Please find our point-by-point response below. The line numbers refer to the line numbers in the first submission of the manuscript. The review comments are given in blue and our reply in black.

Referee #1

The authors address the vegetation influence on interannual variability of surface energy and carbon fluxes. This topic is important for understanding ongoing land surface and climate changes affecting the water cycle, and related difficulties in numerical modeling. The study includes many sites and ecosystems globally, thus helping to fill some gaps in the literature. However, the manuscript could be revised so as to clarify the scope and generality of the results, and to provide additional analyses needed to support some of the conclusions.

We very much thank the referee for his review and his useful comments to improve the manuscript.

Major comments 1: The authors use LAI as a proxy to describe vegetation state, but the paper is worded more broadly as a critique of how strongly water/energy/carbon fluxes are constrained by vegetation, and specifically stomatal control. It is unclear whether the weak constraint inferred at some sites or ecosystems is due to the LAI proxy missing some aspects of the vegetation influence, or if that influence is in fact negligible for some ecosystems (e.g., deciduous broadleaf forest). There is a practical issue in that LAI is often used where in-situ flux measurements of canopy-scale photosynthesis (of GPP or NEE, or some more direct measure of photosynthesis) are not available, and it is used in models to scale from the leaf to canopy - but land models account for many other aspects of vegetation that affect evapotranspiration beyond LAI. Thus some care is warranted to avoid setting up LAI in a 'straw man' argument. The question and problem statement could be clarified to be more about whether LAI is a good proxy for describing vegetation influences on water/energy fluxes, and when and where it is suitable for that purpose. The study's focus is on interannual variability, but this is not reflected in the title and abstract. The choice of this timescale could also be better motivated in the introduction. We know that the seasonal variation in LAI is important for water/energy fluxes in most ecosystems and climates. The relationship between LAI and water/energy fluxes on interannual timescales is perhaps more subtle given relatively smaller interannual variations in LAI and (potentially) large variations between sites related to water-use efficiency or how efficiently plants use their leaves.

The first major comment raised is that we discuss the vegetation control on water, energy, and carbon fluxes, while we only studied leaf area index (LAI) and LAI does not capture the whole spectrum of vegetation control. The water, energy, and carbon fluxes measured by flux towers are indeed influenced by vegetation through a combination of stomata, vegetation biophysical properties (shadowing, interception, energy distribution), and soil properties. The objective of our manuscript is 'to get an insight about the intrinsic link between vegetation LAI and land-atmosphere exchange of water, energy, and carbon for different vegetation types across an aridity gradient'. Next to the discussion of the link between LAI and these fluxes, we aim to discuss the 'vegetation control' (one paragraph, line 258-267) and how LAI is implemented to model or extrapolate land-atmosphere fluxes (one paragraph, line 269-275). To clarify the text, we propose the following changes:

- Line 19: we changed vegetation into leaf area index
- Line 21: we changed 'vegetation control on' into 'link between leaf area index and'.
- In the paragraph about vegetation control (line 258-267), we changed the first sentences into: 'Our statistical analysis cannot be used to study causality between LAI and surface fluxes, or to study vegetation control on the surface fluxes. The correlation between LAI and water fluxes is confounded by the effect of soil moisture, especially in arid and semi-arid ecosystems, where both canopy development and LE increase with water availability (Kergoat, 1998; Mallick et al., 2018). Similarly, precipitation is the main controller for spatial

variability in both vegetation and GPP (Koster et al., 2014). Furthermore, LAI is related to vegetation properties, but not a direct measure of canopy conductance. Despite, there are similarities..'
- In the conclusions, we deleted the sentence about vegetation and stomatal control (line 286)

Major comment 2: The present study combines interannual variability and site-to-site variability which makes it difficult to interpret the results even when aggregated by ecosystem type. The lack of correlation between LAI and water/energy fluxes at interannual timescales could be due to such site variations. This would ideally be addressed with additional analyses to separate the two factors (site dependence and LAI), or at least could be acknowledged with a strongly worded caveat in the abstract and discussion/conclusions.

The year-to-year variability in surface fluxes and LAI is added to the manuscript. The new figure is an illustration of the link between LAI and fluxes for ten different flux tower sites that have the largest number of available data. The new paragraph and figure are:

'Temporal (year-to-year) variability in LAI and surface fluxes was smaller than spatial (site-to-site) variability (Figure 1). For both SAV sites, and one of the two GRA, EBF, and DBF sites, LAI and LE were positively correlated in time. For H, one EBF site showed a significant negative correlation with LAI, and for EF, and one of the two SAV, GRA, EBF, and DBF sites showed a positive correlation with LAI ($p \leq 0.1$ or $p \leq 0.05$). For GPP

