, (re-)establishment and conservation efforts should focus on maintaining site-specific dominant species with tall canopy height and specific leaf area — supplemented by a few complementary species— to increase structural diversity and facilitate recovery rates. L37-41.

R3.5 Line 42: How can we quantify this "limited" number of other species? The term limited seems very subjective. Could the authors rephrase it?

Answer: Thank you for comment. Please see our response to your previous comment; R.3.4)

R3.6 Keywords: I don't think "Remote Sensing of Mangrove Resilience" is a keyword; maybe remote sensing, MODIS, or kNDVI would work better here.

Answer: Thank you for this valuable comment. We have revised the key words as first reviewer also made similar comment (Please see below).

Remote Sensing, Mangrove Forest resilience, climatic effect, biodiversity, functional traits. L42-43

R3.6 Line 82: I am uncertain if NDVI accurately reflects species richness; could the authors provide a reference for this?

Answer: Thank you for this important comment. We have removed the species richness. It should be productivity.

R3.7 Line 178: "We investigate objective ii, instead of 2".

Answer: Thank you for this comment. We have replaced “2” with “ii”..

R3.8 Figure 1: I think readers would benefit from seeing in Figure 1b the $\lambda_{AC1} / \lambda_{VAR}$ MAP, rather than the histogram, from which the content could be presented in the text.

Answer: Tank you for this valuable suggestion. We have added λ_{VAR} and $\lambda_{AC1} / \lambda_{VAR}$. Please the updated figure in the result below.

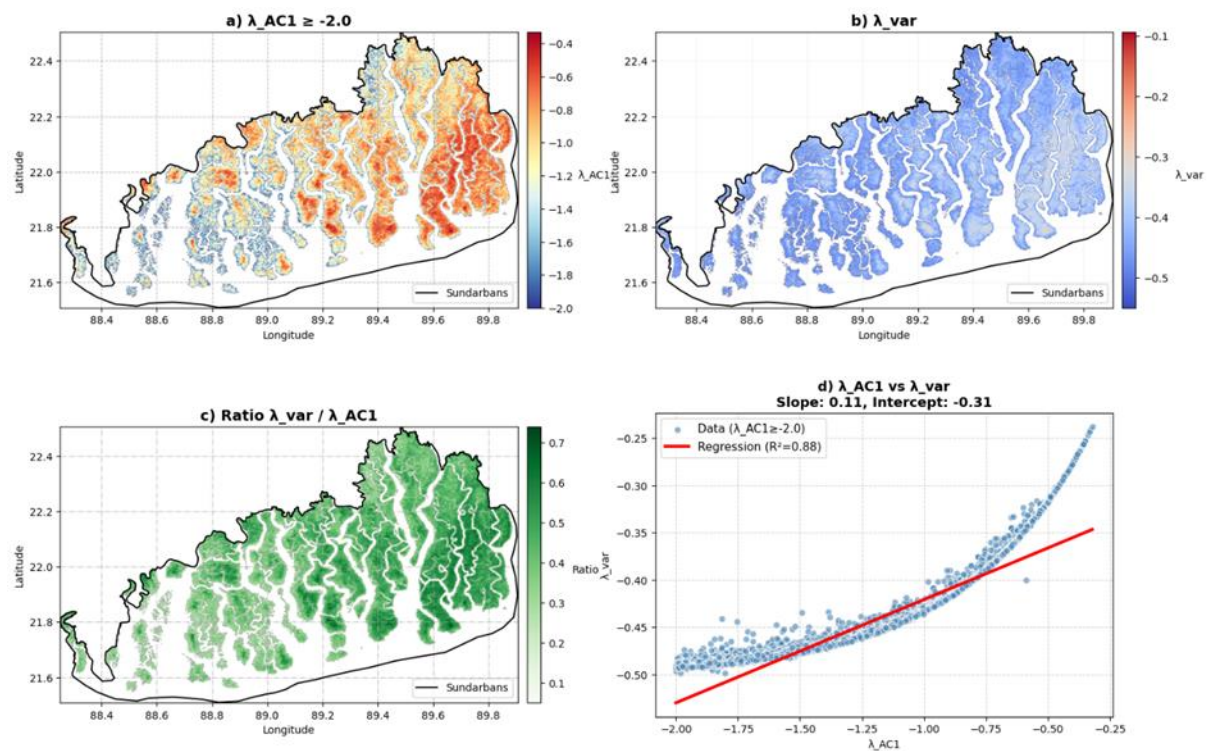


Fig 3. Spatial patterns of mangrove forest resilience indicators (λ_{AC1}) in the Sundarbans. (a) Recovery rate λ_{AC1} , estimated from the 1-lag autocorrelation of pixel-level kNDVI residuals; (b) Recovery rate λ_{var} , derived from the temporal variance decay of kNDVI residuals; (c) The ratio $\lambda_{var} / \lambda_{AC1}$, (d) Scatter plot, indicating a strong spatial similarity between λ_{var} and λ_{AC1} . Forest areas with λ values close to zero exhibit low resilience. L309-313

R3.9 Figure 2: What is the time window used for this figure (Kendall’s tau trend analysis)? Please specify in the caption.

Answer: Thank you for pointing out it. We have revised the caption as below. Also, in response to second reviewer’s similar comment in method, we have explained how we measured rolling mean (please see the response in R2.13).

Fig 5. Annual, mean and rolling mean resilient status from 2000-2024, based on the class transition total gain and loss relative to 2000. *R1* = Weakly Resilient (red; Q1: kNDVI $\leq$ 0.39), *R2* = Moderately Resilient (yellow; Q2 $0.39 < \text{kNDVI} \leq 0.49$), and *R3* = Resilient (green; Q3: kNDVI > 0.49). These resilience classes are based on the quantile threshold baseline year (2000). The five-years rolling mean was quantified for 2002-2022: as our study period covers 2000–2024, we were unable to apply a full 5-years rolling window for the boundary years 2000, 2001, 2023 and 2024 due to insufficient adjacent data. L338-344

R3.10 Figure 2: There are numerous conclusions regarding the spatial relationship between resilience loss and environmental settings. Could the authors provide additional base MAPs that illustrate these environmental settings, as well as the distribution of plots and soil and vegetation characteristics? I find this information is crucial for connecting the results with the authors' discussions and conclusions.

Answer: Thank you for your insightful comment. In the revised manuscript, we have expanded our analysis to include threshold-based resilience classification for each year from 2001 to 2024, as well as the mean resilience relative to the year 2000 using a quantile-based approach (Fig. 4). We have also included updated visualizations of resilience status (Fig. 5 and Table 1-2).

In response to your comment (R3.10), as well as related suggestions from Reviewer 2 (R2.2 and R2.7), we have added a figure illustrating mean kNDVI dynamics (Fig. 1), which captures vegetation changes and resilience indicators for five representative points (Fig. S1-4). Additionally, Fig. 2 now includes perturbation frequency and two disturbance metrics.

To further address your request (R3.21), we have incorporated a detailed study area map (Fig. S7). This map includes vegetation types, salinity zones, carbon inventory plot locations, and soil sample sites. These additions aim to strengthen the spatial context and better connect our results with the environmental settings discussed throughout the manuscript. For further details, please refer to our response to 2nd Reviewer's comment R2.7.

R3.11 Table 1: Could the authors improve the caption for Table 1? What do these results represent? Are they *R* or *R*², or what? The description of the level of significance should also be presented.

R3.12 Additionally, could the authors provide a better explanation of the differences in correlations shown in Figure 4 and Table 1?

E.g. between resilience and MAP? Moreover, what is the resilience metric used here? It's not clear in the results and in the methods as well.

Answer: It was standardized beta based on structural equation model in figure 6. Please see out response to R1.1 for details in result, method to R1.6, also the caption for figure 6 and table two.

Fig 6. Structural Equation Model illustrating the mechanisms connecting biodiversity measures, abiotic factors and resilience (λ_{VAR}). Hypothesized paths with asterisks (***: $P < 0.001$, **: $P < 0.01$, *: $P < 0.05$) indicate significant associations between variables; non-

significant associations ($P > 0.05$) are not shown for the sake of clarity (please see Table 2). The non-significant χ^2 (Chi-Square) of 2.489 ($P = 0.288$), with a goodness of fit index (GFI) of 0.997, with a comparative fit index (CFI) of 0.999 and a standardized root mean square residual of 0.009 suggests no significant deviation from the model and datasets at 2 degrees of freedom. Orange lines indicate negative associations, while purple lines indicate positive associations between covariables. Numbers on the arrows show the standardized associations of predictors with dependent variables. R^2 Coefficient of Determination within the endogenous variables represent their explained variance by all predictors. *MAP* mean annual precipitation, *MAT* mean annual temperature, *SS* sediment salinity, *SR* Species richness, *FCMCH* functional composition of maximum canopy height, *SD* Structural diversity (variation of diameter at breast height), *FCSLA* functional composition of specific leaf area, *FDLS* functional diversity leaf succulence, *P* sediment phosphorus concentration, *SF* sediment iron concentration, *SSF* sediment sulfide concentration, *pH* sediment pH level, *STS* sediment texture silt, *PF* perturbation frequency. L411-427

Table 3: Standardized direct, indirect and total associations of abiotic and biotic drivers with resilience (λ_{VAR}) in the Sundarbans mangrove forest, based on SEM (Figure 6). The SEM model was validated with 1000 bootstrap sampling. L430-431

R3.13 Is it Kendall's tau?

Answer: Yes. Thank you for the comment. We have fixed the typo across the whole manuscript.

R3.14 For what period?

Answer: Thank you for pointing out it. It was for 2002-2022. We have revised the caption. Also, in response to second reviewer's similar comment in method, and your comment R3.9, we have revised the confusion on rolling year issue. Please see the full expiation to the response for R2.13.

R3.15 Line 422: When authors suggest that "greater resilience" is found in "old-growth or mature stands," is there a way to illustrate this? If a MAP isn't available, could there be plots that show the relationship between greater resilience, vegetation, and environmental settings?

Answer: Thank you for your comment. We made this statement in our previous version because functional composition was the main driver, which represent the dominant species while the trait maximum tree height, represent the tallest individual's contribution. If functional composition of maximum tree height has a significant positive and dominant association with any response variable, we can make this type of statement (Finegan et al., 2015; Rahman, Zimmer, et al., 2021). Based on the first and 2nd reviewer comment (adding disturbance metric in SEM), we have tested total 6 SEMs and revised the whole result and discussion. Even though, adding disturbance metrics, and other new environmental variables, the function composition of maximum canopy height and specific leaf area play the stronger role in driving resilience. Please see the also our responses to R1.1, R1.7, R2.5, and R2.6 above.

R3.16 Line 434-435: Please rephrase it.

Answer: Thank you for your suggestion. In our current version, we fully revised the whole discussion based on new resilience and SEM analysis. Please see the also our responses to R1.7, R2.4, and R2.5 above and discussion section.

R3.17 Line 442: The authors mention positive correlations but do not indicate whether these correlations are weak or strong. In both Figure 4 and Table 1, we observe several positive and negative correlations; however, these correlations are generally weak. Could the authors clarify the nature of these correlations throughout the text?

Answer: In our current version, we have revised it across the whole manuscript. For example, “Mangrove forest resilience or recovery from disturbances in the Sundarbans is strongly driven by the functional composition of whole-plant traits and the leaf economic spectrum. Our findings reveal that the functional composition of MCH and SLA qualify as the strongest biotic predictors of mangrove forest resilience in the Sundarbans. This result suggests that the selection effect theory (Finegan et al., 2015; Tilman et al., 2009)—dominant species with their key functional traits drive ecosystem process—is primarily governing mangrove forest resilience in the Sundarbans. L491-494

The moderate total positive association of mean annual precipitation with resilience highlights their pivotal role in mangrove forest resilience. L527-528

R3.18 Line 489: “by climate change and human pressures.”

Answer: Thank you for this suggestion. We have revised it.

“Ultimately, adopting such a strategy will foster multiple ecosystem processes and enhance the resilience of mangrove forest against the growing challenges posed by climate change and human pressures.” L603-605

Method and materials

R3.19 Line 19: Typo of “Kernel”. Please correct it. Please also check throughout the text (and supplemental material) the word “Kendall”, as it was mistyped in many places.

Answer: Thank you for pointing those typos. In our current version, we have meticulously addressed all of those kinds of typos.

R3.20 Lines 22-39: Could the authors please provide a figure that illustrates an example of the time series, along with the smoothing process and potentially the application of the autoregressive model? Additionally, could they clarify the time window for the 1-lag autocorrelation? Is it the 16-day interval between MODIS composites?

Answer: Thank for this more than important suggestion. Now we have added the full time series vegetation dynamics at this location (89.731360, 22.029473, Fig. 1; and four other points, Fig. S2-4). This pixel location is dominated by *Heritiera fomes* with 16m canopy height and belong to Sharankhola Range, in the eastern Sundarbans. In our current, version we have also detected perturbation with cyclone flagging within eight months. Please see the relevant response in first reviewer's comment section (R2.4-R2.6) for the details of the figure and the changes we have made in method, result and discussion.

R3.21 Line 42: Please provide a clearer description of the number of plots, their sizes, and their distribution. It appears that the vegetation data was collected from a different set of plots than the soil data, and this distinction needs to be clearly stated. Could the authors include a figure that displays the spatial distribution of plots from both campaigns/projects? It would be helpful to detail the number of plots, their sizes, and the dates of data collection in the figure caption.

Answer: Thank you for your comments and suggestion on inventory plots. We have revised them accordingly to your suggestion. Please see the second reviewer's response section for similar comments on plot description (R2.2; for Fig S7), the added text below.

A total of 150 plots were surveyed from 5 December 2009 to 30 May 2010 (Rahman et al., 2015). Each plot consisted of five 10-meter radius nested subplots. From the central subplot, the other four subplots were 50m (Fig. S7) away towards four-cardinal directions (Rahman et al., 2015). In our current study we 100 plots the remaining 50 plots have either fully under water or subplot with waterbody more than 20% due to presence of small canal or on the bank of the river or big canal (Rahman, Zimmer, et al., 2021; Rahman et al., 2015). L102-107

“We extrapolated the soil physiochemical properties (sediment phosphorus (P), sediment ammonium (NH₄), sediment potassium (K) and sediment sulphide) using field data that was collected by Saker et al.(2021) from 110 permanent sample plots (each plot size 120 × 20 m) in the Sundarbans, during January – June 2014.” L37-141

R3.22 Lines 67 to 69: Please clearly state that the study uses pixel-based historical averages of temperature and precipitation. There is no analysis of climate change or rising temperatures, as far as I can understand. Is that correct?

Answer: We thank for this suggestion. We have revised the sentence.

The long-term monthly temperature and precipitation data from 1980 to 2010 and 2011 to 2040, were averaged at pixel based for calculating mean annual temperature (yearly average) and precipitation (yearly total). L133-136

R3.23 Line 72: size of the plots

Answer: Thank you for comment. Please see the response to your comments R3.21 and (R2.2; for Fig S7).

R3.24 Until line 80: Please clearly describe how the authors harmonized the datasets in time and space (MODIS-derived resilience, Chelsea, and plot-level data).

Answer: Thank you for your comment. In our current version, we have explain it. Please the revised section in methods.

“By using the temporary carbon plot shapefile (100 plots, each plot is composed of five 10m radius circular subplots), we extracted the mean soil properties from these spatial maps that were extrapolated from 110 permanent plots (Fig. S7), MODIS derived resilience and Chelsha climatic data (Rahman et al., 2019a, 2015). We used Google Earth Engine’s, reduceRegions() function applies ee.Reducer.mean() with a scale of 30 meters to summarize data within each plot geometry (Gorelick et al., 2017).” L143-148

R3.25 Lines 82-85: Did the authors validate these results?

Answer: In our current version we have also conducted, threshold-based classification relative to baseline in line with similar comment, of second reviewer comment R2.2 and R2.15. Based on this classification and resilience class transition we have quantified resilience status, rather than only trend-based approach. For average resilience status from 2001-2024, mean kNDVI quartile threshold-based classification relative to baseline 2000, the resilience loss was approximately 606.83 while for five year rolling mean (2002-2022, see method) it was 988.81 km² (~10 -15%). It also highly varied, with severe cyclone years (Fig. 4-5, Table 2). Please see the details methodology, results and relevant discussion in our response to comment R2.2.

R3.26 Line 92: How did the authors define the thresholds?

Answer: Thank you for this comment. In ecology, the most commonly used threshold is 5 or 10 as a cut-off for variance inflation factor. We selected a VIF threshold of 10 to identify problematic multicollinearity, as this is a widely accepted cutoff in ecological studies. This threshold is supported by several key references, including Zuur et al. (2010), who recommend VIF > 10 as an indicator of substantial multicollinearity in regression models commonly used in ecology (*Methods in Ecology and Evolution*, 1:3–14). Similarly, O’Brien (2007) notes that a VIF of 10 balances the need to detect problematic correlations while retaining meaningful predictors in observational studies (*Quality & Quantity*, 41:673–690). Dormann et al. (2013) further endorse VIF thresholds between 5 and 10, with 10 being appropriate for species distribution models to avoid excluding ecologically relevant variables (*Ecography*, 36:27–46). Graham (2003) also supports VIF = 10 in ecological regressions, highlighting that stricter thresholds like 5 may unnecessarily remove biologically important predictors (*Ecology*, 84:2809–2815). Given the correlated nature of our environmental predictors (e.g., NDVI and climate variables), a VIF threshold of 10 ensures robust model stability while preserving ecological interpretability. However, all we have selected 10 as a threshold value, in our final model all the variable had VIF less than 5.5 and our SEMs satisfied also all fit index (Fig. 6, Table S3).

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., ... Lautenbach, S. (2013). Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. *Ecography*, 36(1), 27–46. <https://doi.org/10.1111/j.1600-0587.2012.07348.x>

Fox, J. (2016). *Applied regression analysis and generalized linear models* (3rd ed.). Thousand Oaks, CA: Sage Publications.

Graham, M. H. (2003). Confronting multicollinearity in ecological multiple regression. *Ecology*, 84(11), 2809–2815. <https://doi.org/10.1890/02-3114>

O'Brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality & Quantity*, 41(5), 673–690. <https://doi.org/10.1007/s11135-006-9018-6>

Zuur, A. F., Ieno, E. N., & Elphick, C. S. (2010). A protocol for data exploration to avoid common statistical problems. *Methods in Ecology and Evolution*, 1(1), 3–14. <https://doi.org/10.1111/j.2041-210X.2009.00001.x>

R3.27 Line 97: “..a resilience metric” is too vague. Please describe this metric and how you harmonized it over time with other variables.

Answer: Thank you for your comments. We have revised the sentence as below by specifically mentioning the resilience type.

With these seven functional trait-based diversity metrics, three disturbance-related variables (Perturbation frequency, Average drop disturbance index (ADI) Weighted Average drop disturbance Index (WDI)) two recovery rate (λ_{AC1} and 2 for λ_{VAR}), species richness as a measure of taxonomic diversity), co-efficient of variation of DBH as a measure of structural diversity (Ali et al., 2016, 2019; Ali & Mattsson, 2017), and eight environmental covariates— sediment sulfide, sediment phosphorus, sediment iron concentration, sediment pH, sediment texture silt precipitation, temperature and sediment salinity— we conducted six structural equation models (SEM; Table S3). L170-176

Response to Reviews (Ref.: Ms. No. COMMSENV-25-1428A)

Dear Reviewers,

Thank you for your kind comments on our revised manuscript and for raising additional suggestions to improve its legibility. We sincerely appreciate the time and effort you dedicated to reviewing our manuscript. Our Manuscript has been significantly enhanced with higher clarity and rigor by your insightful suggestions and comments. We have carefully addressed each of your comments and made the necessary revisions accordingly.

Below, we outline the main changes incorporated in the revised version.

1. Diversify and update references across the whole manuscript. Additionally, we removed some references that were added as duplicates.
2. Explain comments on the scatter plot between λ_{AC1} and λ_{VAR}
3. Clarify the strength of the standardized regression coefficient (β) in the method, result, figure, and table captions.

Thank you once again for your comprehensive, thoughtful, and positive feedback. Your expert commentary has been instrumental in strengthening the overall impact of our manuscript and in showcasing its key messages. We have carefully considered each of your suggestions and incorporated them into the revised manuscript (marked in yellow) for your convenience. We believe these revisions fully address all concerns raised during the review process and have significantly improved the paper's overall quality.

Thank you once again for your time and support.

