We would like to thank the editor for the opportunity to publish our manuscript at EGUsphere and to the nine referees for their thorough evaluations with constructive comments that will improve the manuscript greatly. In the following, we will address the referees' comments point by point. We mark the comments given by the referee in red, provide our answers and comments in black, and indicate how we will address the amendments in the manuscript that we plan to submit upon editor's decision in green. Note, that we add the concrete amendments planned not at all points as this in parts make the replies less readable and only where we will add/adapt a section directly and concisely. In many parts we only conceptually explain how we will adapt content, while the exact implementation remains until the revised version.
We would like to announce that should the manuscript advance to the revision stage; Verena Haring from the Department of Biology at the University of Graz will be included as a co-author in recognition of her valuable assistance with the point-by-point responses.

Tiago Silva, on behalf of all co-authors.

RC2: 'Comment on egusphere-2024-2571', Anonymous Referee #2, 21 Oct 2024

Dear Silva et al. & the editors of Copernicus Biogeosciences,
Thank you for the invitation to review this manuscript. It's a great privilege to contribute to our scientific community. Please see the text below for my review of the manuscript, "Bio-climatic factors drive spectral vegetation changes in Greenland" by Tiago Silva et al. This study seeks to identify bioclimatic drivers of changes in greenness and greenness distribution across Greenlands ice-free terrestrial ecosystem. Understanding the impacts of climate change on this ecosystem is extremely important, particularly in the context of recent studies highlighting changes in vegetation ("Arctic greening") and permafrost dynamics. The authors do a good job summarizing the major points of current literature in these regions and highlighting the importance of their study.
The authors seek to assess these drivers by combining remotely sensed NDVI as observed from AVHRR and VIIRS between 1991 - 2023 with a gridded climate data set, the Copernicus Arctic Regional Reanalysis (CARRA). The authors use Principal Component Analysis (PCA) to identify correlations between "greenness" and a matrix of bioclimatic variables. Additionally, they use non-parametric methods to identify trends in bio-climatic indicators and assess their directionality in magnitude over time across 5 sensibly delineated ecoregion across the terrestrial Greenland ecosystem.

General Comments
I commend Silva et al. for their ambitious analysis of a substantial amount of data from a sensitive ecosystem of broad scientific interest. For this reason, it is my opinion that the study's aim is well suited for the readership of Copernicus Biogeosciences and is an important undertaking. However, I have major concerns about the implementation of methods and the interpretation of results. Most importantly, there is a critical misalignment between the stated goals of the study and the methods used to achieve these goals (as well as the title of the paper).

To summarise my concerns: The authors sought "to gain a deeper understanding of the spatio-temporal patterns of spectral vegetation changes across ice-free regions of Greenland (ln 90)" and "examine the combined effects of bio-climatic indicators ranging from sub-surface factors (such as soil water availability) to above-surface factors (such as the thermal growing season, heat stress, and frost) with summer spectral greenness (ln 91 - 95)." However, the authors provide contradictory statements about the goals of the PCA. Throughout the paper they explicitly state that they use PCA to assess drivers of *changes* in NDVI over time within a pixel, as well as having used PCA to assess drivers in changes of greenness *distribution*. Reviewing the methods and results of the PCA, it seems that the dimensionality reduction algorithm was actually used to assess bio-climate indicators that correlate with average summer spectral greenness ("greenness distribution"). I elaborate on these concerns below.

Specific comments

Major Concerns

Thank you for the comprehensive statement. We will break the explanation of point 1 into several sub-points.

1) There is a critical misalignment between the stated goals of the study and the methods used. In Section 3.4, the authors mention that "PCA was used to investigate the combined influence among bio-climatic indicators on summer greenness _changes_" (ln 249-250; _emphasis added_). However, in the Results section, it is stated that "PCA was used to investigate the combined influence among bio-climatic indicators with summer greenness" (ln 307), which suggests an analysis of greenness levels rather than _changes_ in spectral greenness.