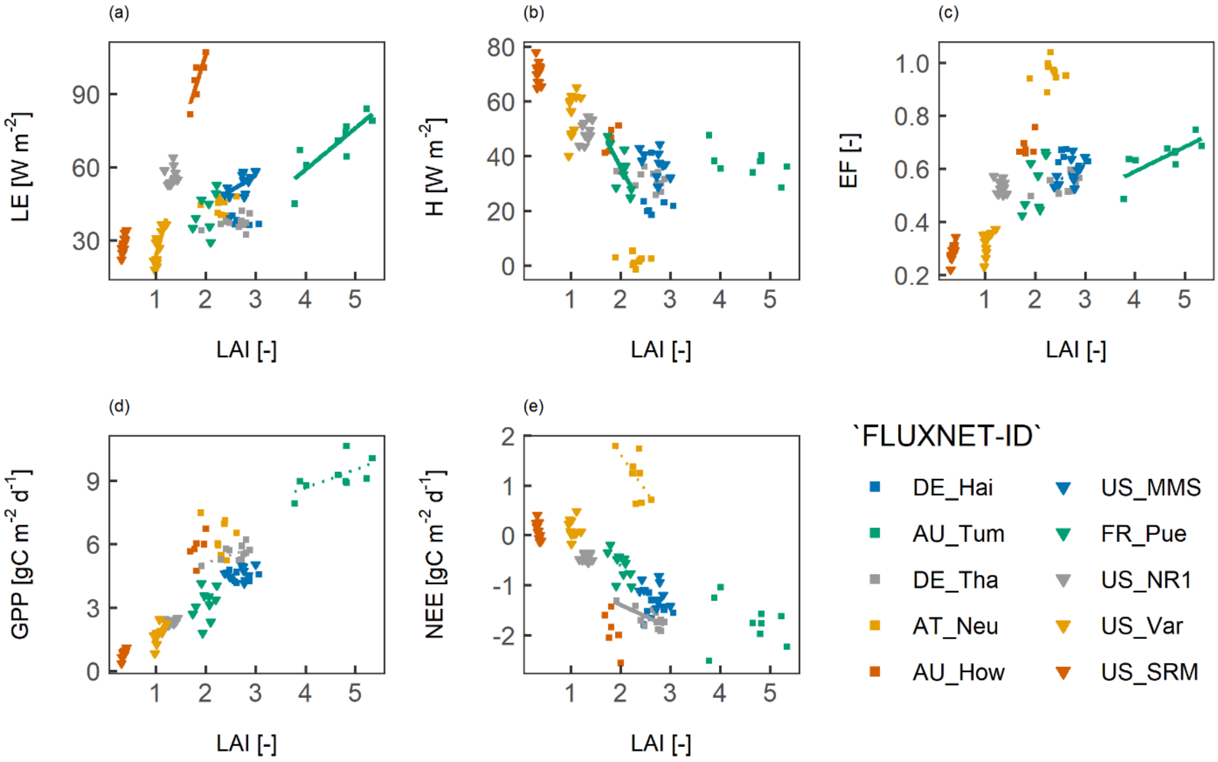

Figure 1 An illustration of the temporal correlation between annual mean surface fluxes and leaf area index (LAI). For each land cover type, two sites were selected that had the highest number of available data. The colours of the symbols indicate the land cover type as in Fig 4 and Fig 5. Panels show (a) the latent heat flux (LE), (b) the sensible heat flux (H), (c) the evaporative fraction (EF), (d) gross primary productivity (GPP), and (e) net ecosystem exchange (NEE). A line indicates a significant correlation at $p < 0.05$ and a dashed line indicates a significant correlation at $p < 0.1$.

and NEE, one of the SAV, GRA, EBF, and ENF sites showed a positive correlation, and for NEE. Overall, the temporal correlations between LAI and surface fluxes was of similar direction as the spatio-temporal and spatial correlations. For more than half of the sites in Figure 1, however, year-to-year variability in LAI and surface fluxes was low and variability in fluxes was not significantly correlated with variability in LAI.'

Line 16: what does 'large-scale' mean in this context?
We realised that 'large-scale' is not the right term to use. Therefore we changed the sentence into 'We aim to study the link between vegetation and surface fluxes by combining MODIS leaf area index with flux tower measurements of water (latent heat), energy (sensible heat), and carbon (gross primary productivity and net ecosystem exchange).' We also removed 'large-scale' from the sentences in line 23, 24, 76, 267, 285, and 291.

Line 21: qualify that this is on annual average or interannual timescales
In line 17 we specified that we study yearly average values.

Line 23: 'insight into'
Changed as suggested

Line 25: As noted above, the conclusion of the study needs as currently stated is more broadly worded than what the results and methods allow. Of course LAI is a necessary variable for modeling in order to scale photosynthesis and transpiration from leaf to canopy, so stating that it is not 'useful' is confusing. It may not be as helpful to consider LAI to be a 'parameter' either (line 64), in the sense of an adjustable factor or tuning knob. It is more like a variable that is either predicted or prescribed in order to model canopy-scale processes such as light interception. More specifically, what the authors seem to be saying is that LAI plays less of a role in explaining interannual variability of annually-averaged fluxes than other variables such as net radiation.
We changed 'parameter' in line 64 into 'variable', thank you for the suggestion. To constrain the conclusion to fit the method and results, we changed the second part of the sentence in: 'LAI is only of limited use in deciduous broadleaf forest and evergreen needleleaf forest to model variability in water and energy fluxes'. The conclusion, L284 is changed into 'This suggests that using LAI to model or extrapolate fluxes of water and energy is well possible in SAV, GRA, and EBF, but is limited in DBF and ENF'.

Line 30: Is the phrase "on the other hand" necessary or appropriate? Maybe "additionally" is more appropriate, since there is not a strong contrast between this sentence and what came before?
Changed as suggested. Furthermore 'on one hand' was removed.

Line 53: Was the cited reference a modelling study, or an analysis of model output?
We clarified that they based the conclusions on remote sensing data and model output.

There are other references in which LAI was experimentally changed in models to show what impact it has on climate predictions, which could also be cited here; for example Boussetta et al. 2013, but there are probably others. Boussetta, Souhail, et al. "Impact of a satellite-derived leaf area index monthly climatology in a global numerical weather prediction model." International journal of remote sensing 34.9-10 (2013): 3520-3542.
Thank you for the suggested reference.

Line 56: "indicative of"
Changed as suggested.

Line 68: The discussion of saturation of NDVI is appreciated and relevant to the interpretation of forest results. There is also potentially a slight nonlinear saturation of the effect of LAI on EF and LH that may explain the weaker correlation between the two on interannual timescales.
We could indeed expect to find a nonlinear saturation of the change in EF and LE with a change in LAI. At high LAI, an unit increase in LAI will correspond to a lower increase in energy availability (because of shadowing) and lower increase in LE as compared to a similar increase in LAI at low LAI. We do however not see this nonlinearity in the results.

Line 76: Again, I'm not sure what 'large-scale' means or what idea about scale the authors are trying to convey. What would be considered small scale? Do you mean canopy scale, as opposed to leaf scale? Flux measurements are not what I consider to be 'large-scale' from a meteorological point of view. Those measurements typically need to be scaled up to be interpreted at the scale of a meteorological model grid cell (100 km).
We realised that 'large-scale' is not the right term to use. Therefore we changed the sentence into 'allows for an analysis of the link between vegetation characteristics and surface fluxes'.

Line 108: "In some land cover types, the surface fluxes and LAI showed seasonal variation." This statement understates the importance of the seasonal cycle. More realistically, most land cover types exhibit some kind of seasonal variation. Some sites may have muted seasonal variations, but even tropical sites have a wet and dry season.
We reworded this sentence into: 'For most sites, the surface fluxes and LAI showed seasonal variation.'