Sincerely,

Qihao Weng (on behalf of the author team)

First reviewer comment

The authors had revised and improved the manuscript following my comments and suggestions, which were complements with comments and suggestions of other reviewers. The manuscript revision was done in all parts including title, abstract, introduction, methods, and discussion. It looks well and the present form of manuscript is acceptable for publication. However, if it is possible please avoid many repetitions of citation for similar references in the text particularly in the introduction part. There were many other appropriate references can be cited rather than replication of similar citation references.

Response:

Thank you for your kind comment on our revised manuscript and for your suggestion to diversify the citations. We have added recent, most relevant references in the field of mangrove biodiversity, ecosystem services, vulnerability, and climate change impact on mangrove blue carbon. We also diversify the reference in the field of resilience and its drivers. Please see the chronological list below.

References

5. Lovelock, C. E. *et al.* Mangrove biodiversity and ecosystem services. *Nature Reviews Biodiversity* <https://doi.org/10.1038/s44358-025-00103-3> (2025) doi:10.1038/s44358-025-00103-3.
6. Hülsen, S., Dee, L. E., Kropf, C. M., Meiler, S. & Bresch, D. N. Mangroves and their services are at risk from tropical cyclones and sea level rise under climate change. *Commun. Earth Environ.* 6, (2025).
9. Sasmito, S. D. *et al.* Half of land use carbon emissions in Southeast Asia can be mitigated through peat swamp forest and mangrove conservation and restoration. *Nature Communications* 16, (2025).
10. Mo, Y., Hall, J. W., Baldwin, A. H., Simard, M. & Donohue, I. *Shifting Cyclone Travel Speed and Its Impact on Global Mangrove Ecosystems*. *Sci. Adv* vol. 11 <https://www.science.org> (2025).
11. Duncan, C., Thompson, J. R. & Pettorelli, N. The quest for a mechanistic understanding of biodiversity–Ecosystem services relationships. *Proceedings of the Royal Society B: Biological Sciences* vol. 282 Preprint at <https://doi.org/10.1098/rspb.2015.1348> (2015).
13. zu Ermgassen, P. S. E. *et al.* Mangroves support an estimated annual abundance of over 700 billion juvenile fish and invertebrates. *Commun. Earth Environ.* 6, (2025).
14. Lee, S. Y. *et al.* Ecological role and services of tropical mangrove ecosystems: a reassessment: Reassessment of mangrove ecosystem services. *Global Ecology and Biogeography* 23, 726–743 (2014).
15. Beselly, S. M. *et al.* Strategic mangrove restoration increases carbon stock capacity. *Commun. Earth Environ.* 6, (2025).
16. Gajre, R. B. *et al.* Bridging conservation and policy: evaluating national targets to reduce mangrove loss under the Kunming–Montreal biodiversity framework. *Environmental Research Letters* 20, (2025).
19. Lovelock, C. E. & Reef, R. Variable Impacts of Climate Change on Blue Carbon. *One Earth* 3, 195–211 (2020).
20. Chen, S. *et al.* Amazon forest biogeography predicts resilience and vulnerability to drought. *Nature* 631, 111–117 (2024).
21. Verbesselt, J. *et al.* Remotely sensed resilience of tropical forests. *Nat. Clim. Change* 6, 1028–1031 (2016).
22. Smith, T. & Boers, N. Global vegetation resilience linked to water availability and variability. *Nature Communications* 2023 14:1 14, 1–11 (2023).
23. Smith, T., Traxl, D. & Boers, N. Empirical evidence for recent global shifts in vegetation resilience. *Nat. Clim. Chang.* 12, 477–484 (2022).
29. Wang, Z. *et al.* Vegetation resilience does not increase consistently with greening in China’s Loess Plateau. *Commun. Earth Environ.* 4, (2023).

Response to second reviewer

Thank you for your good comments on our revised manuscript and for pointing out some remaining issues. In our current version, we have revised them and conducted proofreading (yellow highlighted).

Response to Reviewer Comment R3.17:

We sincerely thank the reviewer for raising this important point. We agree that clarity regarding the nature and interpretation of the reported associations is essential.

In our current version have addressed the issue and would like to clarify that the values presented in **Table 3** and visualized in **Figure 6** are **not correlation coefficients**, but rather **standardized path coefficients (β)** from our Structural Equation Model (SEM, a sophisticated integrative modelling approach that can capture direct, indirect and total association of predator variables with target variable that correlation or linear regression model cannot do). These represent **direct, indirect, and total effects**—i.e., conditional regression weights—within a hypothesized causal framework, estimated while accounting for all other variables in the model. Unlike bivariate correlations and simple linear regression, these path coefficients reflect the strength and direction of *predicted* relationships under multivariate control, guided by theory and hypotheses.

To avoid any potential misinterpretation, we have revised the captions of **Figure 6** and Table 3 below to clearly state that the numbers on the arrows are **standardized regression weights (β)**, **not correlation coefficients**. The updated caption now reads:

Fig 6. Structural Equation Model illustrates the mechanisms connecting biodiversity measures, abiotic factors, and resilience (λ_{VAR}). Hypothesized paths with asterisks (***: $P < 0.001$, **: $P < 0.01$, *: $P < 0.05$) indicate significant associations between variables; non-significant associations ($P > 0.05$) are not shown for the sake of clarity (please see Table 2). The non-significant χ^2 (Chi-Square) of 2.489 ($P = 0.288$), with a goodness of fit index (GFI) of 0.997, a comparative fit index (CFI) of 0.999, and a standardized root mean square residual of 0.009, suggests no significant deviation from the model and datasets at 2 degrees of freedom. Orange lines indicate negative associations, while purple lines indicate positive associations between covariables. Numbers on the arrows represent standardized regression weights (β) rather than correlation coefficients between predictors and dependent variables. The association was estimated to use maximum likelihood and validated with 1000 bootstrap samples. For interpretation, we follow conventional benchmarks for standardized regression coefficients in ecological SEMs: $\beta < 0.2$ indicates a weak association, $0.2 < \beta < 0.5$ a moderate association, and $\beta \geq 0.5$ a strong association^{59,60}. R^2 Coefficient of Determination within the endogenous variables represents their explained variance by all predictors. *MAP* mean annual precipitation, *MAT* mean annual temperature, *SS* sediment salinity, *SR* Species richness, *FCMCH* functional composition of maximum canopy height, *SD* Structural diversity (variation of diameter at breast height), *FCSLA* functional composition of specific leaf area, *FDLS* functional diversity leaf succulence, *P* sediment phosphorus concentration, *SF* sediment iron concentration, *SSF* sediment sulfide concentration, *pH* sediment pH level, *STS* sediment texture silt, *PF* perturbation frequency. (L1052-1072)

Table 3: Standardized direct, indirect, and total associations of abiotic and biotic drivers with resilience (λ_{VAR}) in the Sundarbans mangrove forest, based on Structural Equation Model (SEM) shown in Figure 6. All the values are standardized regression weights (β), not

correlation coefficients. The association was estimated using maximum likelihood and validated with 1000 bootstrap samples. For interpretation, we follow conventional benchmarks for standardized regression coefficients in ecological SEMs: $\beta < 0.2$ indicates a weak association, $0.2 < \beta < 0.5$ a moderate association, and $\beta \geq 0.5$ a strong association^{59,60}. Significance levels: $P < 0.05$, $*P < 0.01$, $**P < 0.001$. (L1092-1096)

In the Results section, we mentioned it as

Biotic and abiotic variables displayed distinct types of associations with resilience, with biotic variables exerting the dominant role (Fig. 6). For instance, perturbation frequency exhibited a significantly moderate negative association with resilience ($\beta = -0.29$, $P < 0.05$; Fig. 6, Table 2; according to the conventional benchmarks for standardized regression coefficients in ecological SEMs: $\beta < 0.2$ indicates a weak association, $0.2 < \beta < 0.5$ a moderate association, and $\beta \geq 0.5$ a strong association^{59,60}), whereas neither precipitation nor temperature demonstrated any significant direct association ($P > 0.05$; Table 2). (L294-300)

In Methods, we also add the sentence below:

We defined the association impact size of the predictor on the target variables according to the conventional benchmarks for standardized regression coefficients in ecological SEMs: $\beta < 0.2$ indicates a weak association, $0.2 < \beta < 0.5$ a moderate association, and $\beta \geq 0.5$ a strong association^{59,60}. (L703-706)

Response to the comment on λ_{VAR} vs λ_{AC1} plot

Thank you for raising this point regarding the λ_{VAR} vs λ_{AC1} scatter plot. In remote sensing-based resilience studies, several validation strategies are commonly used to ensure robustness. These include employing more than one resilience metric (variance, autocorrelation, recovery rate)(Dakos et al., 2015; Sakschewski et al., 2016; Smith & Boers, 2023), assessing resilience trends with different rolling windows (3,5,7)(Smith & Boers, 2023; Wang et al., 2023) and examining the degree of agreement between variance- and autocorrelation-based indicators (e.g., through ratios, correlation, or linear relationships (Smith & Boers, 2023; Van Passel et al., 2024)).

Our intention in presenting the scatter plot was to illustrate the spatial correspondence between λ_{VAR} and λ_{AC1} . While an exponential/power/polynomial fit may indeed capture the relationship best, our primary goal was to highlight the overall spatial association (linear fit, $R^2=0.88$) between the two metrics rather than to identify a single optimal functional form. Furthermore, a very low relationship ($R^2= 0.02$, $P < 0.001$) has also been used to justify the similarity between VAR and AC1-based trends (Van Passel et al., 2024).

Proofreading the whole manuscript and responding to minor comments on the Methods

Thank you for thoroughly reviewing and pointing out the issue with the climatic data. Please see the list number 23. Additionally, we have thoroughly reviewed the entire manuscript

again as proofread and enhanced its legibility (Yellow highlighted). For your quick view, I have listed them chronologically below:

Title

1. Functional composition and structural diversity enhance mangrove forest resilience in the Sundarbans

Abstract:

2. We added space between the equal sign and the beta value (L39-43)
3. The functional composition of maximum canopy height (MCH) was the strongest driver of mangrove forest resilience ($\beta = 0.61$), followed by specific leaf area (SLA; $\beta = 0.56$) and precipitation ($\beta = 0.44$). Structural diversity ($\beta = 0.22$), though weakly associated, mediated the positive association of species richness with resilience. Perturbation frequency had a significant negative direct ($\beta = -0.29$) and total ($\beta = -0.33$) association on resilience, whereas temperature exhibited only a total negative association ($\beta = -0.20$).

Introduction

4. We added space between “full stop” and “Integrating” in line 177.
5. We added key findings and the main conclusion according to the Journal guidelines (Line 205-214).

We found that approximately 610 to 990 km² (~10-15% of the total Sundarbans area) of mangrove forests exhibited declining resilience. The structural equation model revealed that the functional composition of maximum canopy height was the strongest driver of mangrove forest resilience, followed by specific leaf area and precipitation. Perturbation frequency had a significant negative direct and total association with resilience, whereas temperature exhibited only a total negative association. These findings underscore the urgent need for trait-based conservation and restoration strategies that prioritize site-specific dominant species with tall canopy height and high specific leaf area—supplemented by a few complementary species—to enhance structural diversity and facilitate mangrove recovery against disturbances and stressors.

Results

6. We revised the following sentences as below

To observe the resilience status, we followed two complementary methods. First, we used quantile threshold-based resilient classes (Fig. 4)—Low Resilient (Q1: kNDVI $\leq$ 0.39), Moderately Resilient (Q2: 0.39 < kNDVI $\leq$ 0.49) and Resilient (Q3: kNDVI > 0.49)—and evaluated their transitions relative to the 2000 baseline, Fig. 5). Second, we quantified temporal trends using Kendall’s tau rank correlation with three-year, five-year, and seven-year overlapping windows with a one-year shift (see method; Fig. 5, Fig. S5-6).

7. Added space between P and < in line 268.
8. Convert resilience indicators as a subscript with recovery rate λ in line 280 and across the whole manuscript “ λ_{ACI} and 3 for λ_{VAR} ” (L349, 474, 680, 692).

Methods

Perturbation detection, disturbance metric, recovery rate

9. We detected a perturbation in the residual time series using a moving window approach²³. We employed a window size of 24 (12 months). We used 95% thresholding to detect the perturbation frequency on the residual time series²³. Furthermore, the method may flag non-significant fluctuations, especially in time series lacking strong disturbances. To mitigate this, we applied a minimum amplitude threshold: the raw time series must decrease by at least 0.01 to qualify as a valid perturbation²³. Further, we employed a Savitsky-Golay filter with a 7-point window to reduce high-frequency noise in the resultant derivative time series^{23,87}. (L537-543)
10. To assess whether the recovery rate was significant — and thus confirm that the system returned to its original state rather than shifting to an alternative state— we performed a two-sample Kolmogorov–Smirnov test ($P < 0.05$) comparing the residual kNDVI values. The baseline was defined as the dynamic mean of residual kNDVI during the year preceding perturbation detection⁴⁸ and the post-perturbation period spanned the subsequent five years. For each valid perturbation, we identified a local minimum in the residual kNDVI time series within a 4-month window around the detected event to account for potential lags in response, then fitted an exponential equation to estimate the recovery rate. For pixels experiencing multiple perturbations, we used the average recovery rate²³. We also incorporated potential cyclone occurrence using a 90-day window; 34 cyclones formed in the Bay of Bengal from 2000 to 2024 (Table S6). Based on the total count of valid perturbations, we develop two disturbance metrics: (1) average drop in kNDVI, and (2) weighted average drop in kNDVI (combine count, decay factor, and severity; Equations 2-3). In both disturbance metrics, higher values indicate greater impact of perturbations. (L544-557)
11. Average drop disturbance index (AD) = $\sum_{i=1}^N d_i$ (2) (L558)
12. Weighted Disturbance index (WD) = $N \left(\frac{\sum_{i=1}^N d_i e^{-\frac{t_i}{365}} \frac{d_i}{\max(d)}}{\sum_{i=1}^N e^{-\frac{t_i}{365}} \frac{d_i}{\max(d)}} \right)$ (3) (L559)
13. Where N is the number of valid perturbations, d_i is the drop magnitude of residual kNDVI induced by the i -th perturbation, t_i is the number of days, and $\max(d)$ is the maximum drop magnitude observed for the pixel. (L560-562)

Resilience

14. We measured resilience as the recovery rate (λ) — the rate at which a system returns to equilibrium following a small perturbation. Assuming that local dynamics near equilibrium can be approximated by an Ornstein-Uhlenbeck process, the continuous-time dynamics of deviations X_t from equilibrium is described by equation 4. (L569-572)
15. where $\lambda < 0$ denotes the recovery rate (higher negative values indicate faster recovery to equilibrium and thus higher resilience), σ is the noise intensity, and ξ_t is a Wiener process (i.e., integrated Gaussian white noise). (L574-576)
16. where X_n is the system state (e.g. kNDVI anomaly) at discrete step n , $a = e^{\lambda \Delta t}$ is the lag-1 autocorrelation coefficient, $\tilde{\sigma}$ is the standard deviation of the discrete driving noise, and $\eta_n \sim N(0,1)$ is independent Gaussian white noise. (L580-582)

17. Under this formulation, two independent estimates of recovery rate λ can be derived directly from the observed kNDVI time series (Equations 6-7): (L583-584)
18. From the variance of the kNDVI time series (L587)
19. Both λ_{AC1} and λ_{VAR} depend only on quantities directly quantifiable from the observed kNDVI time series: the slope α and the residual variance $\tilde{\sigma}^2$ from the linear regression in equation (5), and the total variance $\text{Var}[X]$. Under the ideal critical slowing down (CSD) conditions—namely, stationarity, linearity near equilibrium, and the additive Gaussian noise—the two estimates should approximately equal. Therefore, deviation from a one-to-one relationship between λ_{AC1} and λ_{VAR} can serve as a diagnostic for the validity of the CSD-based resilience estimate derived from a given time series²⁵. (L591-597)
- 20.

Baseline and forest condition change

21. We analyzed mangrove vegetation dynamics from 2000 to 2024, using the mean kNDVI relative to the baseline condition in 2000. Based on the empirical distribution of kNDVI in 2000, we defined three resilience-based health classes using quantile thresholds: Resilient (Q3; kNDVI > 0.49), Moderately Resilient (Q2; 0.39 < kNDVI ≤ 0.49), and Low Resilient (Q1; kNDVI ≤ 0.39). Applying this fixed threshold, we classified annual mean kNDVI value for 2000-2024, average for 2001-2024, five-year rolling mean for each year from 2002-2022 and the mean of those rolling windows (Fig. 4). Using this classification, we tracked interannual transitions among resilience classes and developed spatial maps depicting stability, gain, and loss in mangrove health status for all the periods mentioned above (Fig. 4, Table 1-2). (L96-104)
- 22.

Forest stand structure and diversity, environmental data

23. We used ground-measured plot-level live tree species DBH (diameter at breast Height) ≥ 10 cm data from the Sundarbans Forest carbon inventory 2010³⁵. A total of 150 plots were surveyed from 5 December 2009 to 30 May 2010³⁵. Each plot comprised of five nested subplots with a 10-meter radius: one central subplot and four additional subplots located 50m away in the cardinal directions (Fig. S7)³⁵. In our current study, we used 100 plots; the remaining 50 plots were excluded because they were either fully underwater in the river due to riverbank erosion, or subplots with water bodies more than 20% due to the presence of a small canal, or on the bank of the river or a big canal^{7,35}. To estimate taxonomic diversity, we counted the total number of species in each plot. We used publicly available plant trait data specific to the Sundarbans, acquired in recent years^{45,88}, for calculating functional trait-related diversity.

The seven functional traits that were used in this study (Table S5) fall into three categories: leaf traits (specific leaf area, leaf litter nitrogen, leaf dry matter content, leaf photosynthesis rate, and leaf succulence), stem traits (wood density), and whole plant traits (maximum

canopy height)^{7,45,88–90}. We averaged the leaf litter nitrogen values across the three distinct seasons in the Sundarbans: pre-monsoon (February to May), monsoon (Jun to September), and post-monsoon periods (October to January)^{35,88}. We used the community to mean trait for species whose trait value was unavailable (relative abundance < 2%)⁷.

To quantify functional trait diversity, we used two diversity metrics: functional diversity (functional dispersion; Equation 9) and functional composition (community-weighted mean; Equation 10). We used the FD package in R⁹¹ to calculate both functional dispersion and community-weighted mean, where the species-wise sum of basal area in a plot was used as a weighting factor, provided that basal area represents the best contribution of a species in a plot or community⁶⁴. The data were log-transformed and standardized to a zero mean and one standard deviation.

$$FDis = \frac{\sum a_j z_j}{\sum a_j}, \quad (9)$$

where a_j is the basal area proxy for abundance of species j , and z_j is the distance of species j to the weighted centroid c , which signifies the centroid of the n species within the trait space.

$$CWM_{tj} = \sum_{i=1}^S P_{ij} t_i, \quad (10)$$

where CWM_{tj} is the community-weighted mean for particular trait t for the j th plot, S refers to the number of species, P_{ij} is the relative contribution to the total basal area of a specific species i for a plot j , and t_i represents the average trait value of species i . (L609-639)

24. In ecology, 30-year mean climatic data are commonly used. However, because the second reviewer requested that we include the remaining 14 years of data, we obtained these additional years from the same high-resolution (1 km) source to match the resolution of the historical dataset (1980–2010) derived from the projected climatic data. Please see the revised version below:

Long-term monthly temperature and precipitation data spanning historical (1980-2010) and future projections (2011-2040), were employed to calculate pixel-wise mean annual temperature (derived from monthly average) and annual precipitation (sum across months). We extrapolated the soil physiochemical properties—including sediment silt content, sediment phosphorus (P), sediment ammonium (NH₄), sediment potassium (K), and sediment sulphide)—using field data collected by Saker et al.⁴⁵ from 110 permanent sample plots (plot size: 120 × 20 m; Fig. S7) in the Sundarbans, between January and June 2014. These plots encompass nearly all forest types in the Sundarbans, as the permanent sample plots were stratified by vegetation type and salinity zone. We used the Google Earth Engine (GEE) platform to generate spatial maps of soil physiochemical properties using Inverse Distance Weighted Interpolation⁹². By using the temporary carbon plot shapefile (100 plots, each comprising five circular subplots with 10-m radii), we extracted mean soil properties from the extrapolated maps, MODIS-derived resilience layers, and Chelsha climatic data^{35,83}. For each plot geometry, we applied GEE's, reduce Regions() function with ee.Reducer.mean() at a 30-m scale to summarize values⁸⁵. (L643-657)

Statistical analysis

25. We assessed the trends in recovery rate (λ) using Kendall's τ with overlapping 5-year windows spanning 2002-2022²⁵. For example, the window centered on 2002 included data from 2000–2004, the window for 2003 used data from 2001–2005, and so on, up

to 2022, which incorporated data from 2020–2024. As our study period covers 2000–2024, we could not compute a full 5-year rolling window for the boundary years 2000, 2001, 2023, and 2024 due to insufficient adjacent data. (L659-664)

26. We employed structural equation modelling⁵⁹ to investigate the interactive association among covariates. To satisfy the linearity assumption⁹³ We applied the Box-Cox transformation and standardized all variables to a mean of 0 and a standard deviation of 1. We performed a multicollinearity test by calculating variance inflation factors (VIFs) to identify and eliminate highly correlated variables among trait-specific functional composition and functional diversity metrics. Following a widely used threshold in the literature (VIF<10)^{7,67,83,94}, we retained only those variables with VIF value below 10. This resulted in four traits of functional diversity (Table S2) and three traits of functional compositions (Table S3). The traits included in the functional diversity group were specific leaf area, maximum canopy height, leaf succulence, and leaf litter nitrogen, while those in the functional composition group were specific leaf area, maximum canopy height, and leaf litter nitrogen.