This is a very valid point, and we apologize for having caused confusion. Our intention was the same in both sentences. We recall that the PCA encompasses data since 1991 to 2023. This means that the PCA outcome is a statistical result of the biosphere-atmosphere-cryosphere interaction on the course of the three decades in our study. By colouring each score with its corresponding greenness, we show that the densely vegetated/greenest regions are clustered by the first two principal components because of “the combined influence among bio-climatic indicators with summer greenness”. This result is only achieved by considering the spatio-temporal changes of all bio-climatic indicators, where greenness is included.

This discrepancy is further supported by the caption for Figure 4, which notes that the biplots' scores "are colour-coded based on the summer spectral greenness as in Figure 1," where spectral greenness is defined as the "averaged spectral greenness (based on the period 1991-2023) for June, July, and August."

We apologize for the misunderstanding caused in this specific sentence from the Figure 4 caption. The caption was not meant to indicate that the scores are color-coded based on the summer averaged greenness of 1991-2023, but rather to direct the reader to the greenness scale for better interpretation of the colormap used. In Figure 1 the reader would also recall the omittance of the scale of greenness. Therefore, we will include scales in each sub-panel of Figure 4 and adapt the caption.

Additionally, greenness is included in the PCA but defined differently as "seasonally averaged monthly NDVI," a quantity briefly mentioned in Section 3.1.

Monthly averaged NDVI is used in Figure 1 to show the evolution of spectral greenness in summer in each ecoregion.

In Section 3.1 we state that "we calculated a seasonally averaged NDVI, hereafter referred to as spectral greenness and interchangeably as vegetation." We will revise our text to make the methodology clearer by changing the description in Section 3.2 to: Spectral greenness was compiled for summer months, in order to capture the period with maximum solar radiation in Greenland and to avoid snow cover.

The authors highlight that PC1 and PC2 "largely capture and explain Greenness distribution" (ln 320-321), suggesting a focus on greenness levels rather than changes.

The biplot shows that the scores with high spectral greenness are grouped in areas of low elevation (PC1) with varying degrees of influence in precipitation and snow patterns (PC2). Therefore, the outcome of our PCA not only captures where vegetation prevails but also where vegetation, especially at low laying areas, develops.

It may be possible that the inclusion of "changes" in lines 249-250 was unintentional. However, the broader context suggests that the issue extends beyond a simple wording error. The title ("Bio-climatic factors drive spectral vegetation changes in Greenland"), the abstract (ln 10-15: "GrowDays... emerged as the pivotal factor across all ecoregions...to promote vegetation growth."), and the discussion (e.g., ln 417-419: "Our [PCA] results suggest that in the northern ecoregions, the reduction in soil ice during summer...is enabling vegetation growth, leading to northward expansion of vegetation."

Thanks for highlighting this most important confusion. Indeed, we look both at the state as well as the changes. Our Results aim to investigate spatio-temporal changes in Greenness and its co-variability with atmospheric and snow indicators based on values from 1991 to 2023. The monthly averaged Greenness state is only shown in Figure 1. We will revise our text to make this clearer.

and ln 433-435: "The combined effect of soil nutrients with increased soil water availability in spring (SoilWaterMAM) and T2mMAM, promotes early plant growth. Therefore, leaves are more developed in early summer, which in association with increased T2mJJA and longer periods of solar radiation, allow for greener vegetation.") all imply a focus on changes in greenness values over time.

Our interpretations will be supported by additional references in the revised version.

As the analysis currently stands, PCA is used to assess the variation in climate variables, which is then visually compared to average summer greenness from 1991-2023 with biplots. Separately, the authors explore trends in vegetation expansion using Mann-Kendall tests and thresholds of NDVI between two discrete periods (1991 – 2007 and 2008 - 2023). Despite a lack of generative or predictive models linking these two goals, the authors then interpret PCA loading vectors as "explaining" changes in greenness and greenness distribution. It is also not clear to me how the authors made these interpretations; I speculate this was done by visual comparison of the maps of PCs in the supplementary material with the maps of greenness distribution and greenness change over time in Figure 6.

We hope that with the explanations provided above, it is clearer to the referee how PCA and trend analysis were interpreted. The use of generative or predictive models goes beyond the scope of this study. For that, we would need the output of models

considering sub-surface processes, for example, vegetation and microbial dynamics, to better cover essential aspects for quantitative greenness distribution and the associated changes.
We will combine information of several figures (e.g., Fig. 4 and Fig.6c) to reinforce our results and interpretations.