Lines 110-114: I appreciate this discussion of the nonlinearity and what it means to average over the seasonal cycle. However it is still unclear how this coarse-scale temporal averaging affects the results and interpretation. For example, for deciduous broadleaf forests, the winter months are irrelevant for inferring the stomatal control on latent heat flux, so why include those months in the analysis if the goal is to quantify the vegetation influence on fluxes? Are the conclusions (that these sites show little vegetation or stomatal control on annually-averaged heat fluxes, based on correlations) dependent on the fact that for more than half of the year there is no active vegetation present?
The non-growing season might indeed be non-relevant for finding the link between fluxes and vegetation. Using growing season data only, however, created difficulties. The different ecosystems have a different timing and number of growing seasons. Also, for some towers, the growing season did not overlap with the peak in LAI and fluxes. Because of the high variability between flux tower sites, using e.g. time series analyses to extract growing season data was not successful. We prefer to be consistent and use one measure of LAI and fluxes that can be applied to all flux towers, therefore we decided to use mean yearly values. In the methodology we added the sentence: 'The non-growing season might be non-relevant for finding the link between LAI and surface fluxes, however, selecting growing season values only lead to difficulties. The vegetation types differ in the timing, number, and length of growing seasons, and time-series analysis did not successfully select the growing seasons.'

Figure 3 - I'm assuming that there is a mistake and 'arid grassland' should have red markers, and 'humid grassland' should have blue.
We thank the reviewer for pointing out the mistake in colours and we updated the figure.

This figure could be described more clearly and with more information. What is meant by a 'moving window of aridity index'. What exactly do the markers represent? The caption mentions '30 site years...', and the paragraph (Line 165) mentions 'with a minimum of 15 site years for the lowest and highest aridity boundary), and figure itself shows about 20 data points for the humid and 23 for the arid, which is neither 15 nor 30. My best guess is that all the site years were pooled within ecosystem types (mixing different sites into the same pool), and then ranked by aridity index. Then, the correlation between EF and LAI was calculated for the top and bottom 30 most humid and arid site years. But then why are there only 20 or so datapoints?

To clarify the figure and methodology, we adjusted paragraph 2.2 to 'To study the link between LAI and surface fluxes, we performed a linear regression between LAI and the surface fluxes. We calculated the correlation coefficient for 1) site-year data, 2) multi-year average data (spatial variability) and 3) yearly data for a few specific sites (temporal variability). Afterwards, to study if the link between LAI and fluxes changed with aridity, all site-years within one ecosystem type were ranked by aridity, from most arid to most humid. For each consecutive 30 site-years in this ranking, we performed a linear regression between LAI and the fluxes. For some site-years, part of the data was missing that was needed to calculate the regression. Within each window of 30 site-years, the slope of the regression was calculated if at least 15 complete site-years were available (Figure 3).'

Another question is whether the top and bottom years ranked by aridity are dominated by a small subset of sites (i.e., sites with intermediate aridity are not shown in Fig. 3), and what impact the site-to-site variation has on the results. For example, some ecosystems may be more productive or have higher water-use efficiency than others for various reasons (soil type and nutrients, age of stand, amount of photosynthetically active radiation, etc) even within a given ecosystem type (grassland, forest, etc). I suspect that for each site, there is indeed a relationship between LAI and EF, but the slope of that relationship is different for different sites even within the same vegetation type category. Some sites/species use their leaves more efficiently than others. If that were the case, then pooling all of the sites together could result in the weak relationships shown here. The 'all-year averages' shown in Fig. 6 indicate that most of the variation explored here is indeed due to variation across sites and not necessarily due to the variation in LAI alone.

The year-to-year and site-to-site variability is addressed above and included in the manuscript.

Line 171: It would help to know whether this result holds when calculating the correlation separately for each site. Either way, the discussion of these results should mention this issue.

The year-to-year variability is added to the manuscript and addressed above.

Figure 7: Consider better notation such as r(Flux, P) to denote the correlation between the two, and likewise for r(Flux, Rn), and then in the caption specify 'The correlation coefficient (r) between surface fluxes and ...)'.

Changed as suggested

Line 230: There is some good discussion here on the role of canopy interception/evaporation, which one would think would contribute to a stronger relationship between LAI and LH or EF in forests, but as the authors noted this is not the case for temperate and boreal forest in this study. Again, the discussion is good, but it remains unclear why this study finds such a weak relationship and whether this is related to site variability and the chosen interannual timescale. It is also worth noting that the LAI derived from NDVI is "green" leaf area index, which is not necessarily the leaf area that is intercepting rainfall. There may be 'brown' leaves that participate in rainfall interception but result in a smaller 'green' LAI derived from NDVI

From our study we do not show why we find a weak link for temperate and boreal forest, but we do provide a few suggestions. We will adjust the discussion to clarify that we find this result for the site-to-site variability, as well as for the site-year analysis. Also we will add a note about the effect of brown leaves on interception, thank you for the suggestion. This sentence reads 'The high interception evaporation is due to the large leaf area (both green leaves included in the LAI and brown leaves after leaf senescence) with a high canopy water storage capacity and a high turbulence, enhancing fast evaporation'

Referee #2

This article evaluated the link between vegetation and surface fluxes by using MODIS LAI with flux tower measurements of LE, H, GPP and NEE. The analyses are inclusive and comprehensive. This work is crucial to understand the complex relationships of water, energy and carbon fluxes. The article can be published after revisions.

We thank the reviewer for his review and the useful comments to improve the manuscript.

1. The research progress in the effects of AI (or the water conditions) on the measured fluxes can be mentioned in the Introduction.

The aridity index (AI) is an indicator for dryness on yearly timescale. Several studies report vegetation-atmosphere for different climate types, although they do not necessarily include the AI as an indicator of climate. We extended the paragraph (line 47-54) by citing four papers:

'Mallick et al. (2018) showed that vegetation control on evapotranspiration was stronger in arid ecosystems as compared to the mesic ecosystems. Similar results were found for dry and wet Amazonian forest (Costa et al., 2010; Mallick et al., 2016) and dry and wet grassland (De Kauwe et al., 2017)'

2. Are the precipitation data from the flux measurement sites? Or other meteorological sites?

We used the precipitation data delivered with the FLUXNET dataset. This precipitation data is downscaled from the ERA-interim reanalysis data. To clarify this in the document, we changed line 131 to 133 into: 'Meteorological measurements are delivered with the flux tower data. Precipitation data is downscaled from the ERA-interim reanalysis data (Vuichard and Papale, 2015). Net radiation and air temperature are measured at the flux tower and gap filled using the MDS (Marginal Distribution Sampling) method (Reichstein et al., 2005).'