Using perturbation frequency and the two-disturbance metrics—along with climatic, sediment physicochemical properties, and taxonomic, structural, and functional trait diversity—we constructed six structural equation models (SEM): three for λ_{AC1} and three for λ_{VAR} (Table S1). Each pair model incorporated one of the three disturbance-related variables: perturbation frequency, average drop disturbance index (AD), and weighted average drop disturbance Index (WD). The biotic variables included seven functional trait-based diversity metrics, species richness (as a measure of taxonomic diversity), and co-efficient variation of DBH (as a measure of structural diversity)^{67,95}. Environmental covariables comprised eight sediment and climate variables—sediment sulfide, sediment phosphorus, sediment iron concentration, sediment pH, sediment texture silt, precipitation, temperature, and sediment salinity. We gradually removed the hypothesized path with the highest p-value until the model satisfied the model-fitting measures⁷. In this approach, from the functional diversity group, specific leaf area, wood density, and maximum canopy height were dropped, while from the functional composition group, leaf litter nitrogen was dropped. The final model, with 14 covariates and a target variable (λ_{AC1} and three for λ_{VAR}), satisfied the model-fitting statistics (Fig. 6, Table 3; Table S1), with final VIF values for all variables below 10 (Table S4). The retained predictor covariables were species richness, functional diversity of leaf succulence, functional composition of specific leaf area, maximum canopy height, structural diversity, sediment salinity, sediment sulfide, sediment phosphorus, sediment iron concentration, sediment pH, sediment texture silt, perturbation frequency, precipitation, and temperature. (L659-697)

27. We defined the association impact size of the predictor on the target variables according to the conventional benchmarks for standardized regression coefficients in ecological SEMs: $\beta < 0.2$ indicates a weak association, $0.2 < \beta < 0.5$ a moderate association, and $\beta \geq 0.5$ a strong association^{59,60}. (L703-706).
28. We evaluated the SEM⁹⁶ models using four commonly used goodness-of-fit statistics: an insignificant chi-squared (χ^2 ; equation 11) value; a goodness-of-fit index (GFI; equation 12) closes to 1; a comparative fit index (CFI; equation 13) closes to 1; and a standardized root mean square residual (SRMR; equation 14) nearly zero. These indicate that the model does not significantly deviate from our dataset^{59,96}.

$$\chi^2 = (N - 1)f \quad , \quad (11)$$

$$GFI = \frac{\text{trace}(S - \Sigma(\hat{\theta}))^2}{\text{trace}(S^2)}, \quad (12)$$

$$CFI = \frac{\max(\chi_0^2 - df_0) - \max(\chi_k^2 - df_k)}{\max(\chi_0^2 - df_0)}, \quad (13)$$

$$SRMR = \sqrt{[\rho^{*-1}(e'W_s e)]}, \quad (14)$$

where χ^2 represents the Chi-square test statistic; CFI stands for Comparative Fit Index; SRMR is the Standardized Root Mean Square Residual; N denotes the sample size; f refers to the minimized discrepancy function; 0 indicates the baseline model; df stands for degrees of freedom; k is the tested or hypothesized model; S denotes sample covariance matrix; $\Sigma(\theta)$ is referred as the model-implied covariance matrix; trace is denoted as the trace of a matrix, which is the sum of the diagonal elements; ρ^* indicates the number of non-duplicated elements in the covariance matrix; e is a vector of residuals from the covariance matrix; s refers to the vector of the ρ^* non-redundant elements in the observed covariance matrix; W denotes the weight matrix; and W_s is a diagonal weight matrix used to standardize the elements of the covariance matrix. (L708-727).

Ref.: Ms. No. COMMSENV-25-1428-T

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Additionally, the authors can not justified the complex relationships among biotic and abiotic factors in simple way by using simple correlation or regression models because these factors complement each other, while SEM can be used to model how multiple biotic and abiotic factors affect forest composition, structure, and productivity, etc.

The authors had made many hypotheses, but this is better to simplified the hypothesis. The

However, the authors did not explained well regarding the application of structural equation
Title:

Better to specify the title as follows:

Abstract:

The abstract part should be reconstructed to improve this part as follows.

The general statement is to long sentences, and the authors not need to mention references in the abstract part.

Provide the result of SEM analysis in the abstract part.
resilience capacity.

3. Keywords should be corrected.

Introduction:

There were many recent publication of mangroves worldwide close related to this study. To improve the introduction part, please look and site at the more recent blue carbon studies including relation of mangrove vulnerable and blue carbon stock. For examples: (1) <https://esj-journals.onlinelibrary.wiley.com/doi/abs/10.1111/1440-1703.12374>

(2) <https://www.frontiersin.org/journals/ecology-and-evolution/articles/10.3389/fevo.2024.1420827/full>

(3) <https://www.science.org/doi/10.1126/sciadv.adk5430>

and many others.

Methods:

Please improve manuscript by adding more analysis and applying the structural equation modelling (SEM).

Results and discussion

Please elaborate results and discussion from new analysis by applying SEM.

Response to Reviews (Ref.: Ms. No. COMMSENV-25-1428-T)

Dear Reviewers,

Thank you for your thoughtful and constructive feedback on our manuscript. We sincerely appreciate the time and effort you dedicated to reviewing our manuscript. Our Manuscript has been enhanced significantly with higher clarity and rigor by your insightful suggestions and comments. We have carefully addressed each of your comments and made the necessary revisions accordingly.

Below, we outline the main changes incorporated in the revised version.

1. We detected significant perturbation using standard method at pixel level from 2000-2024. Perturbation frequency, damage, decay factor and time we develop two disturbance metrics. Additionally, we estimate the empirical recovery rate recovery rate. We also show all the step — from raw timeseries, smoothing process —at five points with cyclone flagging and resilience indicators (Fig 1).
2. We applied Quantile Threshold based resilience classification for 2001-2024, and their mean, relative to baseline year 2000. First, we used the 2000 mean kNDVI as the baseline and classified it using a quantile-based approach: Resilient (Q3) where $kNDVI > 0.49$, Moderately Resilient (Q2) where $0.39 < kNDVI \leq 0.49$, and Low Resilient (Q1) where $kNDVI \leq 0.39$. Using these thresholds, we then classified all years from 2001 to 2024 and calculated their mean resilience. We further analyzed class transitions, including gains, losses, and stable areas (Figs. 4–5, Table 1).
3. We reanalyzed the resilience indicators using 3- and 5-year rolling windows. Additionally, we employed six new structural equation models (SEMs), incorporating two resilience metrics ($\lambda AC1$ and λVAR) and three disturbance-related variables. The SEM based on perturbation frequency and λVAR performed better, showing a negative association between perturbation frequency and λVAR . Nonetheless, our original conclusion remains robust: functional composition—specifically functional identity—was the dominant driver of resilience, best represented by canopy height, followed by specific leaf area and precipitation.
4. We added study area map with vegetation type and salinity zones. We also showed the carbon inventory plots and permanent sample plots that are distributed across the ecological zones (vegetation type and salinity zones).
5. Based on these four main tasks, we have comprehensively revised the entire manuscript.

Thank you once again, for your comprehensive, thoughtful and positive feedback. Your expert commentary has been instrumental in strengthening overall impact of our manuscript to showcase the manuscripts key messages. We have carefully considered each of your suggestions and have incorporated them into the revised manuscript, which is attached with track changes as well as clean revised part with blue heightened enabled for your convenience. We believe these revisions fully address all concerns raised during the review process and have significantly improved the overall quality of the paper.

Thank you once again for your time and support.

Sincerely,

Qihao Weng (on behalf of the author team)

REVIEWER COMMENTS:

Reviewer # 1

Thank you for your valuable comments and suggestion. We have diligently addressed each of your comments in the revised version. Please see below our point-by-point responses, with your comments are shown in black and our responses in blue.

Sincerely,

Qihao Weng (on behalf of the author team)

Reviewer #1 (Remarks to the Author):

Dear authors

Ref.: Ms. No. COMMSENV-25-1428-T

The title of manuscript is sound good. However, the authors were not explained well regarding the application of structural equation model or SEM in this study. It seemed just correlation analysis rather than model for forest ecosystem resilience. SEM allows researchers to model relationships between multiple variables, including both observed and unobserved constructs, which are common in complex ecological systems.

Additionally, the authors can not justified the complex relationships among biotic and abiotic factors in simple way by using simple correlation or regression models because these factors complement each other, while SEM can be used to model how multiple biotic and abiotic factors affect forest composition, structure, and productivity, etc. SEM can also model the impact of climate change on forest ecosystems, considering how climate change affects forest composition for example, increased tree species richness might lead to increased resilience capacity.

R1.1: The authors had made many hypotheses, but this is better to simplified the hypothesis. The authors can use SEM to answer the hypothesis because SEM allows researchers to test hypothesized relationships between variables, confirming or refuting theoretical models of forest ecosystem dynamics.

Answer: Thank you for your comments. We have already applied structural equation model (Fig 6, direct association; Table 3, direct, indirect and total association). In the table 3, is the standardized beta (β) of indirect and total association predictors (exogenous variable, column) on response (Endogenous variable) and based on structural equation model (in figure 6). We have updated the table caption as well as added the direct association of all the predictors as we showed only significant paths in figure 6 in order to make it visually less complex. In our

current, version we have added perturbation frequency (to observe disturbance effect on resilience) tested it with both resilience metrics (Autocorrelation and variance-based recovery rate). Additionally, we also tested the four more SEMs with two disturbance metrics (ADI, based average drop and perturbation frequency; WDI, Weighted average drop and perturbation frequency) with both Autocorrelation and variance-based recovery rates (Table S3; please also see the relevant response to your specific comment, R1.7 and second reviewer, R2.4-2.6, for details methodology, changes in result and discussion section). In all the four models (two λ_{ACI} and 2 for λ_{VAR}), the disturbance metric has no significant association with resilience, even reduces the performance of model fit index particularly AIC and R^2 . SEM with variance-based recovery and perturbation frequency out performed all other SEMs. So, in our current version, we selected the variance-based recovery and perturbation frequency.

My specific comments are as follows:

R1.1 Title:

Better to specify the title as follows:

High Functional Distinctiveness and Structural Diversity Strengthen Resilience of Sundarbans Mangrove Forest

Answer: Thank you for your suggestion. Second (“distinctiveness”) and third reviewers (“Against rising Temperature”) also made comments on title editorial board also suggest to use “High Functional and structural diversities”. However, in our case function diversity (e.g., functional dispersion) was not the main drivers. Instead, functional composition—specifically, the functional identity of traits measured by community-weighted means—played the dominant role. Therefore, using “diversities” would misleading. Accordingly, in our current version, we have changed the title as below.

“Functional composition and Structural Diversity enhance Mangrove Forest Resilience in the Sundarbans.” L1-2

Abstract:

The abstract part should be reconstructed to improve this part as follows.

R1.2. The general statement is too long sentences, and the authors not need to mention references in the abstract part.

Answer: Thank you for your comment on this large sentence. We have concise the sentence as below. Regarding reference, initially we submitted it to “*Nature*” and followed their structure. We have removed the reference from abstract as it is not necessary in *Communications Earth & Environment*. Please see the change below:

“Mangrove forests offer nature-based solutions for climate change mitigation by storing atmospheric CO₂, while also supporting biodiversity, livelihoods and coastal protection. Yet, they face increasing threats from deforestation, salinity and extreme weather events.” L23-25

R1.3. Provide the result of SEM analysis in the abstract part.

Answer: In Nature and its sister journals, it has been prescribed to write the abstract simple language and without any technical and statistical jargons. Furthermore, the word limitation in most cases 150 words which is hard to maintain the word limit if we want to show SEM result quantitatively. So, we wrote the SEM result in abstract as verbal text. What we written in abstract in our previous and current version were based on SEM not simple correlation. Even though, as you recommend, we have mentioned the standardized beta value in abstract in our current version. Please see the result section of abstract below:

“The functional composition of maximum canopy height (MCH) was the strongest driver of mangrove forest resilience ($\beta=0.61$), followed by specific leaf area (SLA; $\beta=0.56$) and precipitation ($\beta=0.44$). Structural diversity ($\beta=0.22$), though weakly associated, mediated the positive association of species richness on resilience. Perturbation frequency had significant negative direct ($\beta=-0.29$) and total ($\beta=-0.33$) association on resilience whereas temperature exhibited only a total negative association ($\beta=-0.20$).” L31-37

R1.4. Keywords should be corrected.

Answer: Thank you for this valuable comment. We have revised the key word as below:

“Keywords: Remote Sensing, Mangrove Forest resilience, climatic effect, biodiversity, functional traits.” L42-43

Introduction:

R1.5: There were many recent publications of mangroves worldwide close related to this study. To improve the introduction part, please look and site at the more recent blue carbon studies including relation of mangrove vulnerable and blue carbon stock. For examples:

(1) <https://esj-journals.onlinelibrary.wiley.com/doi/abs/10.1111/1440-1703.12374>

(2) <https://www.frontiersin.org/journals/ecology-and-evolution/articles/10.3389/fevo.2024.1420827/full>

(3) <https://www.science.org/doi/10.1126/sciadv.adk5430>

and many others.

Answer: We agreed with you. In this current version, we have referred those excellent recent blue carbon studies. We have also included several sentences that are relevant to previous studies on cyclone induced mangrove damage, mangrove condition change and risk, and empirical recovery. By doing so, we also mentioned how our study can improve our understanding on how mangrove recovery, what are roles of different dimension of biodiversity.

Mangrove forests provide a wide range of ecosystem services, including the support of livelihoods of coastal communities, the protection of lives and properties from tropical cyclones and tidal surges (valued at more than \$US 65 billion annually), the provision of habitat

for biodiversity and high carbon sequestration and storage rates(Analuddin et al., 2023, 2024; Bourgeois et al., 2024; Donato et al., 2011; Rahman, Zimmer, et al., 2021). With these invaluable ecosystem services, mangrove forests can serve as nature-based solutions for climate change mitigation and adaptation(Analuddin et al., 2023, 2024; Bourgeois et al., 2024; Macreadie et al., 2019; Rahman, Zimmer, et al., 2021; Rovai et al., 2018). Despite these benefits, mangrove forests face multiple threats including land cover-change, rising temperatures, sea level-rise, disrupted freshwater flows, increasing salinity and more frequent cyclones and other extreme events(Analuddin et al., 2024; Bourgeois et al., 2024; Goldberg et al., 2020; Lagomasino et al., 2021). These stressors collectively contribute to the degradation of mangrove habitats, affecting species richness, composition and abundance, as well as diversity and composition of functional traits, thus, plant ecophysiological processes, physicochemical processes in sediments and blue carbon stocks both in the biomass and the sediment(Analuddin et al., 2023, 2024; Bourgeois et al., 2024; Rahman, Zimmer, et al., 2021). Such changes potentially undermine the resilience of mangrove forests—their capacity to recover from disturbances(Boulton et al., 2022; Forzieri et al., 2022)—thereby restricting their ability to provide multiple ecosystem services sustainably under changing environmental and climatic conditions. L48-62

Cyclone impacts (Mandal & Hosaka, 2020; Mohammed et al., 2024; Mondal et al., 2022; Sharma et al., 2022; Yang et al., 2024), associated risks(Mo et al., 2023), driver of dieback(Asbridge et al., 2019) and empirical recovery rates(Lagomasino et al., 2021) in mangrove forests have been documented across various regions and globally. Most existing studies focus on historical cyclone damage assessments using MODIS- and Landsat imagery-derived vegetation indices with thresholding, machine learning and deep learning approaches, or case studies of individual cyclone events(Asbridge et al., 2019; Lagomasino et al., 2021; Mandal & Hosaka, 2020; Mo et al., 2023; Mohammed et al., 2024; Sharma et al., 2022; Yang et al., 2024). However, most previous studies have concentrated on tracking mangrove forest condition and empirical recovery and future risk, while paying less attention to understanding how mangrove forest recover, what drives their post-disturbance recovery, or which role multidimensional diversity plays in shaping their recovery. L126-135

Methods:

R1.6: Please improve manuscript by adding more analysis and applying the structural equation modelling (SEM).

Answer: Thank for your comments. We have investigated more SEMs in our current version. Please see our explanation to your first general comment.

Results and discussion

R1.7 Please elaborate results and discussion from new analysis by applying SEM.

Answer: Please see the response to R1.1. Based on the new SEM analysis, we have updated both methods (L173, -L188), result (L346-L408, also see, Fig. 6 and Table 2 L430-438), and discussion (L454-464, L493-568.). Please see some of the major changes, below.

Result: (L346-L408, also see, Fig. 6 and Table 2 L430-438)

Drivers and mechanisms of mangrove forest resilience

Using the perturbation frequency and the two-disturbance metrics along with climatic, physicochemical sediment properties and taxonomic, structural and trait diversity, we developed six structural equation models (SEM): 3 for λ_{AC1} and 3 for λ_{VAR} (by adding separately three disturbance-related variables). Based on the fit indices (Chi Square = 2.464, $p = 0.292$, Goodness of Fit Index of 0.999, Comparative Fit Index of 0.999 and a standardized root mean square residual of 0.009), our fitted SEM models did not show any significant deviation from our dataset (Fig. 6; Table S3). However, according to the Akaike Information Criterion (AIC) and the Co-efficient of determination (R^2), SEM λ_{VAR} exhibited (AIC= 3776.63 and $R^2= 0.49$) a better performance than λ_{AC1} (AIC= 3786.92 and $R^2= 0.44$) with disturbances as perturbation frequency. Thus, we report the variance-based SEM. The model fitted well with 14 predictors, including mean annual temperature (hereafter, temperature), total annual precipitation (hereafter, precipitation), sediment salinity, sediment pH, sediment concentrations of sulfide, phosphorus and iron, sediment texture (silt content), perturbation frequency (count of perturbations), species richness, structural diversity, functional compositions of maximum canopy height and specific leaf area and the functional diversity of succulence (other functional traits had a variance inflation factor over 10; Supplementary Table 1-2xx).

Biotic and abiotic variables displayed distinct types of associations with resilience, biotic variables exerting the dominant role (Fig. 6). For instance, perturbation frequency exhibited a significant negative association with resilience ($\beta = -0.29$, $P < 0.05$; Fig. 6, Table 2), whereas neither precipitation nor temperature demonstrated any significant direct association ($P > 0.05$; Table 2). Both sediment pH and phosphorus content had direct significant negative association with resilience ($P < 0.05$, Table 2). However, sediment salinity and the sediment contents of iron and sulfide did not have any significant direct association (Table 2).

Structural diversity showed significant positive direct association with resilience, while species richness and functional diversity did not exhibit any significant direct association (Fig. 6; Table 2). The functional compositions of maximum canopy height ($\beta = 0.62$, $P < 0.05$; Fig. 6, Table 2) and specific leaf area height ($\beta = 0.62$, $P < 0.05$; Fig. 6, Table 1) showed a strong significant positive association with resilience. Thus, functional composition diversity metrics were the dominant driver of mangrove forest resilience in the Sundarbans. We did not find any direct association of sediment salinity with resilience ($P > 0.05$). However, we observed an indirect weaker negative association of sediment salinity with resilience through species richness to structural diversity pathways ($\beta = -0.25$; $P < 0.05$; Fig. 6).