2) Loading vectors should not be interpreted causally in the way the authors have. While it is true that alignment between two loading vectors indicate correlation and orthogonal vectors are uncorrelated, PCA is a function purely on a matrix of features without explicit regard for response variables. Since PCA is generally used for dimensionality reduction, data compression, or exploratory analysis, its application to infer causal relationships between bio-climatic factors and greenness requires further qualification. If the goal is to assess the relative importance of climate variables on changes in greenness, a causal (or at least an interpretable predictive) model is required.
Thank you for the remark. We agree that Greenness is not a response variable due to the reasons mentioned in point 1. Indeed, causal interpretation is difficult and not justified. Wherever we find evidence that is in line with literature, we will in the revised manuscript more carefully connect the evidence of the PCA with reasoning based on literature.

3) The inclusion of "seasonally averaged" spectral greenness as a feature in the PCA and then coloring the scores in the biplots of Figure 4 based on average summer spectral greenness over the growing seasons (1991-2023) raises concerns about circular reasoning. Further clarification on how this aspect was handled could help alleviate these concerns.
This is a misinterpretation of our analysis, as the PCA is performed for all pixels available in every ecoregion between 1991 and 2023. The corresponding colouring indicates the Greenness of each pixel in a particular year. The co-variability of Greenness with the remaining components is shown on loading vector 6 and the colouring of the scores helps to better understand how Greenness is distributed along PC1 and PC2. We will rewrite the caption and implement scalebars in every subpanel to avoid misunderstandings.

4) Generally, the methods are not described in enough detail. In addition to my confusion about the methods as described above:
4a) I agree with a note from another reviewer, the calibration procedure addressing potential systematic biases between AVHRR and VIIRS NDVI should be elaborated.
The NOAA Climate Data Record (CDR) of AVHRR NDVI - Version 5 and the NOAA CDR of VIIRS NDVI - Version 1 are developed by Eric Vermote and colleagues (Vermote et al. 2018 and 2022) for NOAA's CDR Program. Both records have been processed considering the same atmospheric features as in Miura et al. (2012) and both processed records are posterior to Miura et al. (2012) proposed correction. Also, the correction proposed by Miura et al. (2012) is not assessed in polar regions, which may contribute to additional uncertainties.

We follow similar approaches of recent literature (e.g., Madson et al. 2023, Pourmohamad et al. 2024) that make use of the full AVHRR NDVI and VIIRS NDVI without additional corrections. As stated in Section 2.2, Vermote and colleagues for NOAA's CDR Program use MODIS to spectrally calibrate AVHRR (Vermote et al., 2018) and VIIRS (Skakun et al., 2018). As NOAA does not provide an overlapping period for AVHRR and VIIRS, we are unable to compare both processed products and quantify biases in polar regions. Nevertheless, we will make sure that we add to the discussion that the potential mismatches between AVHRR and VIIRS NDVI products cannot be discarded and, in a revised version we will provide the greenness trends before and after the sensor change in order to assess potential mismatches between sensors, bearing in mind that differences can also rise from other sources such as the interannual variability of the atmospheric conditions before and after 2014.

4b) The calculation of "seasonally averaged NDVI" is somewhat unclear. I assume this involves averaging monthly NDVI across the growing season, but further explanation would be helpful.

Yes, the Spectral Greenness is seasonally averaged monthly NDVI, as described in Section 3.1 and 3.2. We plan to add a more comprehensive explanation of the procedure in the revised version, for instance:

To calculate the NDVI for each month, we started by averaging the NDVI retrievals that we obtained each month ($monthly\ NDVI = \frac{\sum_{i=1}^{n} NDVI_i}{n}$), when NDVI > 0.15. However, before 2014, the AVHRR algorithm was less strict in its data quality control compared to VIIRS from 2014 onwards, which results in more data points (n) before 2014. With n representing the total number of data points per month for NDVI calculation (see Figure S1 for n interannual variability), a higher n previously leads to lower monthly NDVI values.