3. What do the different cycles in Fig. 6 represent?

Figure 6 represents the slopes of the scatterplot between LAI and land-atmosphere fluxes. This figure shows the sensitivity of the fluxes to LAI across a broad range of aridity values.

Referee #3

A note upfront from the submitting person: This review was prepared by four master students in geography at the University of Zurich. The review was part of an exercise during a second semester master level seminar on "the biogeochemistry of plant-soil systems in a changing world", which is organized by prof. Dr. Michael Schmidt and myself. We would like to highlight that the depth of scientific knowledge and technical understanding of these reviewers represents that of master students. We enjoyed discussing the manuscript in the seminar, and hope that the comments will be helpful the authors.

We very much thank the students for the review of our manuscript and useful comments, and we thank Marijn van de Broek for uploading the review.

The objective of using the LAI as a predictor for modelling and extrapolation of surface fluxes was thus achieved with reservations and can be used if the limits and uncertainties are taken into account. The research is particularly relevant in the context of climate change, its potential impact on vegetation properties and its influence on the carbon cycle. The text is reader-friendly, the structure is clear and the writing style of the paper is well chosen. We appreciate the broad data set used in the study to support the conclusions, as well as the detailed description of the data source, selection and processing. The authors make clear statements about the aim of the study, the research questions, the hypotheses and the possible results of the analysis. Furthermore, they continuously reflect uncertainties and limitations in the use of methods and indices. In principle, we think that the study fills some knowledge gaps, provides material for further research in this area and should, therefore, be published after some revisions. Below we describe our general comments to the manuscript.

We thank the referees for their assessment.

First of all, we would like to focus on the structure and division of the chapters. In chapter 2, the data part (2.1) was very well explained, whereas the method part (2.2) only got one sentence of explanation. Our advice is to include table 2, which compares the two methods site-year and multi-year average, in chapter 2.2, and to explain there why the site-year method was chosen, to avoid confusions in chapter 3. The restructuring of the text will make it easier to understand which data were used to prove the hypothesis.

Following a suggestion of referee #1, the results section will be extended with analysis on yearly data of a few sites to show the year-to-year variability in surface fluxes and LAI. We like the suggestion to move table 2 to the methods, but given the extra analyses, we believe it is best to keep the table in the results section. In order to clarify the structure of the paper, we added a few sentences to chapter 2.2. These sentences are (line 164) ‘To study the link between surface fluxes and LAI, we performed a linear regression between the surface fluxes and LAI. We calculated the correlation coefficient for 1) site-year data, 2) multi-year average data (site-to-site variability) and 3) yearly data for a few specific sites (year-to-year variability). Afterwards, to study ..’. In this way, chapter 2.2 outlines the structure of the results.

Secondly, the reliability of LAI is questioned. According to the authors, 62.5 % of the MODIS LAI is well estimated when compared to FLUXNET ground measurement data. However, in the remaining third of the data, MODIS LAI overestimated measured LAI on the ground. The question is whether it is reasonable to use MODIS LAI to study the link between vegetation and surface fluxes when LAI is an inaccurate index in determining vegetation characteristics. In this context, we could not find any statement or evaluation of a potential input error for the LAI in the regression model.

MODIS LAI is indeed not the true LAI. None of the satellite derived LAI data products is perfect. MODIS LAI has a few advantages that made MODIS LAI the preferred data product for our study. These advantages include the long record length, the good (and free) data availability, good spatial coverage, and high temporal revisit time. Furthermore, MODIS LAI is frequently used in land-atmosphere studies. The mentioned uncertainties in LAI (e.g. overestimation in some sites and saturation at high LAI) could introduce noise in the LAI data. We do however not expect this noise to change the direction of the regression models or increase the strength of the correlations. To the methodology (line 149) we added: ‘Despite this overestimation, MODIS LAI was used, because it has a long record length, good (and free) data availability, good spatial coverage, and high temporal resolution. The overestimation and saturation of the signal at high LAI could introduce noise in the LAI data. We do however not expect this noise to change the conclusions of our analysis.’

A third point is related to the methods of statistical analyses. Numerous past studies have used linear regression models to describe the relationship between LAI and surface fluxes. However, we partly question this approach, for example for GPP. At some point, there is a trade-off between primary productivity through photosynthesis and transpiration (closing of stomata to avoid dehydration in warmer or drier climates). Given that the stomata close at a certain level of moisture, the photosynthesis rate should slow down. Were the analyses also performed using non-linear models?

The analyses were also performed using non-linear regression models. For almost all surface fluxes, the data showed a linear distribution, and therefore, we decided to use linear regression. We agree that some relations are theoretically non-linear, e.g. LE, that includes soil evaporation, transpiration and interception evaporation, is not expected to increase linearly with LAI at high LAI. In the range of surface fluxes and LAI included in our analyses, however, the relations show as linear.

Finally, maybe a clearer focus and a reduction in factors would improve the comprehension. In general, we think the paper would be easier to understand when either water and energy fluxes or carbon fluxes were investigated and not all of the three. The paper mostly focuses on water and energy fluxes and only a few statements are made for the carbon fluxes. Focusing only on water and energy fluxes would reduce the complexity within the graphs and results.

We thank the reviewers for their comment. We highly value easy-to-understand papers, and we agree that showing water and energy fluxes only would reduce the complexity. Several previous papers focussed on two of the three, and to our knowledge, there is no similar research that combines these different parameters. We believe that it is beneficial to study the water, energy, and carbon fluxes together, as they are coupled. Also, the combined approach shows how the results differ for water and energy fluxes, as compared to carbon fluxes. We do admit that we could discuss the carbon fluxes in more detail. In the introduction we added one reference discussing carbon and we strengthened the discussion regarding carbon dynamics by adding: ‘In contrast to the spatial variability, year-to-year variability in GPP was only in part of the sites correlated to LAI. Water availability is an important driver for temporal variability in GPP (Williams and Albertson, 2004; Kutsch et al., 2008), and GPP is strongly reduced under drought conditions (Vicca et al., 2016). The effect of drought is also visible in reduced LAI, but on a longer time scale of one or two years in forest (Le Dantec et al., 2000; Kim et al., 2017). This different response time to water availability for forest LAI and GPP could partly explain the absence of a temporal correlation for part of the sites.’