Species richness showed a significant positive association with structural diversity ($\beta = 0.35$; $P < 0.05$; Fig. 6). Consequently, through this specific pathway, species richness showed significant weaker positive associations with resilience ($\beta = 0.08$; $P > 0.05$; Fig. 6; Table 2). However, the total indirect and total association of species richness with resilience was not significant ($P > 0.05$; Table 2). While the total association of functional diversity on resilience was negative and weaker ($\beta = -0.22$, $P < 0.05$; Fig. Table 2). Although precipitation showed no direct association with resilience, it exhibited an indirect association with resilience through specific functional trait pathways. Notably, precipitation showed an indirect positive association through the functional composition of maximum canopy height path ($\beta = 0.34$, $P < 0.05$; Fig. 6, Table 2). Conversely, precipitation also showed an indirect negative association with resilience through the specific pathway of the functional composition of specific leaf area ($\beta = -0.22$, $P < 0.05$; Fig. 6). However, the positive association through canopy height was higher than the negative association through specific leaf area ($\beta = 0.12$; Fig. 6). Precipitation

also showed a negative association with resilience through the sediment salinity to functional composition of maximum canopy height pathway (Table 2). More importantly, precipitation also showed a positive indirect association with resilience through reducing the perturbation frequency which was weakly negatively related to resilience ($\beta = 0.10$, $P < 0.05$; Fig 6 and Table 2). These indirect positive and negative associations, combined with weaker positive direct association, resulted in the moderate total positive association of precipitation with resilience ($\beta = 0.44$, $P < 0.05$; Fig. 6; Table 2). Temperature exhibited an indirect negative association with resilience through functional composition of maximum canopy height ($\beta = -0.40$, $P < 0.05$; Fig. 6; Table 2) and through the sediment salinity to species richness to structural diversity pathway (Fig. 6; Table 2). Conversely, temperature also showed an indirect positive association with resilience through the functional composition of specific leaf area ($\beta = 0.33$, $P < 0.05$; Fig. 6; Table 2). However, the total association of temperature with resilience was negative ($\beta = -0.20$, $P < 0.05$; Table 2). The total association of perturbation frequency with resilience was significant and negative ($\beta = -0.29$, $P < 0.05$; Table 2). Although we observed strong positive direct association of the functional compositions of both maximum canopy height and specific leaf area with resilience, the total association of the functional composition of maximum canopy height ($\beta = 0.61$, $P < 0.05$; Table 2) outperformed that of specific leaf area ($\beta = 0.56$, $P < 0.05$; Table 2).

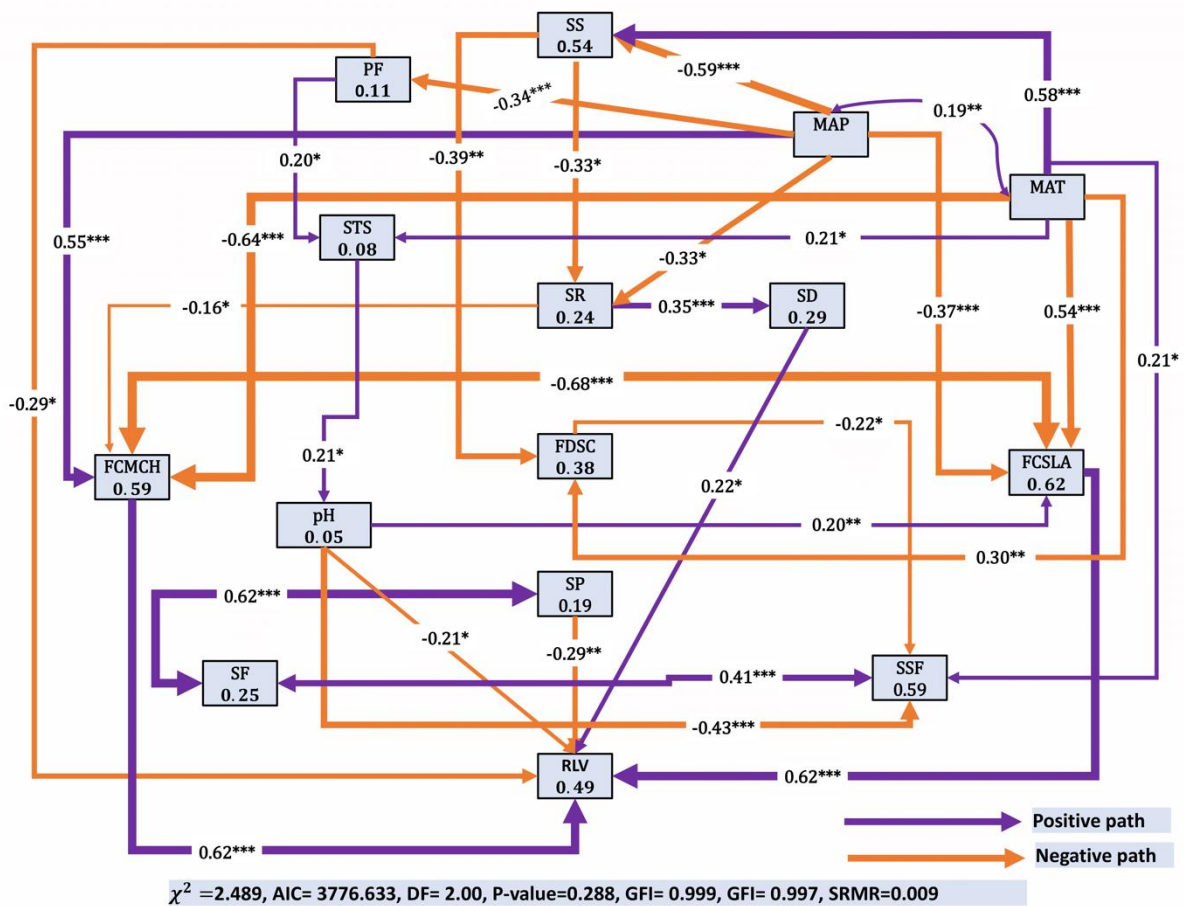


Fig 6. Structural Equation Model illustrating the mechanisms connecting biodiversity measures, abiotic factors and resilience (λ_{VAR}). Hypothesized paths with asterisks (***: $P < 0.001$, **: $P < 0.01$, *: $P < 0.05$) indicate significant associations between variables; non-

significant associations ($P > 0.05$) are not shown for the sake of clarity (please see Table 2). The non-significant χ^2 (Chi-Square) of 2.489 ($P = 0.288$), with a goodness of fit index (GFI) of 0.997, with a comparative fit index (CFI) of 0.999 and a standardized root mean square residual of 0.009 suggests no significant deviation from the model and datasets at 2 degrees of freedom. Orange lines indicate negative associations, while purple lines indicate positive associations between covariables. Numbers on the arrows show the standardized associations of predictors with dependent variables. R^2 Coefficient of Determination within the endogenous variables represent their explained variance by all predictors. *MAP* mean annual precipitation, *MAT* mean annual temperature, *SS* sediment salinity, *SR* Species richness, *FCMCH* functional composition of maximum canopy height, *SD* Structural diversity (variation of diameter at breast height), *FCSLA* functional composition of specific leaf area, *FDLS* functional diversity leaf succulence, *P* sediment phosphorus concentration, *SF* sediment iron concentration, *SSF* sediment sulfide concentration, *pH* sediment pH level, *STS* sediment texture silt, *PF* perturbation frequency.

Discussion:

With SEM analysis, we found that mangrove forest resilience in the Sundarbans is primarily driven by the functional composition of maximum canopy height (MCH) and specific leaf area (SLA), while structural diversity and species richness play minor roles (hypothesizes H2). Mean annual precipitation was the dominant abiotic driver of resilience, mainly mediated by MCH and SLA, whereas perturbation frequency and sediment phosphorus content showed negative associations (hypothesizes H1 and partly H3). Thus, mangrove forest resilience in the Sundarbans is shaped by a dynamic interplay of functional trait dominance, structural complexity and precipitation. These findings highlight the urgent need to integrate trait-based approaches and disturbance regimes into conservation and (re-)establishment strategies under changing environmental conditions. L454-464

Mangrove forest resilience or recovery from disturbances in the Sundarbans is strongly driven by the functional composition of whole-plant traits and the leaf economic spectrum. Our findings reveal that the functional composition of MCH and SLA qualify as the strongest biotic predictors of mangrove forest resilience in the Sundarbans. This result suggests that the selection effect theory (Finegan et al., 2015; Tilman et al., 2009)—dominant species with their key functional traits drive ecosystem process—is primarily governing mangrove forest resilience in the Sundarbans. Mangrove stands with tall-growing species capitalize on vertical light gradients (Finegan et al., 2015), enabling rapid canopy reformation and biomass accumulation after disturbances. Concurrently, high SLA—reflecting an acquisitive leaf strategy along the leaf economic spectrum (Wright et al., 2004)—supports faster photosynthesis, nutrient turnover and growth rates (Finegan et al., 2015). Together, these traits synergistically accelerate post-disturbance recovery, reinforcing the critical role of functional trait composition for mangrove forest resilience, similar to other ecosystem process and properties (Finegan et al., 2015) (e.g., biomass, productivity and carbon storage).

Studies in mangrove and terrestrial ecosystems, consistently link species diversity and structural diversity (variation in DBH and tree height) to key ecosystem properties and processes, such as productivity, aboveground biomass, carbon storages, and these descriptors of community composition can also promote ecosystem resilience (Dănescu et al., 2016; Godlee et al., 2021; Rahman, Kundu, et al., 2021; Rahman, Zimmer, et al., 2021). Our findings of a direct positive association of structural diversity with resilience, and an indirect positive association of species richness through increasing structural diversity, aligns with this growing body of work, indicating the minor relevance of a niche complementarity effect (Finegan et al.,

2015; Tilman et al., 1997) on mangrove forest resilience. Forest stands with high DBH variation reflect both horizontal and vertical heterogeneity (Ali, 2019; Dănescu et al., 2016; Messier et al., 2013), characterized by the spatial co-existence of trees with different sizes and growth forms. This complexity promotes niche partitioning, reduces competitive exclusion, and enhances microhabitat diversity, leading to more efficient light capture and resource use (Onoda et al., 2014). In this way, structural diversity buffers mangrove forests against disturbance and enhances their recovery potential. Additionally, species-rich forest stands with high structural diversity may prevent catastrophic canopy collapse during "super cyclones". For example, if dominant tall trees are damaged, smaller or intermediate-sized individuals maintain partial canopy cover, stabilize sediments through diverse rooting architectures and facilitate faster regrowth (D. M. Alongi, 2008; Krauss & Osland, 2020). Thus, while functional trait composition primarily drives post-disturbance recovery in the Sundarbans, species diversity enhances resilience by promoting structural heterogeneity, increasing the range of growth forms and life-history strategies and fostering functional redundancy (Finegan et al., 2015; Messier et al., 2013; Tilman et al., 2009).

The rapid change in global temperatures is causing more frequent extreme weather events, such as tropical cyclones, as well as rising sea levels and, in conjunction with changing precipitation patterns, fluctuating salinity levels, which could influence the resilience of mangrove forests (D. Alongi, 2018; Kirwan & Megonigal, 2013; Loucks et al., 2010). The moderate total positive association of mean annual precipitation with resilience highlights their pivotal role in mangrove forest resilience. Our SEM analysis also showed how precipitation patterns exerted this positive influence mainly through three different pathways: functional composition of MCH, salinity and perturbation frequency. Higher rainfall plays a crucial role in alleviating water stress, increasing freshwater flow and diluting porewater salinity, which, in turn, reduces the energetic cost of osmoregulation and improves overall physiological performance. This allows mangrove trees to allocate more energy into vertical growth (D. M. Alongi, 2008; Ball, 1988; Krauss & Osland, 2020). Moreover, consistent precipitation helps maintain a hydrological balance and stabilizes sediment conditions (Krauss & Osland, 2020). In this way, rainfall can support enhanced growth capacity of dominant tall species and likely contributes to faster post-disturbance recovery, reinforcing the mass-ratio effect observed in our study.

Our results on the negative direct, indirect and total associations of perturbation frequency (PF), suggest that mangrove forest stands exposed to frequent cyclones, tidal surges and anthropogenic pressures exhibit lower resilience. Severe cyclones typically cause direct physical damage of mangrove trees, including canopy top breakage, uprooting and defoliation^{9,18,19,22,57}. Indirectly, these disturbances alter biogeochemical processes by creating hypersaline condition, increasing the sediment silt content, and elevating sediment pH—all of which are detrimental to mangrove health, productivity and, ultimately, mangrove forest resilience (Krauss & Osland, 2020; Lagomasino et al., 2021; Mo et al., 2023). Increased salinity can render nutrients inaccessible to plant roots or force plants to spend more energy in coping with osmotic stress, thereby weakening their physiological performance (D. M. Alongi, 2008; Ball, 1988; Krauss & Osland, 2020). On the other hand, increased sediment pH, resulting from silt accumulation (Fig. 6) and reduced tidal flushing, can further reduce the availability of essential micronutrients, such as iron and manganese (Krauss & Osland, 2020). This alteration in physicochemical mangrove sediment properties disrupts microbial activity that is critical for nutrient-cycling and organic matter decay, compounding the stress on mangrove ecosystems and diminishing their capacity to recover from disturbance (Pradisty et al., 2021; Quadros et al., 2019).

Phosphorus, although a key essential nutrient for mangroves, playing a crucial role in photosynthesis, growth and sediment microbial activity (Ball, 1988; Krauss & Osland, 2020), can become ecologically disruptive when present in excessive amount. The direct negative association of the sediment phosphorus content with resilience suggests that excessive phosphorus-enrichment in mangrove forest sediments may disrupt the nutrient stoichiometric balance and interfere with microbial processes (Ball, 1988; Krauss & Osland, 2020). In mangrove forest sediments, a balanced ratio of carbon (C), nitrogen (N) and phosphorus (P) is essential for sustaining microbial metabolic processes and ecological interactions. This stoichiometric balance supports efficient microbial activity, organic matter decay and nutrient-cycling (Ball, 1988; Pradisty et al., 2021; Quadros et al., 2019), all of which are critical for mangrove forest health and resilience. High phosphorus levels can skew this ratio, leading to disproportionate growth of microbes that rapidly decay organic matter (Ball, 1988; Krauss & Osland, 2020) which, in turn, accelerates microbial respiration, depleting oxygen in the sediment and creating hypoxic conditions (Krauss & Osland, 2020). Under low oxygen availability, nutrient-cycling is impaired, and root respiration is restricted, ultimately weakening mangrove health and reducing ecosystem resilience.

Reviewer # 2

Thank you for your insightful suggestions and comments. We have carefully and thoroughly followed all your valuable suggestions and comments in our revision. We present below a point to point response with reviewer comments in Black and our corresponding responses in blue.

Sincerely,

Qihao Weng (on behalf of the author team)

Reviewer #2 (Remarks to the Author):

Mizanur Rahman et al., assess mangrove forest resilience in the Sundarbans located within Bangladesh. A resilience metric derived from kNDVI, which is defined as the recovery rate from disturbances based on 1 lag autocorrelation and variance, in 5-year rolling windows, over the study period 2000 – 2024. From this they categorized mangroves as stable, increasingly resilient, and decreasingly resilient, across the entirety of the Sundarbans. Mangrove forest stand structure and diversity were calculated from the national forestry inventory data, in addition to sediment profiles collated from 110 permanent plots. Environmental variables were collated from various repositories. The interaction of these different variables and their influence on the three resilience categories were assessed using structural equation modelling. The main findings of the paper were that mangroves within the Sundarbans (Bangladesh side) were associated with a decrease in resilience, especially those along the seaward fringe. Areas of mangrove that exhibited increases in resilience were located further from the shore, and were associated with larger tree species (e.g., *Heritiera fomes*), and greater species and forest structural diversity. I think that these findings are of interest to those in the mangrove and/or management fields, as the results can inform

restoration/reestablishment best practices in the region, such as not planting monocultures. However, I do have some questions and comments that need to be addressed for this manuscript to be published.

R2.1 Within the title the authors highlight that “High Functional Distinctiveness and Structural Diversity Strengthen Mangrove Forest Resilience Against Rising Temperatures”, it would be good in the paper if you can define what you mean by “Functional distinctiveness” within the context of this study.

Answer: Thank you for your comments on title. Please see the details explanation in our first reviewer’s response section (R1.1). We have revised the title as below.

“Functional composition and Structural Diversity enhance Mangrove Forest Resilience in the Sundarbans.” L1-2.

R2.2 I have some points within the methodology that it would be useful to clarify. Some of this is because I think potentially all the information is there, in regard to the forest inventory, but it is not all in one place and therefore I am not sure of the types of plots or exact number of locations of these plots within the study. It would be useful to have a section briefly outlining the inventory methods and the data used from it.

Answer: Thank you for your concern. The plot type was cluster. Each plot consists of five circular subplots. We have added a figure in method with plots location (both solid sampling plots-permanent sample plots and forest carbon inventory plots why vegetation types (Method; Fig. S7; Response to R3.20). In the method we have also added a description on the field plots.

“A total of 150 plots were surveyed from 5 December 2009 to 30 May 2010¹². Each plot consisted of five 10-meter radius nested subplots. From the central subplot, the other four subplots were 50m (Fig. S7) away towards four-cardinal directions¹². In our current study we 100 plots the remaining 50 plots have either fully under water or subplot with waterbody more than 20% due to presence of small canal or on the bank of the river or big canal ^{12,13}.” (Mthod, L104-109)

“We extrapolated the soil physiochemical properties (sediment phosphorus (P), sediment ammonium (NH₄), sediment potassium (K) and sediment sulphide) using field data that was collected by Saker et al.(2021) from 110 permanent sample plots (each plot size 120 × 20 m) in the Sundarbans, during January – June 2014.” L37-141

Methods – Remote sensing

R2.3. “We used the MODIS ... from October 1, 2000 to September 30, 2024.”

This is a 24-year period, not a 25-year period

Answer: Yes, you are right. In our current version we, added full coverage from 18 February 2000 to 31 December 2024 and revised the results. So, the now it is 25 years period. Please see the relevant revisions that we made in the method below.

“We used the MODIS (Moderate Resolution Imaging Spectroradiometer) 16 days composite Normalized Difference Vegetation Index (NDVI) dataset (products MOD13Q1 (250 m) product, from February, 2000 to December, 2024. We ensured high-quality pixels in our analysis by using the quality assurance band of QC_250m to exclude pixels affected by cloud cover, cloud shadows, and relevant atmospheric effects. For getting stable forest, we intersected between 2000 and 2024 MODIS annual tree cover percentage (>2). As we used MODIS 250m resolution pixel adjacent or over small rivers or canals usually mixed pixel with reflectance comes from vegetation and waterbody. To remove those pixels from our analysis, we further intersected Landsat of 2000 and 2024 after masking waterbody using a Modified Normalized Water Index with a threshold of 0.3(Xu, 2006).” (Method; L4-13)

Methods – Resilience

R2.4. “Theoretical studies suggest that complex systems can reach tipping points—critical thresholds that lead to sudden and irreversible changes.”

Here is would be good to know what **your different thresholds are** – what is the starting **condition of the mangroves in 2000**? My concern is that by just looking at trends you do not establish a **baseline level of resilience status**. While a loss in resilience is not a good thing, a mangrove forest in good condition losing some resilience may still be more resilient that a forest in poor condition that is potentially recovering and increasing its level of resilience (but overall resilience is still low).

Answer: Thank you for this most insightful comment. In our revised version, we first use 2000 mean kNDVI as baseline, classify it by using quantile-based approach where (Resilient (Q3) where $kNDVI > 0.49$, Moderate Resilient (Q2) where $0.39 < kNDVI \leq 0.49$, and Low Resilient (Q1) where $kNDVI \leq 0.39$. Using this threshold, we then classify, all the years from 2001-2024 and their mean. Then we calculated the class transition and gain, loss, and stable (Figs, 4-5, Table 1-2). Please see the text in method and result based on this analysis.