To address temporal heterogeneities, we adjusted the data from the AVHRR period with the number of data points acquired during the VIIRS period. From 2014 to 2023, we identified the minimum, maximum, and average number of good quality data points for each summer month. Using these three numbers, we were able to generate a consistent variability range for calculating monthly NDVI. Hence, the NDVI values from 1991 to 2013 were recalculated by considering a similar reduction of data points as from 2014 to 2023. Figure 2 illustrates the effect of the range of NDVI values using these recalculations to estimate the interannual vegetation extent. This procedure assumes that the environmental conditions influencing the number of data points between 1991 to 2013 are similar to those between 2014 and 2023.

4c) Given the potential impact of cloud cover and other factors on NDVI observations, more information on how observation frequency (described as "n" in Section 3.1) was used to assess uncertainty and uneven sampling would strengthen the analysis. This seems like it was at least tangentially covered given the brief mention of this in Section 3.1 and the first figure in the Supplementary Materials -- but more explanation of the procedures is needed.

As mentioned in Section 2.2, the climate data record for AVHRR and VIIRS NDVI is available on a daily basis. In addition to the area with the total number of available pixels (Fig. S1), we will provide the already generated maps of the 32-year average and standard deviation of annual number of available observations across ice-free Greenland.

4d) More details on the PCA and Mann-Kendall implementations would also be valuable. For example, when using scikit-learn for PCA, describing the optimizer and input data shape would help ensure transparency, as some solvers are better optimized for particular data configurations. Similarly, the choice of the standard Mann-Kendall test variant in pyMannKendall should be justified, especially regarding serial autocorrelation, which is an important consideration in trend analysis. While MK tests are the current state of the art for landscape-scale analysis like this, pyMannKendall offers options that seek to account for autocorrelation, and discussing whether this was assessed in the data would clarify the robustness of the trend analysis.
Thank you for the request. We did not consider relevant the inclusion of the optimizer and input data shape, but we will promptly add it to the revised manuscript.
We did not consider autocorrelation for the atmospheric and snow variables from summer to summer, but we acknowledge that it should have been considered for greenness. We will address this in the revision.

Minor Concerns & Technical Corrections.
In addition to minor concerns pointed out by another reviewer, there are some instances of speculation that are not supported by the PCA analysis in the results section which should removed, or moved to the discussion section and include citations. These are also specific examples of where I think a inappropriate causal interpretation of loading vectors has occurred (Major Concern 2). For example:

- (ln 326) "The decreasing trend of snow rates (SnowDJF and SnowMAM) has led to SWEMAXDOY to occur earlier. Despite the increasing trend in T2mMAM, the still-low solar elevation and the still-low near-surface air-temperatures result in low melting rates of the snowpack (MeltRate). These slow melt rates favour slow meltwater percolation (SoilWaterMAM loading vector opposite to MeltRate loading vector)."
I think this sentence can remain in the Results since it comes as an interpretation of the resulting seasonal accumulated snow, SWE_MAX DOY, MeltRate and SoilWaterMAM trend maps, together with the PCA loading vectors. We will add all the necessary trend maps supporting our results into the Supplementary Material of the revised manuscript.

- (ln 329) "Additionally, the earlier onset of the thermal growing season allows vegetation to produce energy via photosynthesis, particularly in the ecoregions in lower latitudes with adequate 330 sun exposure (Onset loading vector opposite to Greenness loading vector)."
Thank you for the remark. This sentence will be moved to the Discussion.

- (ln 333) "Therefore, increases of RainRatioJJA promote high greenness (aligned loading vectors), as vegetation in such environmentally harsh places likely developed mechanisms to effectively retain/absorb liquid water whenever possible."

Thank you for the remark. This sentence will be moved to the Discussion.

This sentence is a tautological argument:
(ln 465) "The wide-spread summer spectral greening occurs as a result of greener vegetation as certain sites."
Greening shown in Fig. 6a) occurs for several reasons. In this sentence from the Discussion, we meant to say that greening is essentially occurring in regions that already comprise vegetation (white regions in Figure 6c), whereas in other regions greening is observed due to green vegetation expansion (turquoise regions in Figure 6c).