Line 103: How is vegetation disease defined? How is diseased vegetation identified (from the ground, remotely)? Why is diseased vegetation excluded? Maybe you could shortly explain your reasoning to justify the exclusion.

Two sites were removed because they were effected by a decade long beetle outbreak that resulted in high tree mortality and one heavily managed grassland site was removed. We clarified this in the manuscript. This information was available from the online site information.

Line 283: We struggle to relate the two main conclusions. In a) it is mentioned that LAI can model fluxes in SAV, GRA and EBF and b) that the link is strong in arid but weak in humid conditions. This raised the question whether this means by implication that the link is not good in humid SAV, GRA or EBF (but as shown in line 252 the link is strong for humid EBF). If the humid EBF is to be an exception, it would be beneficial to have a short sentence about this. Is it possible to assess which factor (land cover or aridity index) is the main driver of the link between LAI and water, energy and carbon fluxes? We suggest framing the conclusion more precisely to minimize such ambiguities.

Since land cover and aridity index are not entirely independent to each other, the two conclusions do go together. SAV is found in arid regions (and shows a strong correlation between LAI and land-atmosphere fluxes) and the different forest types are found in humid regions (and DBF and ENF show a weak or no correlation between LAI and land-atmosphere fluxes). GRA is found both arid and humid regions. For GRA, the relation is strong when all grassland land sites are studied together, but, as fig. 6 shows, the correlation is absent for H and EF when looking at the humid sites only. As mentioned in the conclusions, EBF forms an exception: the correlation is strong due to the probable role of interception evaporation, despite that most sites are found under humid conditions. We do hypothesise aridity to play a role in the strength of the correlation. With our analysis however, we cannot assess whether land cover or aridity is the main driver of the strength of the correlation.

Fig. 2-6: In most figures, the colors are difficult to differentiate, the data points are clustered and the regression lines are difficult to see. The readability of the figures would increase with higher resolution. We recommend using vector graphics (e.g. EPS format).

The resolution of the figures is improved.

Fig. 3: According to our understanding, the colors for arid and humid grassland in the explanation were mixed up. Therefore, we think arid grassland should be in red, humid grassland in blue. Arid grassland is generally characterized by a low evaporative fraction (EF) and a low AI, while the opposite is true for humid grassland. Furthermore, it would also be helpful for the comprehension to have some further explanation for figure 3. We recommend to clearly explain for which reason this correlation was evaluated and how many of the arid and humid grassland were considered to draw the regression line (minimum 15 site-years line 165, 30 sites in caption, 20 data points for humid GRA in figure).

We thank the reviewer for pointing out the mistake in colours and we updated the figure. To clarify the figure and methodology, we adjusted paragraph 2.2 to ‘To study the link between LAI and surface fluxes, we performed a linear regression between LAI and the surface fluxes. We calculated the correlation coefficient for 1) site-year data, 2) multi-year average data (spatial variability) and 3) yearly data for a few specific sites (temporal variability). Afterwards, to study if the link between LAI and fluxes changed with aridity, all site-years within one ecosystem type were ranked by aridity, from most arid to most humid. For each consecutive 30 site-years in this ranking, we performed a linear regression between LAI and the fluxes. For some site-years, part of the data was missing that was needed to calculate the regression. Within each window of 30 site-years, the slope of the regression was calculated if at least 15 complete site-years were available (Figure 3).’

Fig. 7: In the text (line 208) and the caption the abbreviation Rg is used for the shortwave radiation. In the y-axis you use Rn.

Rn in the axis has been changed into Rg.

Table 1: We think the fact that multi-year averaged data is included in the table is confusing since in the caption it is written: ‘for each site, mean yearly LAI & AI are calculated for the included site-years’. In our opinion, it is more consistent (especially because yearly averaged data is used in the analysis) to include mean site-year averaged LAI and AI in the table and put it in the appendix. Otherwise, we advise adapting the caption for the table

The values for LAI & AI are the mean yearly LAI and AI for each site. We calculated the average for all years of data available in the dataset. The caption has been changed to ‘For each site, yearly average leaf area index (LAI) and aridity index (AI) are calculated for all years included in the dataset’.

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Examining the link between vegetation leaf area and land-atmosphere exchange of water, energy, and carbon fluxes using FLUXNET data

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Abstract

Vegetation regulates the exchange of water, energy, and carbon fluxes between the land and the atmosphere. This regulation of surface fluxes differs with vegetation type and climate, but the effect of vegetation on surface fluxes is not well understood. A better knowledge of how and when vegetation influences surface fluxes could improve climate models and the extrapolation of ground-based water, energy, and carbon fluxes. We aim to study the ~~large-scale~~ link between vegetation and surface fluxes by combining yearly average MODIS leaf area index (LAI) with flux tower measurements of water (latent heat), energy (sensible heat), and carbon (gross primary productivity and net ecosystem exchange). We show that the correlation between ~~leaf area index~~LAI and water and energy fluxes depends on vegetation type and aridity. In water-limited conditions, the link between ~~vegetation~~ LAI and water and energy fluxes is strong, which is in line with a strong stomatal or vegetation control found in earlier studies. In energy-limited forest we found no ~~vegetation control~~link between LAI and ~~on~~ water and energy fluxes. In contrast to water and energy fluxes, we found a strong spatial correlation between ~~leaf area index~~LAI and gross primary productivity that was independent of vegetation type and aridity ~~index.~~. This study provides insight into the ~~large-scale~~ link between vegetation and surface fluxes. ~~The study~~It indicates that for modelling or extrapolating ~~large-scale~~ surface fluxes, LAI can be useful in savanna and grassland, but LAI is only of limited use in deciduous broadleaf forest and evergreen needleleaf forest to model variability in water and energy fluxes.