Change in Method:

Baseline and forest condition change

We empirically observed the vegetation dynamics from 2000 to 2024, using mean kNDVI relative to the baseline condition in 2000. By leveraging quantiles (Q1, Q2, and Q3), we classified mangrove health into three categories: quantile threshold-based approach (Resilient

(Q3) where $kNDVI > 0.49$, Moderate Resilient (Q2) where $0.39 < kNDVI \leq 0.49$, and Low Resilient (Q1) where $kNDVI \leq 0.39$, based on the raw mean $kNDVI$ of the year 2000), relative to initial year of the study 2000 as baseline. Using this quantile thresholding approach, we classify the annual mean $kNDVI$ from 2000-2024, average from 2001-2024, five-year rolling mean for each year from 2002-2022 and their mean (Fig. 5). By using this classified $kNDVI$ distribution relative to baseline, we assessed class transition and developed maps of stable, gain, and loss in mangrove health from 2001 to 2024 and mean of 2001-2024, five-year rolling mean for each year from 2002-2022 and their mean (Fig. 6, Table 1-2).

Change in Results: (L273-306; L314-344)

To observe the resilience status we followed two methods: quantile threshold-based approach (Weakly Resilient (red; Q1: $kNDVI \leq 0.39$), Moderately Resilient (yellow; Q2 $0.39 < kNDVI \leq 0.49$) and Resilient (green; Q3: $kNDVI > 0.49$), relative to the initial status of 2000 as baseline) and Kendall's tau rank correlation, utilizing three-years, five-years, and seven-years overlapping windows with one-year shifts (see method; Fig. 5, Fig. S5-6). This analysis is crucial for understanding how resilience in mangrove stands changed over time and for identifying areas at risk (Fig. 4-5). The spatiotemporal maps of resilience class show that over the past 25 years, a significant number of forest stands had shifted in their resilience classes from their baseline years and with cyclone severity, mostly towards moderate resilience (Fig. 4, Table 1). For example, from 2007-2009 (cyclones Sidr, Rashmi and Aila), an area of 820.97, 732.54 and 1,138.74 km^2 , respectively, shifted from resilient to moderately resilient, whereas areas of 356.89, 784.68 and 945.04 km^2 , respectively, shifted from moderately resilient to weakly resilient (Table 1). When we considered resilient status maps relative to the baseline year 2000, we found that the lowest resilience loss occurred in 2022 (Fig. 4, Table 1), while maximum resilience loss was recorded in 2009 (2110.52 km^2 ; Fig. 4, Table 1). Significant losses were also observed in 2007 (1189.21, km^2), coinciding with Cyclone Sidr on 7 December 2007, and in 2008 (2056.79 km^2 ; Fig. 4, Table 1). The average resilience loss from 2001-2024 was 606.83 km^2 , based on average $kNDVI$ (Fig. 5, Table 1). Notably, in 2004 and in the years after 2009-2012, more than 1000 km^2 of mangrove forests exhibited reduced resilience every year relative to the baselines of 2000 (Table S1). The Kendall's tau values for other window sizes (3, 5 and 7 years), which were assessed to investigate the robustness of our resilience assessment, are provided as supplementary materials (Fig. 5; Figs. S5-S6). Our analysis revealed that 61.4% (4030.88 km^2) of the studied areas show non-significant Kendall's tau values, suggesting stable conditions. Conversely, 23.6% (988.81 km^2) of mangrove stands exhibited negative Kendall's tau ($p < 0.05$), indicating increased resilience (Fig. 5). However, 15.1% (988.81 km^2) of the areas displayed significant positive Kendall's tau values, indicating resilience loss (Fig. 5). The other two windows of trend analysis also exhibited similar spatial patterns of resilience trends, with slight variations in the percentage and area coverage under neutral, resilience gain and resilience loss categories (Figs. S5-S6). Trend-based resilience analysis depicted a steep resilience decrease from the central to western regions and near terrestrial or northern boundaries, along the coastline. However, the southeastern part of the Sundarbans (southern part of Chandpai and Sharonkhola range) exhibited lower resilience losses (Fig 4). L273-306

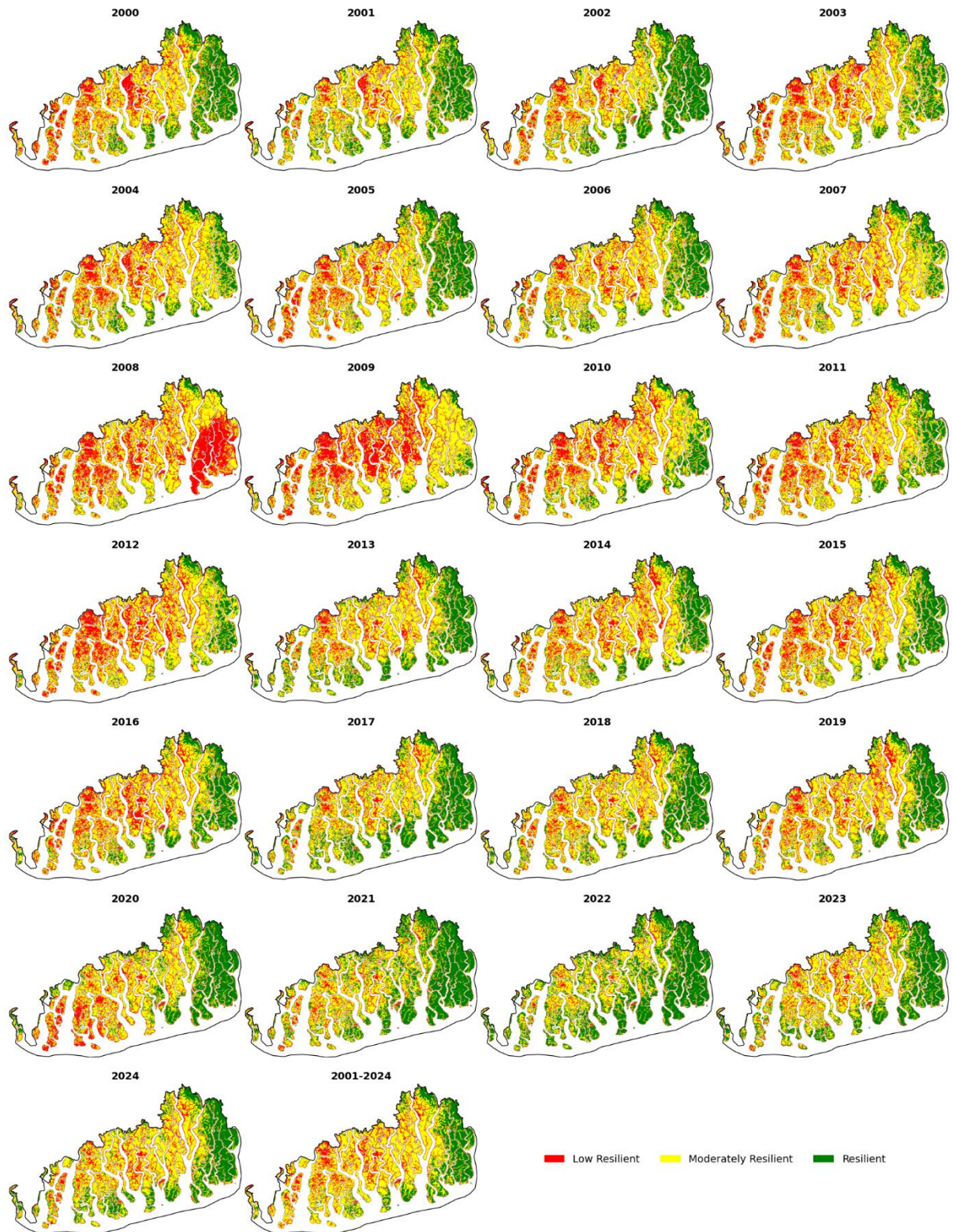


Figure 4: Threshold-Based Vegetation Resilience Classification (2000–2024). Maps categorize vegetation into three resilience classes relative to the baseline (2000) quantile approach: Weakly Resilient (red; Q1: $kNDVI \leq 0.39$), Moderately Resilient (yellow; Q2 $0.39 < kNDVI \leq 0.49$) and Resilient (green; Q3: $kNDVI > 0.49$). Individual years (2000–2024) are shown with bold titles while the bottom-right map depicts spatial patterns of the three-class mean of 2001–2024 and relative to 2000. The black boundary outlines the Sundarbans region.

Table 1. Summary of resilient class transition, total gain and loss from 2001-2024 (annual and mean) relative to baseline year 2000. *R1* Weakly Resilient (red; Q1: kNDVI $\leq$ 0.39), *R2* = Moderately Resilient (yellow; Q2 $0.39 < \text{kNDVI} \leq 0.49$), and *R3* = Resilient (green; Q3: kNDVI > 0.49). These resilience classes are based on the quantile threshold baseline year (2000).

Year	R1 to R2	R1 to R3	R2 to R3	Total Gain	R3 to R2	R3 to R1	R2 to R1	Total Loss	Stable
2001	445.28	11.61	416.74	873.63	281.62	2.49	116.12	400.23	4380.41
2002	424.39	6.01	607.11	1037.51	124.11	2.17	121.47	247.75	4368.4
2003	269.35	6.02	178.37	453.74	592.06	4.93	337.09	934.08	4265.53
2004	275.09	5.96	179.42	460.47	754.64	4.92	336.35	1095.91	4097.34
2005	317.07	3.08	334.86	655.01	324.05	5.69	269.94	599.68	4398.54
2006	396.17	8.89	300.3	705.36	402.76	3.57	205.55	611.88	4336.42
2007	291.43	4.12	145.24	440.79	820.97	11.35	356.89	1189.21	4023.79
2008	211.56	3.25	58.5	273.31	732.54	539.56	784.68	2056.78	3322.86
2009	149.48	5.15	81.99	236.62	1138.74	26.74	945.04	2110.52	3304.63
2010	261.64	9.22	173.44	444.3	753.54	10.05	463.76	1227.35	3981.14
2011	265.55	6.88	168.99	441.42	642.49	11.64	422.49	1076.62	4132.86
2012	212.83	4.66	91.62	309.11	825.01	15.09	610.98	1451.08	3892.27
2013	470.94	31.33	424.74	927.01	336.25	6.49	203.72	546.46	4179.7
2014	369.59	10.23	227.75	607.57	537.82	11.04	342.76	891.62	4154.62
2015	334.4	10.4	209.03	553.83	505.19	8.51	347.7	861.4	4236.87
2016	324.81	10.02	246.47	581.3	489.38	13.85	394.26	897.49	4170.15
2017	573.48	42	711.98	1327.46	242.79	6.17	147.1	396.06	3927.33
2018	504.1	25.94	477.86	1007.9	312.57	8.5	214.61	535.68	4106.51
2019	428.87	16.17	319.55	764.59	397.57	13.7	332.36	743.63	4140.07
2020	514.82	29.06	573.79	1117.67	278.16	27.87	344.43	650.46	3881.75
2021	637.09	42.43	1007.98	1687.5	127.38	10.35	136.14	273.87	3686.49
2022	739.56	98.62	1330.63	2168.81	82.62	7.09	78.61	168.32	3313.72
2023	561.05	47	615.93	1223.98	251.8	11.64	187.34	450.78	3971.95
2024	547.21	31.33	482.4	1060.94	340.06	16.02	233.17	589.25	3997.51
Mean	379.11	1.03	160.43	540.57	430.18	4.55	172.09	606.82	4508.17

Table 2. Summary of, mean resilient class transition and total gain and loss from 2002-2022 (five-years rolling mean and mean) relative to 2000. *R1* Weakly Resilient (red; Q1: kNDVI $\leq$ 0.39), *R2* = Moderately Resilient (yellow; Q2 0.39 < kNDVI $\leq$ 0.49), and *R3* = Resilient (green; Q3: kNDVI > 0.49). These resilience classes are based on the quantile threshold baseline year 2000.

Year (Rolling to)	R1 to R2	R1 to R3	R2 to R3	Total Gain	R3 to R2	R3 to R1	R2 to R1	Total Loss	Stable
2002	283.13	0.27	156.18	439.58	284.14	1.14	113.22	398.49	4817.5
2003	323.28	1.14	200.04	524.45	317.15	1.84	143.66	462.65	4668.46
2004	310.4	1.3	181.37	493.07	348.55	2	166.59	517.14	4645.36
2005	283.76	0.92	114.42	399.1	559.23	2.65	214.93	776.82	4479.65
2006	267.16	0.65	80.28	348.09	939.17	4.82	272.81	1216.8	4090.68
2007	231.88	0.87	62.89	295.63	1039.59	6.65	353.51	1399.75	3960.18
2008	226.24	0.98	60.97	288.18	1100.21	9.78	405.99	1515.98	3851.4
2009	199.53	1.14	47.05	247.71	1142.23	13.56	472.5	1628.29	3779.57
2010	186.68	1.3	44.34	232.33	1144.07	13.46	533.13	1690.66	3732.58
2011	243.48	2.39	91.95	337.81	769.64	7.35	403.14	1180.13	4137.62
2012	296.78	3.03	125.96	425.78	596.09	6.98	308.69	911.76	4318.03
2013	313.13	3.74	134.49	451.35	546.95	6.33	292.96	846.24	4357.97
2014	324.75	3.79	144.52	473.06	518.73	5.74	288.5	812.97	4369.48
2015	406.7	6.44	233.57	646.7	398.42	4.76	205.29	608.48	4400.33
2016	414.33	6.11	240.71	661.15	390.61	5.36	207.24	603.21	4390.93
2017	430.71	7.46	267.05	705.22	355.89	6.39	207.26	569.53	4380.44
2018	474.65	8.43	324.16	807.24	317.62	7.69	188.46	513.77	4334.4
2019	547.23	11.94	455.7	1014.86	244.08	7.58	147.62	399.28	4241.15
2020	598.39	15.77	548.28	1162.44	203.66	7.8	130.56	342.02	4151.11
2021	616.78	17.56	570.39	1204.72	197.41	8.4	125.1	330.91	4119.88
2022	644.92	19.34	618.92	1283.18	182.16	8.94	114.94	306.04	4066.18
Mean	351.66	0.92	135.94	488.52	482.03	4.39	192.24	678.66	4488.38



Fig 5. Annual, mean and rolling mean resilient status from 2000-2024, based on the class transition total gain and loss relative to 2000. *R1* = Weakly Resilient (red; Q1: $kNDVI \leq 0.39$), *R2* = Moderately Resilient (yellow; Q2 $0.39 < kNDVI \leq 0.49$), and *R3* = Resilient (green; Q3: $kNDVI > 0.49$). These resilience classes are based on the quantile threshold baseline year (2000). The five-years rolling mean was quantified for 2002-2022: as our study period covers

2000–2024, we were unable to apply a full 5-years rolling window for the boundary years 2000, 2001, 2023 and 2024 due to insufficient adjacent data. L304-344

Change in discussion: L441-454, L468-491

Mangrove ecosystems worldwide are experiencing frequent external pressures—such as warming, rising sea levels, changing precipitation patterns or fluctuating salinity levels—that could affect the resilience of mangrove forests against disturbances, such as tropical cyclones or stressors such as salinity (D. Alongi, 2018; Kirwan & Megonigal, 2013; Mo et al., 2023). In this study, we assessed mangrove resilience against disturbance in the Sundarbans using years of 25 years of MODIS kNDVI data, applying empirical quantile-based thresholding and theoretical recovery rates (λ_{AC1} and λ_{VAR}) alongside biotic and abiotic drivers. Resilience varied spatially and temporally, with the lowest values in seaward zones (from Satkhira to Sharankhola, Bangladesh) and higher resilience near the northern boundary—although Indian Sundarbans mangrove stands showed lower resilience than their Bangladeshi counterparts (Fig. 3; as indicated by red color gradients). Quantiles-based thresholding and a rolling window-based trend analysis revealed significant resilience loss over time, potentially upon increasing environmental pressure, across 11% (607 km²) and 15% (989 km²) of the region, respectively, with a peak decline in 2009 (37%, or 2110 km²) following three consecutive cyclones (Sidr, Rashmi, and Aila). L441-454

For example, southeastern, northern and southwestern areas showed higher recovery rates than the seaward zones (from Satkhira to Sharankhola) in Bangladesh. The northern boundary typically experiences cyclones with lesser intensity, particularly in the Khulna and Chandpai Range, as these regions are located 75-90 km inland off the coastline. Forests in these boundary regions are highly diverse stands with a mixture of fast-growing (*Avicennia officinalis*, *Excoecaria agallocha*), and slow-growing (*Heritiera fomes*, *Bruguiera sexangular*, *Xylocarpus mekongensis*) species (Rahman et al., 2019b; Simard et al., 2019). These species are characterized by great height, with *Excoecaria agallocha* in the northern boundary area developing greater canopy height than those in the seaward and western forest stand typically associated with higher salinity levels^{18,42}. Additionally, southeastern and northern boundary regions receive more freshwater from the Passur and Baleshwar rivers than the western and central parts of the Sundarbans⁴⁹. One notable exception is the low-resilience hotspot located between the southeastern Chandpai range and the Sharankhola range along both the east and west sides of the Shala River (dark red, Fig 3a; light blue, Fig 3b). Despite receiving more freshwater input than the southern and central western zones of the Sundarbans, being dominated by *H. fomes* and *E. agallocha* with greater canopy height and exposed to moderate perturbation frequency, the area unexpectedly exhibits low resilience. The likely reason is exposure to severe cyclones along their central track—most notably Sidr—followed by successive moderate cyclones (Rashmi, Aila, Mora, Bulbul, Amphan; Fig. 2a and 2b). The spatial map of resilience classes (2007-2013) further reveals that it took six years for these regions to regain its baseline resilient class, similar to 2000, underscoring the long-lasting impact of extreme events like Sidr and the compounded stress from tropical cyclones in the lower upstream reaches compared to the Passur and Baleshwar rivers. L468-491

R2.5. With these baseline levels in mind, it would be good to know if any of the regions of the Sundarbans are subjected to greater levels of disturbances (e.g., cyclones) than others, as this would play a role in understanding the condition of these systems at the start of the study.

Answer: Thank you for this suggestion which added a significant strength of our manuscript. Using a well established perturbation detection methods (Smith and Boers, 20022, 2023, published in *Nature climate Change* and *Nature Ecology & Evolution*), we detected perturbation frequency per pixel during 2000-2024, along with cyclone flagged, empirical recovery rate, two disturbance metrics. We also added an example whole process at five points (as recommended by reviewer 3; R3.19), Please see detail below that we added in the method section.

Change in Method: L27-51

Perturbation detection, disturbance metric, recovery rate

We detected perturbation in the residual time series using a moving window approach (Smith et al., 2022). We employed window size 24 (12 month). We use two thresholds: a strict (Smith et al., 2022) (99th percentile) and a less strict threshold (95th percentile). Furthermore, the method may flag non-significant fluctuations, especially in time series lacking strong disturbances. To mitigate this, a minimum amplitude threshold is applied: the raw time series must decrease by at least 0.01 to qualify as a valid perturbation⁶. Further, we employed a Savitsky-Golay filter with 7-point window to reduce high-frequency noise in the resultant derivative time series (Savitzky & Golay, 1964; Smith et al., 2022).

To assess the significant recovery in order to confirm that the system has not turned into an alternative state rather returned to its original state, we performed a two-sample Kolmogorov–Smirnov test ($P < 0.05$) following a dynamic baseline mean of residual kNDVI, one year before from the date of perturbation detection⁸ to subsequent five-year post perturbation. For each valid perturbation, we then find a local minimum in the residual time series with 4-month window to account a potential lag in detection and fit exponential equation for recovery rate assessment. For pixel with multiple perturbation, we took the average recovery rate (Smith et al., 2022). We also added the potential cyclones with 90 days window (Table S6), there were 34 cyclones formed in the bay of Bengal from 2000 to 2024. With the total valid perturbation counts, we develop three disturbance metrics based on average drop, weighted average drop (combine count, decay factor and severity) and baseline-normalized weighted disturbance index (consider baseline vegetation condition; Eq1-3). In all the three disturbances, a higher value indicates higher disturbance.

$$\text{Average drop disturbance index (ADI)} = \text{perturbation count} \times \text{average drop} \quad (2)$$

$$\text{Weighted Disturbance index (WDI)} = \text{perturbation count} \times \text{weighted average drop} \quad (3)$$

Where, Average drop is the mean drop magnitude across all the valid perturbations

$$\text{Weighted drop} = \frac{\sum(\text{drop}_i \times \text{weight}_i)}{\sum \text{weight}_i} \quad \text{with weight} = e^{-\frac{t_i}{365}} \times \frac{\text{drop}_i}{\text{maximum drop}}$$

Change in result: L198-259

Perturbation count and disturbance index

We estimated the perturbation frequency using residual kNDVI after removing long-term and seasonal trend (see the example along with resilience indicators and empirical recovery rate at five locations in Fig. 1a-f, Fig. S1-4) which showed that every location across the Sundarbans experienced at least one significant perturbation in the past 25 years (Fig. 2a). A high number of perturbations spanned sparsely across the Sundarbans with more homogeneous patches were observed in the seaward zone of Khulna range, northern boundary, and northeastern boundary

and central part of Sundarbans. Interestingly, the forest stands between southeastern zone of Chandpai and northwestern zone of Sharankhola range (blue coloured homogeneous patches, Fig. 2a) had 1-2, perturbations. However, those forest stands, the disturbance indices (Disturbance Index-AD and Disturbance Index-WAD; Fig. 2b-c, see method), revealing similar intensity of damage where the perturbation count more than 4 (Fig. 2a-c).