The importance of solar radiation exposure is described as important in several places, including the conclusions, but are not included explicitly in the PCA or other analyses (ln 327, 435, 534).
The exposure to solar radiation is not considered as the NDVI is only available when there is solar exposure. However, we make use of relevant metrics of the atmospheric circulation patterns in the vicinity of Greenland that promote cloudless conditions (e.g., positive phase of the Greenland Blocking Index, GBI). That is why in Figure 1, we correlated summer greenness with summer GBI, where we report high positive correlations across all ecoregions. Therefore, we cannot discard the role of the interannual variability of atmospheric circulation patterns on greenness, as the previous decade was composed by more frequent cloudless conditions in summer (Silva et al. 2022). We will include additional references in the Discussion regarding this aspect.

Figure 4 - It would be helpful to readers if the PC1 axis was flipped for Ecoregion 2 and 4 so that the quadrants with higher greenness scores were all in the same vicinity in the biplots across Ecoregions.
Thanks for the remark! We will flip the axis for the same orientation across ecoregions.

The color palettes in Figures 5 and 6 rely on a reader's ability to distinguish red and green, which is a common color-blindness.
The colormaps were checked prior to submission following the Copernicus manuscript preparation style and Coblis – Color Blindness Simulator. All figures are supposed to be colour-blind friendly, except for monochromacy.

Grammar checks needed throughout.
Thanks for the remark! We will revise and improve the grammar.

References:

Bengtsson, L., Andrae, U., Aspelien, T., Batrak, Y., Calvo, J., de Rooy,W., Gleeson, E., Hansen-Sass, B., Homleid, M., Hortal, M., Ivarsson, K.-I., Lenderink, G., Niemelä, S., Nielsen, K. P., Onvlee, J., Rontu, L., Samuelsson, P., Muñoz, D. S., Subias, A., Tijm, S., Toll, V., Yang, 575 X., and Køltzow, M. Ø.: The HARMONIE–AROME model configuration in the ALADIN–HIRLAM NWP system, Monthly Weather Review, 145, 1919–1935, https://doi.org/10.1175/MWR-D-16-0417.1, 2017.

Liu, Y.,Wang, P., Elberling, B., and Westergaard-Nielsen, A.: Drivers of contemporary and future changes in Arctic seasonal transition dates for a tundra site in coastal Greenland, Global Change Biology, 30, e17 118, https://doi.org/10.1111/gcb.17118, 2024

Lorenz, E. N. (1956). Empirical orthogonal functions and statistical weather prediction (Vol. 1, p. 52). Cambridge: Massachusetts Institute of Technology, Department of Meteorology.

Madson, A., Dimson, M., Fortini, L. B., Kawelo, K., Ticktin, T., Keir, M., ... & Gillespie, T. W. (2023). A near four-decade time series shows the Hawaiian Islands have been browning since the 1980s. Environmental Management, 71(5), 965-980. https://doi.org/10.1007/s00267-022-01749-x

Masson, V., Le Moigne, P., Martin, E., Faroux, S., Alias, A., Alkama, R., ... and Voldoire, A. (2013). The SURFEXv7. 2 land and ocean surface platform for coupled or offline simulation of earth surface variables and fluxes. Geoscientific Model Development, 6(4), 929-960.

Musselman, K. N., Clark, M. P., Liu, C., Ikeda, K., and Rasmussen, R.: Slower snowmelt in a warmer world, Nature Climate Change, 7, 214–219, https://doi.org/10.1038/nclimate3225, 2017.

Myers-Smith, I. H., Kerby, J. T., Phoenix, G. K., Bjerke, J. W., Epstein, H. E., Assmann, J. J., John, C., Andreu-Hayles, L., Angers-Blondin, S., Beck, P. S., Berner, L. T., Bhatt, U. S., Bjorkman, A. D., Blok, D., Bryn, A., Christiansen, C. T., Cornelissen, J. H. C., Cunliffe, A. M., Elmendorf, S. C., Forbes, B. C., Goetz, S. J., Hollister, R. D., de Jong, R., Loranty, M. M., Macias-Fauria, M., Maseyk, K., Normand, S., Olofsson, J., Parker, T. C., Parmentier, F.-J. W., Post, E., Schaepman-Strub, G., Stordal, F., Sullivan, P. F., Thomas, H. J. D., Tømmervik, H., Treharne, R., Tweedie, C. E., Walker, D. A., Wilmking, M., and Wipf, S.: Complexity revealed in the greening of the Arctic, Nature Climate Change, 10, 106–117, https://doi.org/10.1038/s41558-019-0688-1, 2020