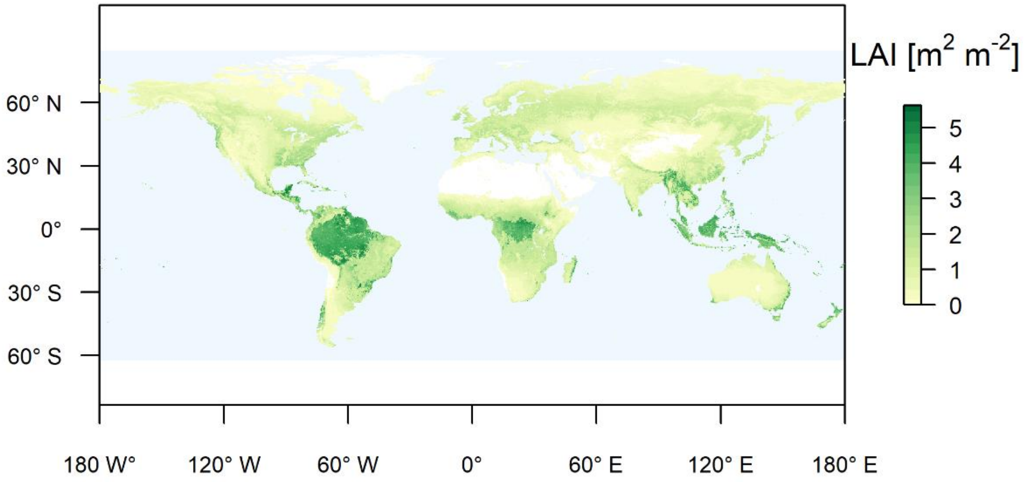
1 Introduction

Vegetation and water, energy, and carbon fluxes are tightly coupled. ~~On one hand, l~~Large-scale vegetation patterns are driven by the long-term memory of water and energy availability (Köppen, 1936; Prentice et al., 1992; Cramer et al., 2001). Recent climate change leads to shifts in the spatial distribution of vegetation, as well as shifts in the timing of the growing season (Jeong et al., 2011; Rosenzweig et al., 2008; Fei et al., 2017). ~~On the other hand~~Additionally, vegetation ~~also~~ plays a crucial role in the exchange of water, energy, and carbon between the land surface and the atmosphere, mainly through its effects on evapotranspiration, turbulence, redistribution of water, and surface heating (Shao et al., 2015; Jia et al., 2014; Esau and Lyons, 2002). Large-scale reforestation and afforestation increased evapotranspiration over most of Europe (Teuling et al., 2019), and large-scale deforestation increased the air temperature in tropical regions and decreased air temperature in boreal regions (Perugini et al., 2017). ~~showed that large-scale changes in vegetation and land cover can have similar impacts on evapotranspiration as climate change.~~ This two-way interaction between vegetation and terrestrial surface fluxes has been known for a long time (e.g. Bates and Henry, 1928; Woodwell et al., 1978), but is still a very relevant research topic today (Forkel et al., 2019; Lu et al., 2019; Teuling and Hoek van Dijke, 2020; Kirchner et al., 2020; Evaristo and McDonnell, 2019), given the importance~~t~~ of understanding the impacts of climate change on vegetation, as well as the effects of land cover change on climate.

Plants regulate the exchange of water, energy, and carbon with the atmosphere through their stomata. The stomatal regulation ~~(stomatal control)~~ of these fluxes depends on available energy, transpiration demand, and available soil moisture in the root zone. When both the available energy and soil moisture are abundant, stomata open and water and carbon can freely move in and out: the stomatal control ~~of~~ on surface fluxes is low. When the available energy is high, but soil moisture is limiting, stomata tend to close and exert a large control on water and carbon fluxes (Mallick et al., 2016; O'Toole and Cruz, 1980). Zooming out from stomatal to canopy scale, there are several other ways in which vegetation influences surface fluxes. Soil and crown mutual shadowing and deep ground water uptake by vegetation influence the latent heat flux whereas soil moisture influences ecosystem respiration and thereby carbon exchange (Chen et al., 2019; Schmitt et al., 2010). The ~~large-scale~~ vegetation control of ecosystem fluxes has been shown by different data or modelling studies and depends on climate and vegetation type (Williams et al., 2012; Xu et al., 2013; Wagle et al., 2015). Williams and Torn (2015) found a strong vegetation control on surface heat flux partitioning in both arid and humid grassland, cropland, and forest, but ~~while~~ Padrón et al. (2017) concluded that globally, vegetation control on evapotranspiration was low and even absent in the equatorial regions.

Chen et al. (2019) showed that for wetland sites, temperature, precipitation and vegetation leaf area explained 91% of the mean annual variability in vegetation carbon uptake. Mallick et al. (2018) showed that vegetation control on evapotranspiration was stronger in arid ecosystems as compared to the mesic ecosystems. Similar results were found for dry and wet Amazonian forest (Costa et al., 2010; Mallick et al., 2016) and dry and wet grassland (De Kauwe et al., 2017). Ferguson et al. (2012) studied land-atmosphere coupling of fluxes, which includes the effect of vegetation as well as other factors as soil wetness, soil texture, and surface temperature. ~~They showed in their modelling study that~~ From remote sensing data and model output, they concluded that transitional zones between arid and humid climates (shrublands, grasslands, and savannas) tend to have a strong land-atmosphere coupling, while in the energy-limited regions, land-atmosphere coupling is weak.

Vegetation is coupled to the atmosphere through its leaves. The leaf area index (LAI) is an important vegetation characteristic and is indicative ~~for~~ of the total amount of foliage that intercepts light and assimilates carbon. Furthermore, both rainfall interception and canopy conductance increase with LAI (Van Heerwaarden and Teuling, 2014; Gómez et al., 2001). A high LAI is therefore related to high vegetation carbon uptake and high canopy evapotranspiration of water (Lindroth et al., 2008; Duursma et al., 2009). Highest mean yearly LAI is found in tropical ~~forests~~and temperate forests, while a low LAI is found in cold ~~or~~ and in arid climate zones (Iio et al., 2014; Asner et al., 2003) (Figure 1). This global LAI pattern closely resembles large-scale patterns in estimates of water, energy, and carbon exchange (Miralles et al., 2011; Jung et al., 2011). With an increasing availability of remotely sensed LAI data, LAI − besides its usage in many remote sensing applications (e.g. Si et al., 2012; Zheng and Moskal, 2009) − became a frequently used ~~parameter~~ variable to represent vegetation in land-surface models



(Williams et al., 2016; Sellers et al., 1997; Lawrence and Chase, 2010 amongst many others) or to estimate or extrapolate regional or global water and carbon fluxes (Beer et al., 2007; Yan et al., 2012; Turner et al., 2003; Xie et al., 2019). The algorithms to retrieve LAI from remotely sensed data improved during the past decades, increasing the accuracy of LAI products (Shabanov et al., 2005; Yan et al., 2016). Nevertheless, it is important to be aware of the product uncertainties, especially over dense forest, where saturated reflectance and canopy clumping can only provide limited information for LAI retrievals (Shabanov et al., 2005; Xu et al., 2018), and at high latitudes, where the solar zenith angle is low (Fang et al., 2019).