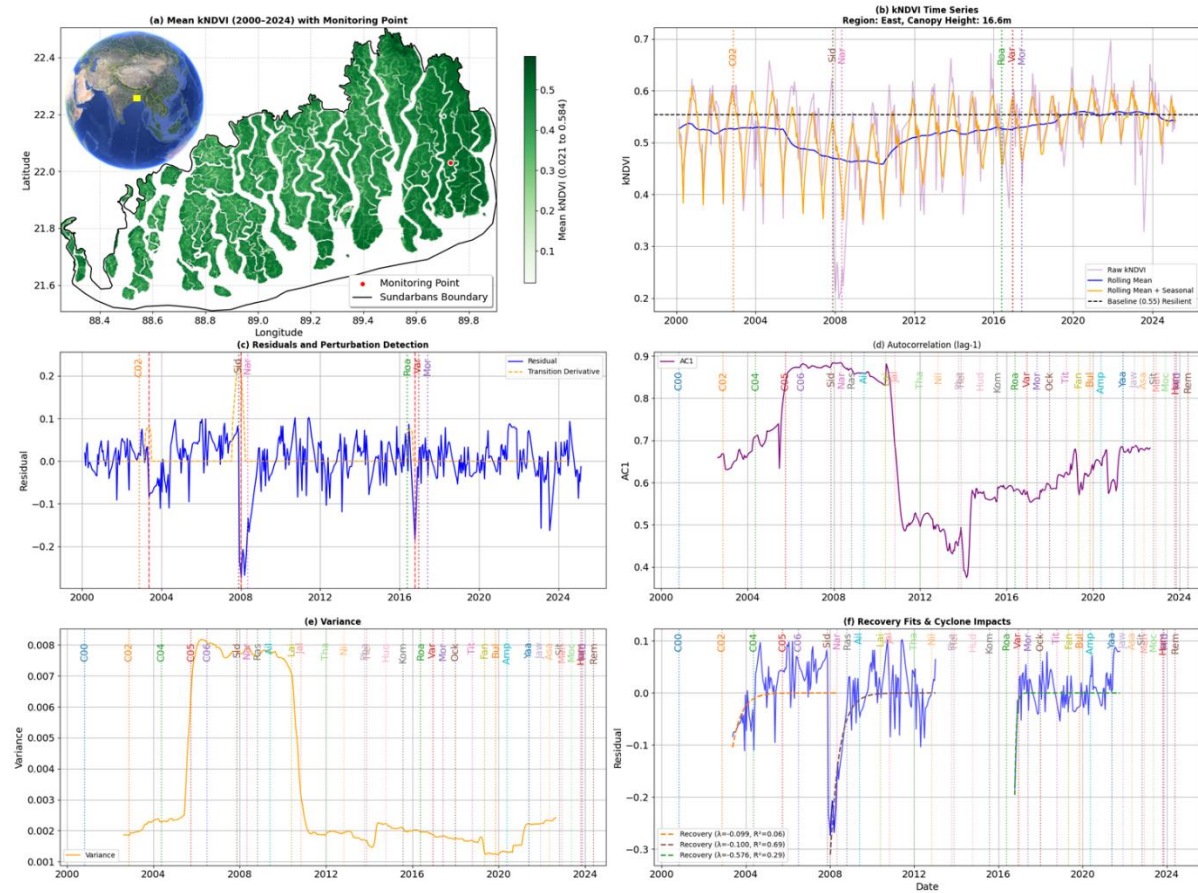


Fig. 1 Vegetation dynamics and resilience indicators in the Sundarbans. (a) Long-term Mean NDVI (2000–2020) in the Sundarbans with monitoring points and boundary; (b) kNDVI time series of particular monitoring sites in the eastern region, showing raw and smoothed kNDVI values, with cyclone impact periods marked; (c) Perturbation detection through 12-months moving windows and 95% thresholding on residual time series, highlighting perturbation periods; (d) Temporal 1-lag autocorrelation of residual kNDVI, signalling the resilience loss or critical slowing down; (e) Variance in residuals captures fluctuations in time series kNDVI with detected perturbations flagged, showcasing critical slowing down; (f) Empirical post-disturbance recovery rate trajectories from local minima, following cyclone impacts, indicating vegetation response and resilience over time. The yellow block in the Google Earth (a) showing the position Sundarbans in the Globe. C00 (Unnamed), C02 (Unnamed), C04 (Unnamed), C05 (Unnamed), C06 (Unnamed), Sid Sidr, Nar Nargis, Ras Rashmi, Ail Aila, Lai Laila, Jal Jal, Tha Thane, Nil Nilam, Pha Phailin, Hel Helen, Hud Hudhud, Kom Komen, Roa Roanu, Var Vardah, Mor Mora, Ock Ockhi, Tit Titli, Fan Fani, Bul Bulbul, Amp Amphan, Yaa Yaas, Jaw Jawad, Asa Asani, Sit Sitrang, Man Mandous, Moc Mocha, Ham Hamoon, Mid Midhili, Rem Remal.

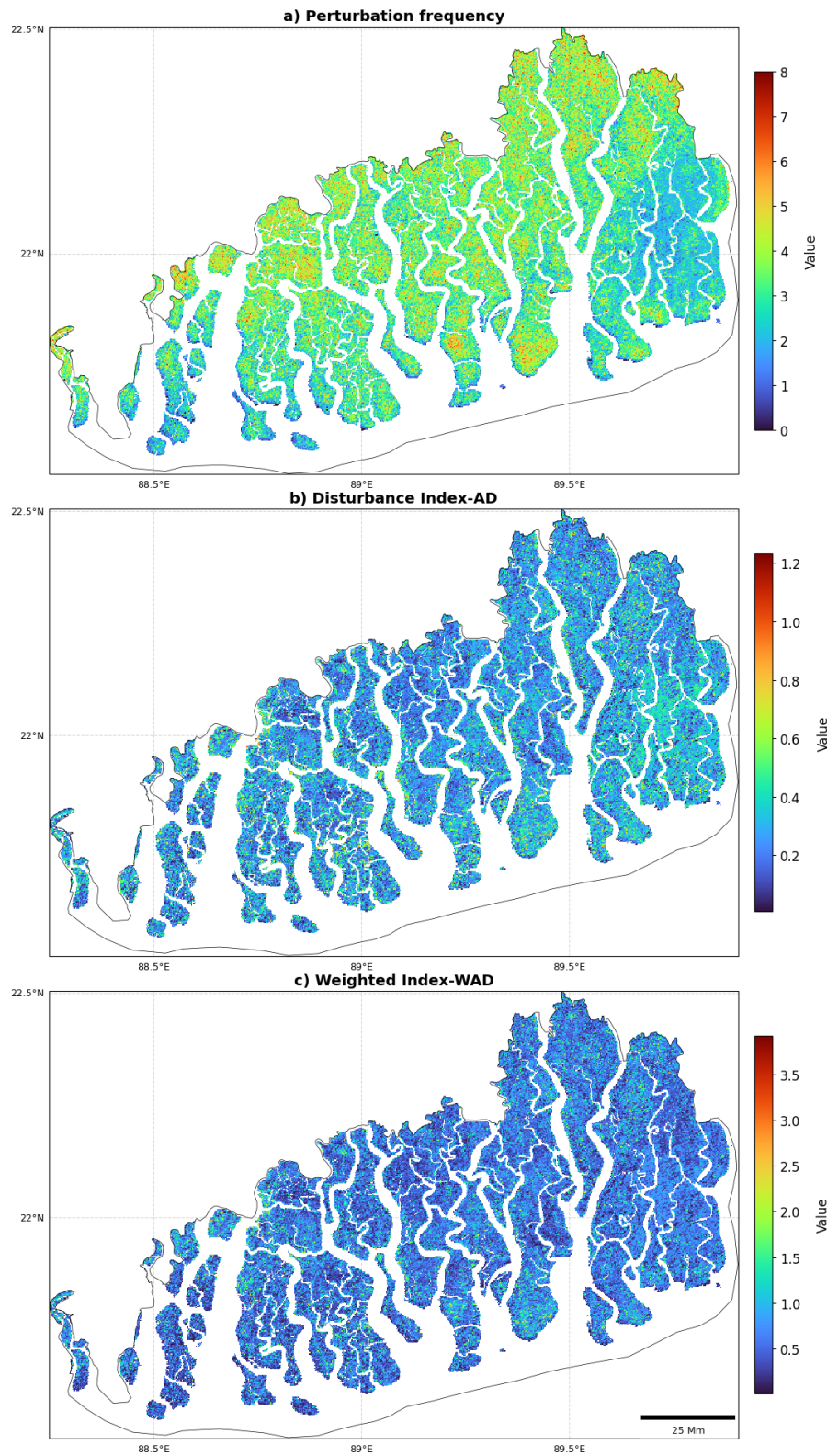


Fig. 2. Spatial pattern of mangrove forest perturbation frequency and damage severity in the Sundarbans. (a) Perturbation frequency map showing the number of disturbance events, with warmer colours (yellow to red) indicating higher frequency; (b) Disturbance Index (AD) -based on the average drop- showing the intensity of disturbance, where red areas represent higher disturbance levels and blue areas indicate lower disturbance; (c) Weighted Index (WAD) – based on weighted average drop, decay factor and time-reflecting cumulative disturbance

impact, with red indicating higher weighted values and blue indicating lower values. White lines denote water channels and geographic boundaries. The consistent layout across all panels allows for comparative analysis of disturbance patterns and resilience gradients within the region.

Change in discussion:

The likely reason is exposure to severe cyclones along their central track—most notably Sidr—followed by successive moderate cyclones (Rashmi, Aila, Mora, Bulbul, Amphan; Fig. 2a and 2b). The spatial map of resilience classes (2007-2013) further reveals that it took six years for these regions to regain its baseline resilient class, similar to 2000, underscoring the long-lasting impact of extreme events like Sidr and the compounded stress from tropical cyclones in the lower upstream reaches compared to the Passur and Baleshwar rivers. L485-491

Our results on the negative direct, indirect and total associations of perturbation frequency (PF), suggest that mangrove forest stands exposed to frequent cyclones, tidal surges and anthropogenic pressures exhibit lower resilience. Severe cyclones typically cause direct physical damage of mangrove trees, including canopy top breakage, uprooting and defoliation^{9,18,19,22,57}. Indirectly, these disturbances alter biogeochemical processes by creating hypersaline condition, increasing the sediment silt content, and elevating sediment pH—all of which are detrimental to mangrove health, productivity and, ultimately, mangrove forest resilience(Krauss & Osland, 2020; Lagomasino et al., 2021; Mo et al., 2023). Increased salinity can render nutrients inaccessible to plant roots or force plants to spend more energy in coping with osmotic stress, thereby weakening their physiological performance(D. M. Alongi, 2008; Ball, 1988; Krauss & Osland, 2020). On the other hand, increased sediment pH, resulting from silt accumulation (Fig. 6) and reduced tidal flushing, can further reduce the availability of essential micronutrients, such as iron and manganese(Krauss & Osland, 2020). This alteration in physicochemical mangrove sediment properties disrupts microbial activity that is critical for nutrient-cycling and organic matter decay, compounding the stress on mangrove ecosystems and diminishing their capacity to recover from disturbance(Pradisty et al., 2021; Quadros et al., 2019). L540-554

R2.6. No large-scale disturbances are taken account within the time frame of the study, in particular cyclones, two major events are noted in the discussion. These will have impacted **the mangrove systems and their potential resilience trends**. I would highly recommend adding cyclone and other major known disturbances into the model, and timings of these events – do multiple events occur in one or more of the 5-year rolling trends of the kNDVI rolling mean? As a declining resilience trend in one area of the Sundarbans could be due to a quick succession of multiple disturbances, where as another area either went unscathed or only received one event and has since been able to recover.

Answer: Thank for this more than important comment. We have detected perturbation at pixel basis. Please see our response to previous comment #R2.5 for relevant change in method, result and discussion. Using the perturbation frequency, and the two-disturbance metrics along with to climatic, soil physical and chemical properties including macro nutrient, and taxonomic, structural, and trait diversity, we developed six SEMs: 3 for λ_{AC1} and 3 for λ_{VAR} (adding separately for three disturbance related variable separately). Interestingly, we have found significant direct and total association of perturbation frequency with resilience. Please also

see our response to first reviewer comment # R1.7, for the changes we have made in results and discussion.

Methods - Forest stand structure and diversity, environmental data

R2.7. “We used ground-measured plot-level data with the number of tree species, their basal area, stem density, maximum tree diameter from the Sundarbans Forest carbon inventory 2010.”

Are you able to provide more details on the methodology of the forest carbon inventory at the start of this section. Are these the 110 permanent plots? What type of plots are they circular, square, are they clustered, and what is the area? I would also like to see on a MAP where all of these plots are, while they may be good for representation of different forest types are the well distributed throughout the entire study site?

Answer: Thank you for your comments and suggestion on inventory plots. We have revised them accordingly to your suggestion. Please see the added text and figure in method below.

We extrapolated the soil physiochemical properties (sediment phosphorus (P), sediment ammonium (NH₄), sediment potassium (K) and sediment sulphide) using field data that was collected by Saker et al.(2021) from 110 permanent sample plots (each plot size 120 × 20 m; Fig. S7) in the Sundarbans, during January – June 2014. (Method; L137-141)

By using the temporary carbon plot shapefile (100 plots, each plot is composed of five 10m radius circular subplots), we extracted the mean soil properties from these spatial maps that were extrapolated from 110 permanent plots (Fig. S7), MODIS derived resilience and Chelsha climatic data (Rahman et al., 2019a, 2015). We used Google Earth Engine's, reduceRegions() function applies ee.Reducer.mean() with a scale of 30 meters to summarize data within each plot geometry (Gorelick et al., 2017). (Method; L143-148)

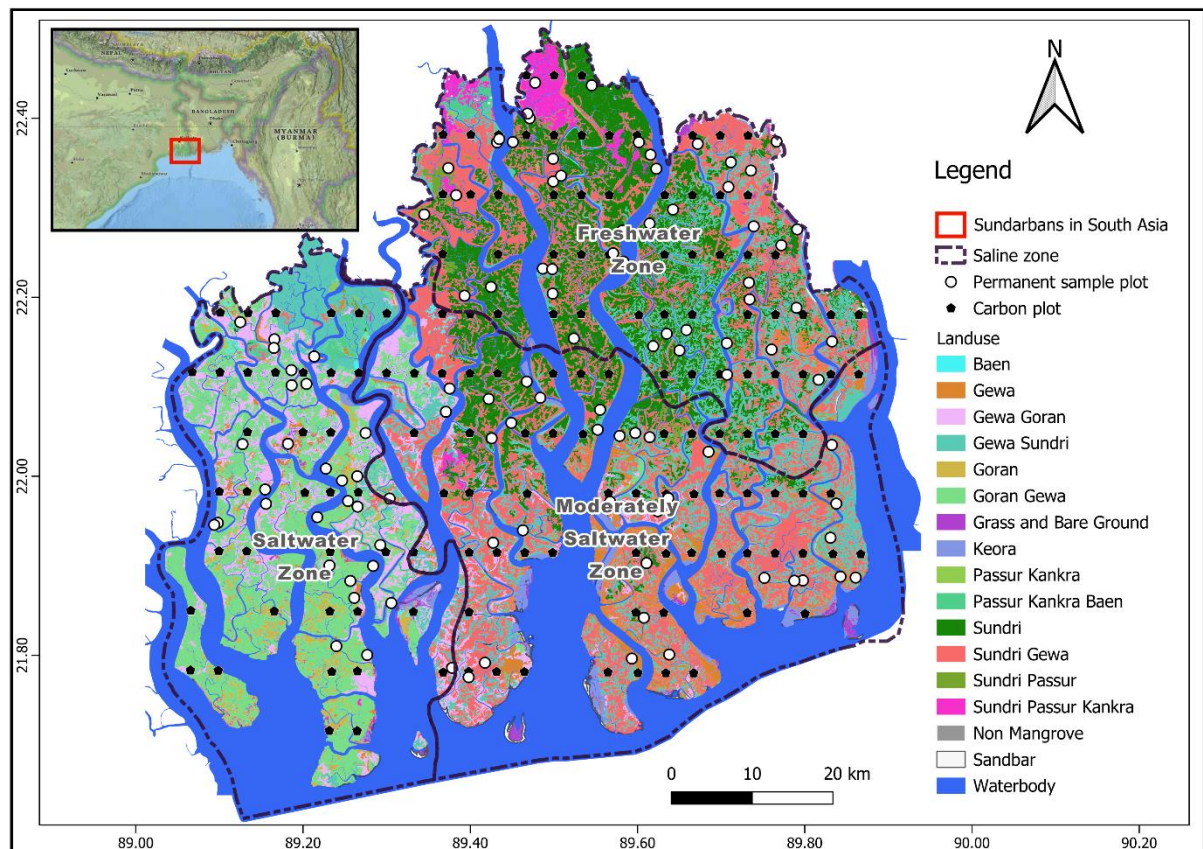


Fig S7. Sundarbans Reserved Forest vegetation with salinity zone, carbon plot and permanent sample plots. Sediment properties were taken from Sarkar et al. 2016, which were surveyed during January – June 2014 at 110 Permanent Sample Plots (white circle) distributed across different vegetation type in Sundarbans. Forest carbon inventory plots (155 plots, five were under water; Black pentagon) also spread across different vegetation types, were collected from Bangladesh Forest Department. The scientific name of species that were shown in the legend as local, are as Sundri, *Heritiera fomes*; Passur, *Xylocarpus mekongensis*; Geowa, *Excoecaria agallocha*; Been, *Avicennia officinalis*, or *A. alba* or *marina*; Goran, *Ceriops decandra*; Keora, *Sonneratia apetala*; Dhundul, *Acanthus ilicifolius* Golpata, *Nypa fruticans* or *Xylocarpus granatum*; Kankra *Bruguiera gymnorhiza* or *B. sexangular*. Map produced in Quantum Geographic Information System (Version 3.40). Open-Source Geospatial Foundation. <https://qgis.org>. Source of Landuse is Centre for Environmental and Geographic Information Services, Bangladesh. The inset image source is Food and Agricultural Organization.

R2.8. “We used the publicly available plant trait data specific for the Sundarbans acquired in recent years. For example, plant trait data, such as leaf traits...”

I don't think these are examples, seems like you list out all traits used. It might be good to have a table here of all the different traits and how you used them within the analyses, such as structural diversity variables, etc.

Answer: We agreed. We have revised the sentence as below.

The seven functional traits that were used in this study (Table S5) belong to three categories: leaf traits (specific leaf area, leaf litter nitrogen, leaf dry matter content, leaf photosynthesis

rate and leaf succulence), stem traits (wood density) and whole plant traits (maximum canopy height) (Quadros & Zimmer, 2017; Rahman, Zimmer, et al., 2021; Sarker et al., 2021; Yakub et al., 1972). (Method, L110-113)

R2.9. “We averaged the leaf litter nitrogen value that were collected by three distinct seasons (monsoon, pre-monsoon, and post-monsoon periods) in the Sundarbans.”

How many leaves were included in the analyses for each of the seasons? Are the seasons distinct months, if so can you identify the months with each of these season?

Answer: Thank you for your comment. For each species (34 species), 30 leaves were collected in the beginning of each season (Chanda et al., 2015). In Sundarbans, the three seasons are pre-monsoon (February to May), monsoon (Jun to September), and post-monsoon periods (October to January). We have revised the text as below:

We averaged the leaf litter nitrogen value that were collected by three distinct seasons pre-monsoon (February to May), monsoon (Jun to September), and post-monsoon periods (October to January) in the Sundarbans(Chanda et al., 2015; Rahman et al., 2015). (Method, L113-115)

R2.10. “The long-term monthly temperature and precipitation data from 1980 to 2010 were averaged for calculating mean annual temperature and precipitation.”

Were data on temperature and precipitation not available for the period of the study, 2000 – 2024?