Niwano, M., Box, J. E., Wehrlé, A., Vandecrux, B., Colgan, W. T., & Cappelen, J. (2021). Rainfall on the Greenland ice sheet: Present-day climatology from a high-resolution non-hydrostatic polar regional climate model. Geophysical Research Letters, 48(15), e2021GL092942, https://doi.org/10.1029/2021GL092942

Pearson, K. (1901). LIII. On lines and planes of closest fit to systems of points in space. The London, Edinburgh, and Dublin philosophical magazine and journal of science, 2(11), 559-572 , https://doi.org/10.1080/14786440109462720

Pourmohamad, Y., Abatzoglou, J. T., Belval, E. J., Fleishman, E., Short, K., Reeves, M. C., ... & Sadegh, M. (2024). Physical, social, and biological attributes for improved understanding and prediction of wildfires: FPA FOD-Attributes dataset. Earth System Science Data, 16(6), 3045-3060. https://doi.org/10.5194/essd-16-3045-2024

Salmon, V. G., Soucy, P., Mauritz, M., Celis, G., Natali, S. M., Mack, M. C., & Schuur, E. A. (2016). Nitrogen availability increases in a tundra ecosystem during five years of experimental permafrost thaw. Global Change Biology, 22(5), 1927-1941.

Silva, T., Abermann, J., Noël, B., Shahi, S., van de Berg, W. J., and Schöner, W.: The impact of climate oscillations on the surface energy budget over the Greenland Ice Sheet in a changing climate, The Cryosphere, 16, 3375–3391, https://doi.org/10.5194/tc-16-3375-2022, 2022.

Schmidt, N. M., Reneerkens, J., Christensen, J. H., Olesen, M., and Roslin, T.: An ecosystem-wide reproductive failure with more snow in the Arctic, PLoS Biology, 17, e3000 392, https://doi.org/10.1371/journal.pbio.3000392, 2019.

Schyberg, H., Yang, X., Køltzow, M., Amstrup, B., Bakketun, m., Bazile, E., Bojarova, J., Box, J. E., Dahlgren, P., Hagelin, S., Homleid, M., Horányi, A., Høyer, J., Johansson, m., Killie, 750 M., Körnich, H., Le Moigne, P., Lindskog, M., Manninen, T., Nielsen, E. P., Nielsen, K., Olsson, E., Palmason, B., Peralta, A. C., Randriamampianina, R., Samuelsson, P., Stappers, R., Støylen, E., Thorsteinsson, S., Valkonen, T., and Wang, Z.: Arctic regional reanalysis on single levels from 1991 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS), https://doi.org/10.24381/cds.713858f6, accessed on 15-12-2022, 2020.

Skakun, S., Justice, C. O., Vermote, E., and Roger, J.-C.: Transitioning from MODIS to VIIRS: an analysis of inter-consistency of NDVI data sets for agricultural monitoring, International Journal of Remote Sensing, 39, 971–992, https://doi.org/10.1080/01431161.2017.1395970, 2018.

Vermote, E., Justice, C., Csiszar, I., Eidenshink, J., Myneni, R., Baret, F., Masuoka, E., Wolfe, R., Claverie, M., and Program, N. C.: NOAA Climate Data Record (CDR) of Normalized Difference Vegetation Index (NDVI), Version 5, https://doi.org/10.7289/V5ZG6QH9, access date: 2022-05-06, 2018.

Vermote, E., Franch, B., Roger, J.-C., Murphy, E., Becker-Reshef, I., Justice, C., Claverie, M., Nagol, J., Csiszar, I., Meyer, D., Baret, F., Masuoka, E., Wolfe, R., Devadiga, S., Villaescusa, J., and Program, N. C.: NOAA Climate Data Record (CDR) of Surface Reflectance, Version 1, https://doi.org/10.25921/gakh-st76, access date: 2023-07-06, 2022.

Wilks, D. S. (2011). Statistical methods in the atmospheric sciences. Academic press.