The interaction between vegetation LAI and surface fluxes on larger scale is ~~however~~ not yet well understood and vegetation is not well represented in many land-atmosphere and climate models (Williams et al., 2016). A small scale study in temperate deciduous forest, for instance, revealed that the correlation between sap flow and the normalized difference vegetation index (NDVI) can change from positive to negative depending on the season and soil moisture availability (Hoek van Dijke et al., 2019). A detailed knowledge of how and when vegetation LAI is linked to the surface fluxes is required to improve global climate modelling and extrapolation of water and carbon fluxes from canopy to ecosystems. The high availability of remote sensing LAI products, recent developments in cloud-based platforms for geospatial analysis (Mutanga and Kumar, 2019), and the availability of publicly available eddy covariance data from FLUXNET (Baldocchi et al., 2001) allows for an ~~large-scale~~ analysis of the link between vegetation characteristics and surface fluxes. The objective of our study is to get an insight about the link between vegetation LAI and surface fluxes for different vegetation types along an aridity gradient. We address the following research questions: 1) What is the link between LAI versus water, energy, and carbon fluxes in different vegetation types? 2) How is the interaction between LAI versus water, energy, and carbon fluxes governed by climatological aridity? We hypothesise that the link between LAI and surface fluxes is strong in semi-arid and arid climates, owing to the strong stomatal control, while the link is weak in humid climates.

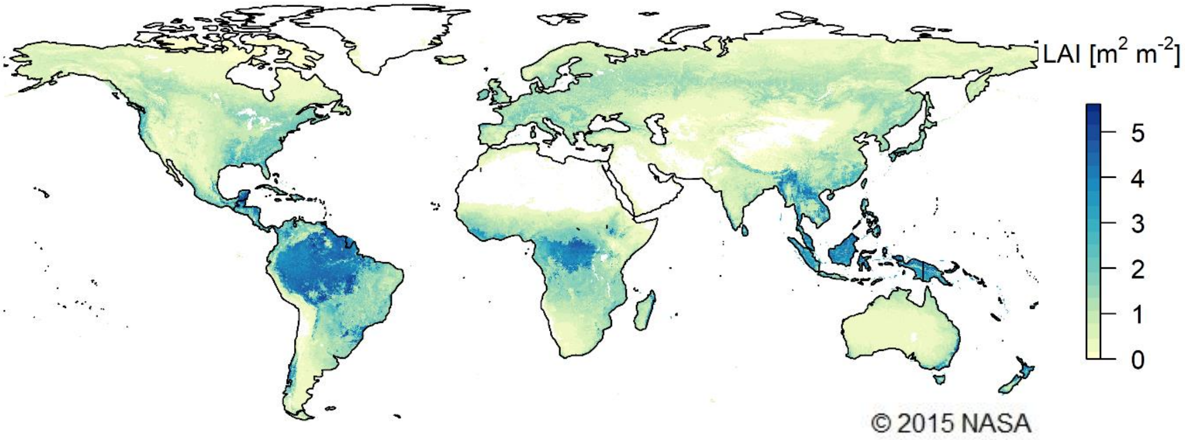


Figure 2 Global distribution of vegetation leaf area index (LAI). The mean LAI, at 5 km resolution, is derived from the MODIS data product MCD15A3H.006 (Myneni et al., 2015).

In our study we focus on five metrics of water, energy, and carbon fluxes measured by flux towers. Latent heat (LE), a measure for the evapotranspiration of water, and sensible heat (H), represent the exchange of water and energy between the Earth's surface and the atmosphere. LE and H are linked through the evaporative fraction (EF). The EF is the ratio of latent heat to the sum of LE and H and is a useful measure of the partitioning of total available energy between the evapotranspiration of water and surface heating. Net Ecosystem Exchange (NEE) is the net exchange of carbon between the land and the atmosphere, which is directly measured by flux towers. Gross primary productivity (GPP) is derived from NEE and is the gross uptake of atmospheric carbon by the vegetation.

2 Data and methodology

2.1 Data

2.1.1 Data selection

This study includes five ~~land cover~~vegetation types: savanna (SAV), grassland (GRA), deciduous broadleaf forest (DBF), evergreen broadleaf forest (EBF), and evergreen needleleaf forest (ENF). The SAV sites include the two classes ‘savanna’ and ‘woody savanna’. These vegetation types follow the International Geosphere-Biosphere Program (IGBP) classification (Loveland et al., 2001). The five ~~land cover~~vegetation types were selected because of the availability of a high number of flux tower sites. For some site-years, LAI, flux, or meteorological measurements were not available. These site-years were included in each of the analyses for which the required metrics were available.

Within the FLUXNET-2015 dataset (Baldocchi et al., 2001), we selected all Tier-1 sites (open and free for scientific purposes) within the five studied ~~land cover~~vegetation types. We completed the dataset with two sites from the OzFLUX network to increase the number of sites in the EBF class (Liddell, 2013a, b). Two forest sites were excluded from the analyses because they were effected by a beetle outbreak that resulted in high tree mortality, and one heavily managed grassland site was excluded from the analysis. ~~A few sites, where vegetation was affected by diseases or pests, were excluded from the analysis.~~ For each site, only years with good-quality data were selected, following the quality selection procedure that is explained below. This site selection procedure, in combination with the quality check, resulted in a dataset of 545 site-years spread over 93 sites (Figure 2, Table 1).