There is limited overlap in some of the key variable from which you are basing much of your findings on. Especially as you are suggesting rising temperatures in the region, but you don't have the last 14-years of data for the study.

Answer: Thank you for your comment. We have added the temperature after 2010. Please see the change we have made in the method section.

The long-term monthly temperature and precipitation data from 1980 to 2010 and 2011 to 2040, were averaged at pixel based for calculating mean annual temperature (yearly average) and precipitation (yearly total). (Method, L133-136)

R2.11. “We used high resolution (1 km) climatic (mean annual precipitation and temperature) from the Coupled Model Intercomparison Project Phase 6 from CHELSA (<https://chelsa-climate.org/>) maintained by the Swiss Federal Institute for Forest, Snow, and Landscape Research.”

This is repeated within the methods section, can remove from line 75 onwards.

Answer: Thank you. We have removed it.

R2.12. “By using the plot shapefile (100 plots, each plot is composed of five 10m radius circular subplots), we extracted the mean soil properties from these spatial MAPs.”

Are these 100 plots from the forest carbon inventory – is this a typo and should be 110, or have you dropped 10 plots or is this another inventory.

Answer: Please our response R2.2, R2.7, we have already addressed relevant comments and also added new figure in the method section. Please also see below we have revised the section in the method.

Methods – Statistical analysis

R2.13. “We assessed the trends in recovery rate λ using Kendall’s τ with overlapping 5-year windows over 2001-2020”

Is this a typo, should it be 2000 – 2024? Or can you explain why there is a difference in the time periods used.

Answer: Thank for the comment. It would be from 2002-2022, for five-year window. Please see the explanation below that we have revised in our current version.

“We assessed the trends in recovery rate λ using Kendall’s τ with overlapping 5-year windows spanning the period 2002-2022. For example, the window for year 2002 included data from 2000–2004, for 2003 from 2001–2005, and so on, up to 2022, which used data from 2020–2024. As our study period covers 2000–2024, we were unable to apply a full 5-year rolling window for the boundary years 2000, 2001, 2023, and 2024 due to insufficient adjacent data. (Method, L151-156)

R2.14. DBH variation (as a proxy for structural diversity)
Not sure why you used a proxy for structural diversity – from the variables you state in the methods you should be able to get structural diversity from calculating the horizontal diversity (DBH) and vertical diversity (tree height) – see LaRue et al., 2023 <https://esajournals.onlinelibrary.wiley.com/doi/10.1002/fee.2586>.

Answer: We have revised the section in the method. We Please see below.

“With these seven functional trait-based diversity metrics, three disturbance-related variables (Perturbation frequency, Average drop disturbance index (ADI) Weighted Average drop disturbance Index (WDI)) two recovery rate (λ_{ACI} and 2 for λ_{VAR}), species richness as a measure of taxonomic diversity), co-efficient of variation of DBH as a measure of structural diversity (Ali et al., 2016, 2019; Ali & Mattsson, 2017), and eight environmental covariates— sediment sulfide, sediment phosphorus, sediment iron concentration, sediment pH, sediment

texture silt precipitation, temperature and sediment salinity— we conducted six SEMs analysis (Table S3).” (Method, L186-194).

R2.15 I really think that the authors need to provide the reader with a threshold resilience value, which provides a general condition status to the forest, from which the maintenance, gain, or loss of resilience can be assessed, rather than a general trend which does not take into account original status. In light of some of these methodologies issues and wondering how they will influence the outcome of any updated results, I am concluding my review with a focus on the methodology, and would ask the authors to revise the manuscript.

Answer: Thank you for your valuable comments. It has enhanced our manuscript significant. We think, we have addressed all of your comments (Please see the comments, R1.7, R2.2-2.26, for details for specific responses and changes we have made in introduction, method, result, and in discussion). We are now looking for your feedback on our revised version.

Reviewer 3

We sincerely appreciate your thoughtful suggestion and comments. We have taken great care to reflect them in our current version. Below, we are happy to present a detailed point -by-point responses, where the reviewer comments were appeared as black and our responses are highlighted as blue.

Sincerely yours,

Qihao Weng (On behalf of the author team)

Reviewer #3 (Remarks to the Author):

Thank you for inviting me to review this paper. It offers valuable insights into understanding the effects of functional, structural, and taxonomic diversity, as well as environmental factors, on the resilience of mangroves to disturbances. The discussion of niche complementary effect theory is particularly beneficial for the mangrove community. I enjoyed reading this paper, which is relevant to both scientists and practitioners. Below, I have listed several major comments to help authors improve the manuscript's quality.

R3.1 : Title: As resilience was evaluated against historical mean temperature rather than "rising temperature," I recommend that the authors exclude "... against rising temperatures," including "... to disturbances," or keeping only "... Mangrove Resilience."

Answer: Thank you for your comments on title. Based on your, first and second reviewer comments as well as editorial board’s suggestion, we have revised our title as below. Please see the details explanation in our first reviewer’s response section (R1.1).

“Functional composition and Structural Diversity enhance Mangrove Forests Resilience in the Sundarbans.” L1-2

R3.2 Abstract: Please don't use citations in the abstract.

Answer: We have removed the citation from abstract.

R3.3 Line 33: Could the authors provide the percentage of mangroves that showed reduced resilience?

Answer: Thank you for suggestion. In our current version, we have revised it as below.

Approximately 610 to 990 km² (~10-15% of the total Sundarbans area) of mangrove forests exhibited declining resilience. L30-31

R3.4 Line 40: The authors didn't study if the resilience is against climate change or human activities, so I suggest rephrasing it as "resilience against disturbances."

Answer: Thank you for suggestion and we agreed. We have replaced "Climate Change with "Disturbances" (please see below)

"Based on these findings, we hold that for enhancing mangrove forest resilience against disturbances and stressors, (re-)establishment and conservation efforts should focus on maintaining site-specific dominant species with tall canopy height and specific leaf area — supplemented by a few complementary species— to increase structural diversity and facilitate recovery rates. L37-41.

R3.5 Line 42: How can we quantify this "limited" number of other species? The term limited seems very subjective. Could the authors rephrase it?

Answer: Thank you for comment. Please see our response to your previous comment; R.3.4)

R3.6 Keywords: I don't think "Remote Sensing of Mangrove Resilience" is a keyword; maybe remote sensing, MODIS, or kNDVI would work better here.

Answer: Thank you for this valuable comment. We have revised the key words as first reviewer also made similar comment (Please see below).

Remote Sensing, Mangrove Forest resilience, climatic effect, biodiversity, functional traits. L42-43

R3.6 Line 82: I am uncertain if NDVI accurately reflects species richness; could the authors provide a reference for this?

Answer: Thank you for this important comment. We have removed the species richness. It should be productivity.

R3.7 Line 178: "We investigate objective ii, instead of 2".

Answer: Thank you for this comment. We have replaced “2” with “ii”..

R3.8 Figure 1: I think readers would benefit from seeing in Figure 1b the $\lambda_{AC1} / \lambda_{VAR}$ MAP, rather than the histogram, from which the content could be presented in the text.

Answer: Tank you for this valuable suggestion. We have added λ_{VAR} and $\lambda_{AC1} / \lambda_{VAR}$. Please the updated figure in the result below.

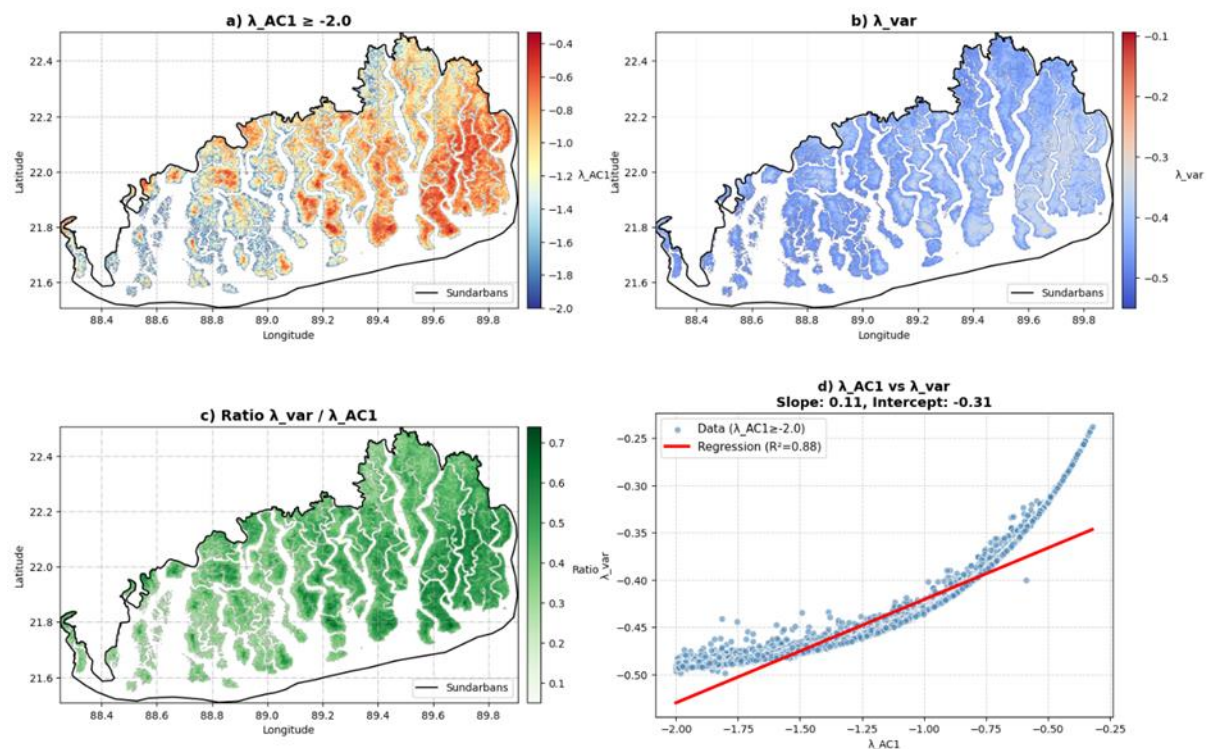


Fig 3. Spatial patterns of mangrove forest resilience indicators (λ_{AC1}) in the Sundarbans. (a) Recovery rate λ_{AC1} , estimated from the 1-lag autocorrelation of pixel-level kNDVI residuals; (b) Recovery rate λ_{var} , derived from the temporal variance decay of kNDVI residuals; (c) The ratio $\lambda_{var} / \lambda_{AC1}$, (d) Scatter plot, indicating a strong spatial similarity between λ_{var} and λ_{AC1} . Forest areas with λ values close to zero exhibit low resilience. L309-313

R3.9 Figure 2: What is the time window used for this figure (Kendall’s tau trend analysis)? Please specify in the caption.

Answer: Thank you for pointing out it. We have revised the caption as below. Also, in response to second reviewer’s similar comment in method, we have explained how we measured rolling mean (please see the response in R2.13).

Fig 5. Annual, mean and rolling mean resilient status from 2000-2024, based on the class transition total gain and loss relative to 2000. *R1* = Weakly Resilient (red; Q1: kNDVI $\leq$ 0.39), *R2* = Moderately Resilient (yellow; Q2 $0.39 < \text{kNDVI} \leq 0.49$), and *R3* = Resilient (green; Q3: kNDVI > 0.49). These resilience classes are based on the quantile threshold baseline year (2000). The five-years rolling mean was quantified for 2002-2022: as our study period covers 2000–2024, we were unable to apply a full 5-years rolling window for the boundary years 2000, 2001, 2023 and 2024 due to insufficient adjacent data. L338-344

R3.10 Figure 2: There are numerous conclusions regarding the spatial relationship between resilience loss and environmental settings. Could the authors provide additional base MAPs that illustrate these environmental settings, as well as the distribution of plots and soil and vegetation characteristics? I find this information is crucial for connecting the results with the authors' discussions and conclusions.

Answer: Thank you for your insightful comment. In the revised manuscript, we have expanded our analysis to include threshold-based resilience classification for each year from 2001 to 2024, as well as the mean resilience relative to the year 2000 using a quantile-based approach (Fig. 4). We have also included updated visualizations of resilience status (Fig. 5 and Table 1-2).

In response to your comment (R3.10), as well as related suggestions from Reviewer 2 (R2.2 and R2.7), we have added a figure illustrating mean kNDVI dynamics (Fig. 1), which captures vegetation changes and resilience indicators for five representative points (Fig. S1-4). Additionally, Fig. 2 now includes perturbation frequency and two disturbance metrics.

To further address your request (R3.21), we have incorporated a detailed study area map (Fig. S7). This map includes vegetation types, salinity zones, carbon inventory plot locations, and soil sample sites. These additions aim to strengthen the spatial context and better connect our results with the environmental settings discussed throughout the manuscript. For further details, please refer to our response to 2nd Reviewer's comment R2.7.

R3.11 Table 1: Could the authors improve the caption for Table 1? What do these results represent? Are they *R* or *R*², or what? The description of the level of significance should also be presented.

R3.12 Additionally, could the authors provide a better explanation of the differences in correlations shown in Figure 4 and Table 1?

E.g. between resilience and MAP? Moreover, what is the resilience metric used here? It's not clear in the results and in the methods as well.

Answer: It was standardized beta based on structural equation model in figure 6. Please see out response to R1.1 for details in result, method to R1.6, also the caption for figure 6 and table two.

Fig 6. Structural Equation Model illustrating the mechanisms connecting biodiversity measures, abiotic factors and resilience (λ_{VAR}). Hypothesized paths with asterisks (***: $P < 0.001$, **: $P < 0.01$, *: $P < 0.05$) indicate significant associations between variables; non-

significant associations ($P > 0.05$) are not shown for the sake of clarity (please see Table 2). The non-significant χ^2 (Chi-Square) of 2.489 ($P = 0.288$), with a goodness of fit index (GFI) of 0.997, with a comparative fit index (CFI) of 0.999 and a standardized root mean square residual of 0.009 suggests no significant deviation from the model and datasets at 2 degrees of freedom. Orange lines indicate negative associations, while purple lines indicate positive associations between covariables. Numbers on the arrows show the standardized associations of predictors with dependent variables. R^2 Coefficient of Determination within the endogenous variables represent their explained variance by all predictors. *MAP* mean annual precipitation, *MAT* mean annual temperature, *SS* sediment salinity, *SR* Species richness, *FCMCH* functional composition of maximum canopy height, *SD* Structural diversity (variation of diameter at breast height), *FCSLA* functional composition of specific leaf area, *FDLS* functional diversity leaf succulence, *P* sediment phosphorus concentration, *SF* sediment iron concentration, *SSF* sediment sulfide concentration, *pH* sediment pH level, *STS* sediment texture silt, *PF* perturbation frequency. L411-427

Table 3: Standardized direct, indirect and total associations of abiotic and biotic drivers with resilience (λ_{VAR}) in the Sundarbans mangrove forest, based on SEM (Figure 6). The SEM model was validated with 1000 bootstrap sampling. L430-431

R3.13 Is it Kendall's tau?

Answer: Yes. Thank you for the comment. We have fixed the typo across the whole manuscript.

R3.14 For what period?

Answer: Thank you for pointing out it. It was for 2002-2022. We have revised the caption. Also, in response to second reviewer's similar comment in method, and your comment R3.9, we have revised the confusion on rolling year issue. Please see the full expiation to the response for R2.13.

R3.15 Line 422: When authors suggest that "greater resilience" is found in "old-growth or mature stands," is there a way to illustrate this? If a MAP isn't available, could there be plots that show the relationship between greater resilience, vegetation, and environmental settings?

Answer: Thank you for your comment. We made this statement in our previous version because functional composition was the main driver, which represent the dominant species while the trait maximum tree height, represent the tallest individual's contribution. If functional composition of maximum tree height has a significant positive and dominant association with any response variable, we can make this type of statement (Finegan et al., 2015; Rahman, Zimmer, et al., 2021). Based on the first and 2nd reviewer comment (adding disturbance metric in SEM), we have tested total 6 SEMs and revised the whole result and discussion. Even though, adding disturbance metrics, and other new environmental variables, the function composition of maximum canopy height and specific leaf area play the stronger role in driving resilience. Please see the also our responses to R1.1, R1.7, R2.5, and R2.6 above.

R3.16 Line 434-435: Please rephrase it.

Answer: Thank you for your suggestion. In our current version, we fully revised the whole discussion based on new resilience and SEM analysis. Please see the also our responses to R1.7, R2.4, and R2.5 above and discussion section.

R3.17 Line 442: The authors mention positive correlations but do not indicate whether these correlations are weak or strong. In both Figure 4 and Table 1, we observe several positive and negative correlations; however, these correlations are generally weak. Could the authors clarify the nature of these correlations throughout the text?

Answer: In our current version, we have revised it across the whole manuscript. For example, “Mangrove forest resilience or recovery from disturbances in the Sundarbans is strongly driven by the functional composition of whole-plant traits and the leaf economic spectrum. Our findings reveal that the functional composition of MCH and SLA qualify as the strongest biotic predictors of mangrove forest resilience in the Sundarbans. This result suggests that the selection effect theory (Finegan et al., 2015; Tilman et al., 2009)—dominant species with their key functional traits drive ecosystem process—is primarily governing mangrove forest resilience in the Sundarbans. L491-494

The moderate total positive association of mean annual precipitation with resilience highlights their pivotal role in mangrove forest resilience. L527-528

R3.18 Line 489: “by climate change and human pressures.”

Answer: Thank you for this suggestion. We have revised it.

“Ultimately, adopting such a strategy will foster multiple ecosystem processes and enhance the resilience of mangrove forest against the growing challenges posed by climate change and human pressures.” L603-605

Method and materials

R3.19 Line 19: Typo of “Kernel”. Please correct it. Please also check throughout the text (and supplemental material) the word “Kendall”, as it was mistyped in many places.

Answer: Thank you for pointing those typos. In our current version, we have meticulously addressed all of those kinds of typos.

R3.20 Lines 22-39: Could the authors please provide a figure that illustrates an example of the time series, along with the smoothing process and potentially the application of the autoregressive model? Additionally, could they clarify the time window for the 1-lag autocorrelation? Is it the 16-day interval between MODIS composites?

Answer: Thank for this more than important suggestion. Now we have added the full time series vegetation dynamics at this location (89.731360, 22.029473, Fig. 1; and four other points, Fig. S2-4). This pixel location is dominated by *Heritiera fomes* with 16m canopy height and belong to Sharankhola Range, in the eastern Sundarbans. In our current, version we have also detected perturbation with cyclone flagging within eight months. Please see the relevant response in first reviewer's comment section (R2.4-R2.6) for the details of the figure and the changes we have made in method, result and discussion.

R3.21 Line 42: Please provide a clearer description of the number of plots, their sizes, and their distribution. It appears that the vegetation data was collected from a different set of plots than the soil data, and this distinction needs to be clearly stated. Could the authors include a figure that displays the spatial distribution of plots from both campaigns/projects? It would be helpful to detail the number of plots, their sizes, and the dates of data collection in the figure caption.

Answer: Thank you for your comments and suggestion on inventory plots. We have revised them accordingly to your suggestion. Please see the second reviewer's response section for similar comments on plot description (R2.2; for Fig S7), the added text below.

A total of 150 plots were surveyed from 5 December 2009 to 30 May 2010(Rahman et al., 2015). Each plot consisted of five 10-meter radius nested subplots. From the central subplot, the other four subplots were 50m (Fig. S7) away towards four-cardinal directions(Rahman et al., 2015). In our current study we 100 plots the remaining 50 plots have either fully under water or subplot with waterbody more than 20% due to presence of small canal or on the bank of the river or big canal (Rahman, Zimmer, et al., 2021; Rahman et al., 2015). L102-107

“We extrapolated the soil physiochemical properties (sediment phosphorus (P), sediment ammonium (NH₄), sediment potassium (K) and sediment sulphide) using field data that was collected by Saker et al.(2021) from 110 permanent sample plots (each plot size 120 × 20 m) in the Sundarbans, during January – June 2014.” L37-141

R3.22 Lines 67 to 69: Please clearly state that the study uses pixel-based historical averages of temperature and precipitation. There is no analysis of climate change or rising temperatures, as far as I can understand. Is that correct?

Answer: We thank for this suggestion. We have revised the sentence.

The long-term monthly temperature and precipitation data from 1980 to 2010 and 2011 to 2040, were averaged at pixel based for calculating mean annual temperature (yearly average) and precipitation (yearly total). L133-136

R3.23 Line 72: size of the plots

Answer: Thank you for comment. Please see the response to your comments R3.21 and (R2.2; for Fig S7).

R3.24 Until line 80: Please clearly describe how the authors harmonized the datasets in time and space (MODIS-derived resilience, Chelsea, and plot-level data).

Answer: Thank you for your comment. In our current version, we have explain it. Please the revised section in methods.

“By using the temporary carbon plot shapefile (100 plots, each plot is composed of five 10m radius circular subplots), we extracted the mean soil properties from these spatial maps that were extrapolated from 110 permanent plots (Fig. S7), MODIS derived resilience and Chelsha climatic data (Rahman et al., 2019a, 2015). We used Google Earth Engine’s, reduceRegions() function applies ee.Reducer.mean() with a scale of 30 meters to summarize data within each plot geometry (Gorelick et al., 2017).” L143-148

R3.25 Lines 82-85: Did the authors validate these results?

Answer: In our current version we have also conducted, threshold-based classification relative to baseline in line with similar comment, of second reviewer comment R2.2 and R2.15. Based on this classification and resilience class transition we have quantified resilience status, rather than only trend-based approach. For average resilience status from 2001-2024, mean kNDVI quartile threshold-based classification relative to baseline 2000, the resilience loss was approximately 606.83 while for five year rolling mean (2002-2022, see method) it was 988.81 km² (~10 -15%). It also highly varied, with severe cyclone years (Fig. 4-5, Table 2). Please see the details methodology, results and relevant discussion in our response to comment R2.2.

R3.26 Line 92: How did the authors define the thresholds?

Answer: Thank you for this comment. In ecology, the most commonly used threshold is 5 or 10 as a cut-off for variance inflation factor. We selected a VIF threshold of 10 to identify problematic multicollinearity, as this is a widely accepted cutoff in ecological studies. This threshold is supported by several key references, including Zuur et al. (2010), who recommend VIF > 10 as an indicator of substantial multicollinearity in regression models commonly used in ecology (*Methods in Ecology and Evolution*, 1:3–14). Similarly, O’Brien (2007) notes that a VIF of 10 balances the need to detect problematic correlations while retaining meaningful predictors in observational studies (*Quality & Quantity*, 41:673–690). Dormann et al. (2013) further endorse VIF thresholds between 5 and 10, with 10 being appropriate for species distribution models to avoid excluding ecologically relevant variables (*Ecography*, 36:27–46). Graham (2003) also supports VIF = 10 in ecological regressions, highlighting that stricter thresholds like 5 may unnecessarily remove biologically important predictors (*Ecology*, 84:2809–2815). Given the correlated nature of our environmental predictors (e.g., NDVI and climate variables), a VIF threshold of 10 ensures robust model stability while preserving ecological interpretability. However, all we have selected 10 as a threshold value, in our final model all the variable had VIF less than 5.5 and our SEMs satisfied also all fit index (Fig. 6, Table S3).

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., ... Lautenbach, S. (2013). Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. *Ecography*, 36(1), 27–46. <https://doi.org/10.1111/j.1600-0587.2012.07348.x>

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Graham, M. H. (2003). Confronting multicollinearity in ecological multiple regression. *Ecology*, 84(11), 2809–2815. <https://doi.org/10.1890/02-3114>

O'Brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality & Quantity*, 41(5), 673–690. <https://doi.org/10.1007/s11135-006-9018-6>

Zuur, A. F., Ieno, E. N., & Elphick, C. S. (2010). A protocol for data exploration to avoid common statistical problems. *Methods in Ecology and Evolution*, 1(1), 3–14. <https://doi.org/10.1111/j.2041-210X.2009.00001.x>

R3.27 Line 97: “..a resilience metric” is too vague. Please describe this metric and how you harmonized it over time with other variables.

Answer: Thank you for your comments. We have revised the sentence as below by specifically mentioning the resilience type.

With these seven functional trait-based diversity metrics, three disturbance-related variables (Perturbation frequency, Average drop disturbance index (ADI) Weighted Average drop disturbance Index (WDI)) two recovery rate (λ_{AC1} and 2 for λ_{VAR}), species richness as a measure of taxonomic diversity), co-efficient of variation of DBH as a measure of structural diversity (Ali et al., 2016, 2019; Ali & Mattsson, 2017), and eight environmental covariates— sediment sulfide, sediment phosphorus, sediment iron concentration, sediment pH, sediment texture silt precipitation, temperature and sediment salinity— we conducted six structural equation models (SEM; Table S3). L170-176

Dear Editor

The authors had revised and improved the manuscript following my comments and suggestions, which were complements with comments and suggestions of other reviewers. The manuscript revision was done in all parts including title, abstract, introduction, methods, and discussion. It looks well and the present form of manuscript is acceptable for publication. However, if it is possible please avoid many repetitions of citation for similar references in the text particularly in the introduction part. There were many other appropriate references can be cited rather than replication of similar citation references.

best regards

Kangkuso Analuddin

Professor in Marine Biology and Wetlands Ecology, Halu Oleo University.

Method and materials

Remote Sensing data source

We used the MODIS (Moderate Resolution Imaging Spectroradiometer) 16 days composite Normalized Difference Vegetation Index (NDVI) dataset (products MOD13Q1 (250 m) product, from February, 2000 to December, 2024. We ensured high-quality pixels in our analysis by using the quality assurance band of QC_250m to exclude pixels affected by cloud cover, cloud shadows, and relevant atmospheric effects. For getting stable forest, we intersected between 2000 and 2024 MODIS annual tree cover percentage (>2). As we used MODIS 250m resolution pixel adjacent or over small rivers or canals usually mixed pixel with reflectance comes from vegetation and waterbody. To remove those pixels from our analysis, we further intersected Landsat of 2000 and 2024 after masking waterbody using a Modified Normalized Water Index with a threshold of 0.3¹. Our analysis was conducted on the Google Earth Engine (GEE) platform², mounted on Google Co-laboratory, providing access to extensive geospatial datasets. We used the most up-to-date vegetation index, the Kernel Normalized Difference Vegetation Index (kNDVI; Equation 1), which is less sensitive to the saturation effect compared to the Normalized Difference Vegetation Index³.

In time series analysis, potential trends derived from seasonal variation and temporal differences can affect the resilience metric⁴. Therefore, before calculating the perturbation detection, disturbance index, empirical recovery rate, theoretical recovery rate and trend analysis we employed two principal methods to detrend the kNDVI dataset to satisfy the assumption of stationarity^{4,5}—the rolling mean, a smoothing technique using a five-year rolling window to remove temporal trends; and harmonic regression, a statistical technique that fits a harmonic model to remove seasonal trends⁴ (Fig. 1).

The Kernel Normalized Difference Vegetation Index (kNDVI) was calculated as

$$kNDVI = \tanh\left(\frac{NIR-RED}{NIR+RED}\right)^2. \quad (1)$$

Perturbation detection, disturbance metric, recovery rate

We detected perturbation in the residual time series using a moving window approach⁶. We employed window size 24 (12 month). We use two thresholds: a strict⁶ (99th percentile) and a less strict threshold (95th percentile). Furthermore, the method may flag non-significant fluctuations, especially in time series lacking strong disturbances. To mitigate this, a minimum amplitude threshold is applied: the raw time series must decrease by at least 0.01 to qualify as a valid perturbation⁶. Further, we employed a Savitsky-Golay filter with 7-point window to reduce high-frequency noise in the resultant derivative time series^{6,7}.

To assess the significant recovery in order to confirm that the system has not turned into an alternative state rather returned to its original state, we performed a two-sample Kolmogorov–Smirnov test ($P < 0.05$) following a dynamic baseline mean of residual kNDVI, one year before from the date of perturbation detection⁸ to subsequent five-year post perturbation. For each valid perturbation, we then find a local minimum in the residual time series with 4-month window to account a potential lag in detection and fit exponential equation for recovery rate assessment. For pixel with multiple perturbation, we took the average recovery rate⁶. With also added the potential cyclones with 90 days window (Table S6), there were 34 cyclones formed in the bay of Bengale from 2000 to 2024. With the total valid perturbation counts, we develop three disturbance metrics based on average drop, weighted average drop (combine count, decay factor and severity) and baseline-normalized weighted disturbance index (consider baseline vegetation condition; Eq1-3). In all the three disturbances, a higher value indicates higher disturbance.

$$\text{Average drop disturbance index (ADI)} = \text{perturbation count} \times \text{average drop} \quad (2)$$

$$\text{Weighted Disturbance index (WDI)} = \text{perturbation count} \times \text{weighted average drop} \quad (3)$$

Where, Average drop is the mean drop magnitude across all the valid perturbations

$$\text{Weighted drop} = \frac{\sum(\text{drop}_i \times \text{weight}_i)}{\sum \text{weight}_i} \quad \text{with weight} = e^{-\frac{t_i}{365} \chi} \frac{\text{drop}_i}{\text{maximum drop}}$$

Resilience

Theoretical studies suggest that complex systems can reach tipping points—critical thresholds that lead to sudden and irreversible changes^{9–11}. As approaching these points, reduced resilience makes systems more vulnerable to shifts from minor, continuous disturbances. These tipping points can be measured through direct observations of slower recovery from perturbations, increased autocorrelation (AC1), and increased variance in the time series kNDVI^{9–11}. We measure resilience as the recovery rate (λ) — the rate at which a system returns to equilibrium following a small perturbation. Under this assumption that local dynamics near equilibrium can be approximated by an Ornstein-Uhlenbeck process, the continuous-time dynamics of deviations X_t from

$$\frac{dX_t}{dt} = \lambda X_t + \sigma \xi_t, \quad (4)$$

where $\lambda < 0$ denotes the recovery rate (higher negative values indicates faster recovery and higher resilience), σ is the noise intensity, and ξ_t Gaussian white noise.

For empirical application, this process is discretized at regular time interval Δt (set to 1 for simplicity), yielding a first order autoregressive (AR1) model

$$X_{n+1} = aX_n + \tilde{\sigma}\eta_n, \quad (5)$$

where X_n is the system state (e.g. kNDVI anomaly) at discrete time step n , $a=e^{\lambda\Delta t}$ is the lag-1 autocorrelation coefficient, $\tilde{\sigma}$ is the standard deviation of the discrete driving noise, and $\eta_n \sim N(0,1)$ is independent white noise.

Thus, from this AR1 model, two independent estimates of recovery rate λ can be derived:

1. From lag-1 autocorrelation⁴ (AC1)

$$\lambda_{AC1} = \frac{1}{\Delta t} \log(\alpha), \quad (6)$$

2. From variance of the time series: The stationary variance of the AR1 process is

$$\lambda_{Var} = \frac{1}{2\Delta t} \log\left(1 - \frac{\tilde{\sigma}^2}{Var[X]}\right), \quad (7)$$

Equation 7 can be solved for λ as below:

$$Var[X] = \tilde{\sigma}^2 \frac{\sigma^2}{1 - e^{2\lambda\Delta t}} = -\frac{\sigma^2}{2\lambda}, \quad (8)$$

These two-recovery rate λ_{AC1} and λ_{VAR} depend only on quantities directly estimate from the observed time series kNDVI: the slope α and residual variance $\tilde{\sigma}^2$ from the linear regression in equation (5), and the total variance $Var[X]$. Under the ideal CSD conditions—stationarity, linearity near equilibrium, and the additive Gaussian noise—the two estimate should approximately similar. Therefore, deviation from one-to-one relationship between λ_{AC1} and λ_{VAR} can be served as diagnostic for the validity of CSD-based resilience estimate from a given time series.

Baseline and forest condition change

We empirically observed the vegetation dynamics from 2000 to 2024, using mean kNDVI relative to the baseline condition in 2000. By leveraging quantiles (Q1, Q2, and Q3), we classified mangrove health into three categories: quantile threshold-based approach (Resilient (Q3) where $kNDVI > 0.49$, Moderate Resilient (Q2) where $0.39 < kNDVI \leq 0.49$, and Low Resilient (Q1) where $kNDVI \leq 0.39$, based on the raw mean kNDVI of the year 2000), relative

to initial year of the study 2000 as baseline. Using this quantile thresholding approach, we classify the annual mean kNDVI from 2000-2024 and average from 2001-2024, five-year rolling mean for each year from 2002-2022 and their mean (Fig. 5). By using this classified kNDVI distribution relative to baseline, we assessed class transition and developed maps of stable, gain, and loss in mangrove health from 2001 to 2024, mean of 2001-2024, five-year rolling mean for each year from 2002-2022 and their mean (Fig. 5-6, Table 1-2).

Forest stand structure and diversity, environmental data

We used ground-measured plot-level data with the number of tree species, their basal area, stem density, maximum tree diameter from the Sundarbans Forest carbon inventory 2010¹². A total of 150 plots were surveyed from 5 December 2009 to 30 May 2010¹². Each plot consisted of five 10-meter radius nested subplots. From the central subplot, the other four subplots were 50m (Fig. S7) away towards four-cardinal directions¹². In our current study we 100 plots the remaining 50 plots have either fully under water or subplot with waterbody more than 20% due to presence of small canal or on the bank of the river or big canal ^{12,13}. To estimate the taxonomic diversity, we counted the total number of species in each plot. We used the publicly available plant trait data specific for the Sundarbans that acquired in recent years¹⁴.

The seven functional traits that were used in this study (Table S5) belong to three categories: leaf traits (specific leaf area, leaf litter nitrogen, leaf dry matter content, leaf photosynthesis rate and leaf succulence), stem traits (wood density) and whole plant traits (maximum canopy height)^{15, 13,14,16,17}. We averaged the leaf litter nitrogen value that were collected by three distinct seasons pre-monsoon (February to May), monsoon (Jun to September), and post-monsoon periods (October to January) in the Sundarbans¹². We used the community mean trait for species whose traits value was not available (relative abundance species < 2%)¹³.

For the functional trait diversity, we used two diversity metrics: functional diversity (functional dispersion; Equation 5) and functional composition (community-weighted mean; Equation 6). We used the FD package in R¹⁸ to calculate both functional dispersion and community-weighted mean where species-wise sum of basal area in a plot was used as weighting factors provided that basal area represents the best contribution of a species in a plot or community¹⁹. The data was log-transformed and standardized to a zero mean and one standard deviation.

$$CWM_{tj} = \sum_{i=1}^S P_{ij} t_i \quad , \quad (9)$$

where CWM_{tj} is the community-weighted mean for particular trait t for the j th plot, S refers to number of species, P_{ij} is the relative contribution to the total basal area of a specific species i for a plot j , and t_i represents average trait value of species i .

$$FDis = \frac{\sum a_j z_j}{\sum a_j} \quad , \quad (10)$$

where a_j is the basal area proxy for abundance of species j , and z_j is the distance of species j to the weighted centroid c , which signifies the centroid of the n species within the trait space.

We used high-resolution (1-km) climatic [observational data from](#) outputs from the Coupled Model Intercomparison Project Phase 6 from CHELSA (<https://chelsa-climate.org/>) maintained by the Swiss Federal Institute for Forest, Snow, and Landscape Research. The long-term monthly temperature and precipitation data from 1980 to 2010 [and 2011 to 2040](#), were averaged [at pixel based](#) for calculating mean annual temperature ([yearly average](#)) and precipitation ([yearly total](#)). For bulk density and organic matter content, we used the Sundarbans Forest carbon inventory data, 2009-2010¹². We extrapolated the soil physiochemical properties (sediment phosphorus (P), sediment ammonium (NH₄), sediment potassium (K) and sediment sulphide) using field data that was collected by Saker et al.¹⁴ from

110 permanent sample plots (each plot size 120×20 m; Fig. S7) in the Sundarbans, during January – June 2014. These datasets cover nearly all forest types of the Sundarbans as the permanent sample plots were laid out based on vegetation types and salinity zones. We used the GEE platform for generating the spatial maps. By using the temporary carbon plot shapefile (100 plots, each plot is composed of five 10m radius circular subplots), we extracted the mean soil properties from these spatial maps that were extrapolated from 110 permanent plots (Fig. 1), MODIS derived resilience and Chelsha climatic data ^{12,20}(Fig. S7). We used Google Earth Engine's, reduceRegions() function applies ee.Reducer.mean() with a scale of 30 meters to summarize data within each plot geometry ²¹.

Statistical analysis

We assessed the trends in recovery rate λ using Kendall's τ with overlapping 5-year windows spanning the period 2002-2022⁴. For example, the window for year 2002 included data from 2000–2004, for 2003 from 2001–2005, and so on, up to 2022, which used data from 2020–2024. As our study period covers 2000–2024, we were unable to apply a full 5-year rolling window for the boundary years 2000, 2001, 2023, and 2024 due to insufficient adjacent data. . A significant positive Kendall's τ means an increase in λ ($P < 0.05$) which indicates a loss of resilience, while a negative Kendall's τ ($P < 0.05$) implies a decrease in λ , and a gain in resilience. Insignificant trends indicate stable conditions. We employed structural equation modelling²² to investigate the independent relationship between covariables and interactive association among them. To satisfy the linearity assumption²³, we used Box-cox transformation and standardized our data at a mean of zero and one standard deviation. As most of the functional diversity and functional composition of different traits were highly correlated, we performed a multicollinearity test for functional composition and functional diversity involving different traits by estimating variance inflation factors with a threshold²⁴ value of 10 that has

been widely used in previous study^{13,25–27}. After VIF analysis, four functional diversity (Table S1) and three functional compositions (Table S2) of different traits were retained with VIF values below 10; these included functional diversity group, specific leaf area, maximum canopy height, leaf succulent, and leaf litter nitrogen, as well as functional composition group, specific leaf area, maximum canopy height and leaf litter nitrogen.

With these seven functional trait-based diversity metrics, three disturbance-related variables (Perturbation frequency, Average drop disturbance index (ADI) Weighted Average drop disturbance Index (WDI)) two recovery rate (λ_{ACI} and 2 for λ_{VAR}), species richness as a measure of taxonomic diversity), co-efficient of variation of DBH as a measure of structural diversity^{25,28,29}, and eight environmental covariates— sediment sulfide, sediment phosphorus, sediment iron concentration, sediment pH, sediment texture silt precipitation, temperature and sediment salinity— we conducted six we conducted six structural equation models (SEM; Table S3). We gradually removed highly correlated variables as well as those with high p-values¹³. Through this approach, from the functional diversity group the leaf area, wood density leaf litter nitrogen and maximum canopy height, while from functional composition group leaf litter nitrogen, were dropped out. Finally, the model fit statistics were satisfied with 14 covariables including species richness, functional diversity of leaf succulence, functional composition of specific leaf area, and maximum canopy height, Diameter at Breast height (DBH) variation, sediment salinity, sediment sulfide, sediment phosphorus, sediment iron concentration, sediment pH, sediment texture silt, perturbation frequency, precipitation and temperature (Fig. 6, Table S3), with final VIF values for all variables below 10 (Table S4).

We evaluated the SEM³⁰ model using four commonly used goodness-of-fit statistics: an insignificant chi-squared value; a goodness of fit index closes to 1; a comparative fit index closes to 1; and standardized root mean square residual (SRMR) nearly zero. This indicates that the model does not significantly deviate from our dataset^{22,30,31}.

We estimated the total association of a predictor by summing its direct and indirect associations through different mediators²². A specific indirect association was estimated by multiplying all the hypothesized paths from that predictor to that mediator²² (to its mediator if the hypothesized paths are available). We constructed the SEM³⁰ in R studio using Lavaan, semPlot, and semTools packages. Additionally, we estimated the indirect and total associations of predictors with endogenous variables in Amos 22. For raster image visualization, we used different R packages³² (sf, raster, ggplot2, dplyr, cowplot, gridExtra, rasterVis).

$$\chi^2 = (N - 1)f, \quad (11)$$

$$CFI = \frac{\max(\chi_0^2 - df_0) - \max(\chi_k^2 - df_k)}{\max(\chi_0^2 - df_0)}, \quad (12)$$

$$SRMR = \sqrt{[\rho^{*-1}(e'W_s e)]}, \quad (13)$$

where χ^2 represents the Chi-square test statistic; CFI stands for Comparative Fit Index; SRMR is the Standardized Root Mean Square Residual; N denotes the sample size; f refers to the minimized discrepancy function; 0 indicates the baseline model; df stands for degrees of freedom; k is the tested or hypothesized model; ρ^* indicates the number of non-duplicated elements in the covariance matrix; e is a vector of residuals from the covariance matrix; s refers to the vector of the ρ^* non-redundant elements in the observed covariance matrix; W denotes the weight matrix; and W_s is a diagonal weight matrix used to standardize the elements of the covariance matrix.

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