2.1.2 Data averaging and aggregation

We studied yearly averaged LAI and surface fluxes for different vegetation types. In most vegetation types, LAI and surface fluxes showed seasonal variability, with high values during the growing season and lower or zero LAI and surface fluxes during the cold or dry season. The non-growing season might be non-relevant for finding the link between LAI and surface fluxes, however, selecting growing season values only lead to difficulties. The vegetation types differ in the timing, number, and length of growing seasons, and for instance time-series analysis did not successfully select the growing seasons. To be consistent in the methodology, yearly averaged fluxes were used for all flux tower sites. ~~In some land cover types, the surface fluxes and LAI showed seasonal variation.We however used yearly averaged values to be able to combine all the different land cover types with and without one or multiple growing seasons.~~ Using yearly averaged values for every site (referred to as 'site-years') ~~means~~ has few implications ~~that~~ 1) we study both ~~temporal~~ spatial (site-to-site) variability and temporal (~~spatial~~ year-to-year) variability simultaneously, and ~~and~~ 2) averaged flux and meteorological measurements might not represent similar conditions. The latter is for example when a site-year receives plenty of precipitation in December, increasing the site-year's aridity index, while this precipitation mainly impacts the next site-year's fluxes or LAI values. ~~.~~ To test the effect of ~~using site-years~~using site-year data, we also studied spatial and temporal variability separately. For these analyses ~~instead of multi-year averages~~, ~~the data was aggregated in two ways~~the data was aggregated in three ways: 1) Site-year data, having one average value per site per year, ~~and~~ 2) multi-year data,~~temporally aggregated data, referred to as multi-year average data,~~ having one multi-year average~~mean~~ ~~flux~~ LAI and ~~LAI~~ flux value per site~~, averaged over all years~~, to study spatial correlation, and 3) yearly average data for a few sites, to study the temporal correlation. ~~Calculating multi-year average values was done~~Sites were included in the multi-year data if at least three years of data were available. The ~~two~~ three aggregation methods led to similar ~~conclusions~~conclusions for water and energy, but slightly different results for carbon, as is shown in the ~~paper~~manuscript.

2.1.3 Flux measurements

Within the FLUXNET 2015 database, LE, H, NEE, and GPP measurements are gapfilled using the MDS (Marginal Distribution Sampling) method (Reichstein et al., 2005), and LE and H are corrected by an energy balance closure correction factor. The MDS method uses the correlation of fluxes with the driver variables (incoming radiation, temperature, and vapour pressure deficit) to estimate flux values during gap periods. The energy balance closure corrects LE and H for the total incoming radiation, assuming that the Bowen ratio (the ratio of the sensible heat flux to the latent heat flux) is correct. A similar energy balance closure correction was applied to the LE and H measurements of the OzFLUX sites. Monthly averaged flux values were discarded if the percentage of measured and good quality gapfill data was below 50%. Yearly ~~mean~~ average fluxes were calculated if measurements for each month were available. The evaporative fraction (EF), the ratio between LE and the total energy available at Earth's surface was calculated using Eq. (1) as follows:

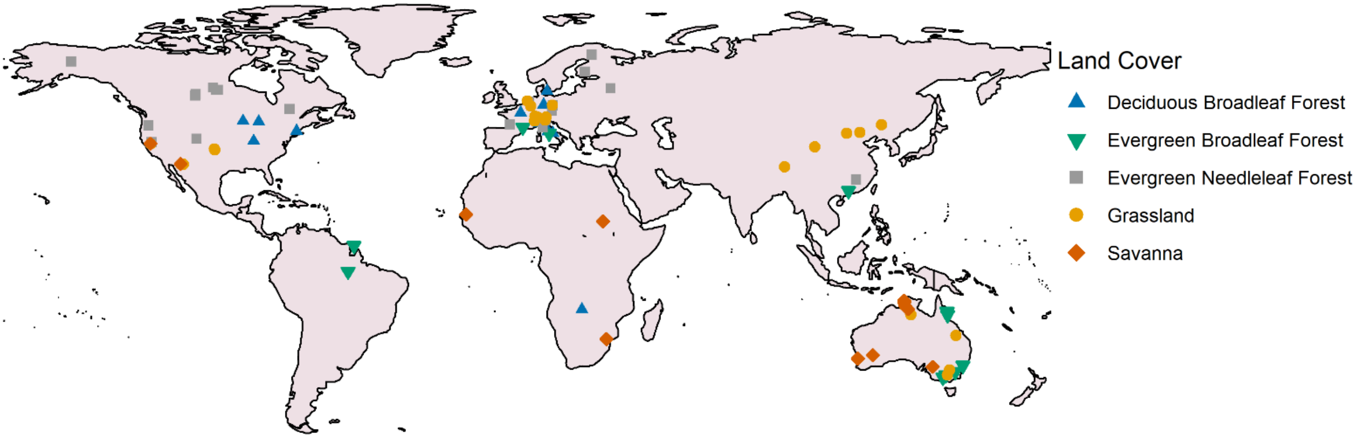


Figure 3 Location and land cover type of the 93 included flux tower sites.

$$EF = \frac{LE}{LE+H}, \tag{1}$$

where LE is the latent heat flux and H is the sensible heat flux.

2.1.4 Meteorological measurements

Meteorological measurements are delivered with the flux tower data. Precipitation data is downscaled from the ERA-interim reanalysis data (Vuichard and Papale, 2015). Net radiation and air temperature are measured at the flux tower and gap-filled using the MDS (Marginal Distribution Sampling) method (Reichstein et al., 2005). ~~These meteorological measurements are measured locally and gap filled using the MDS (Marginal Distribution Sampling)~~

~~method (Reichstein et al., 2005), or are downscaled from ERA-interim reanalysis data (Vuichard and Papale, 2015).~~ Yearly potential evaporation (Ep) was calculated from mean daily air temperature and net radiation using the Priestley-Taylor formulation (Priestley and Taylor, 1972). The Priestley-Taylor equation is a modification of the Penman equation and requires less measurements. The aridity index (AI), an indicator of dryness, was calculated according to Eq. (2)

$$AI = \frac{P}{Ep}, \tag{2}$$

where P is precipitation and Ep is the potential evaporation. An aridity value of one indicates that, on a yearly scale, precipitation equals potential evaporation, while values below one indicate site-years that received less precipitation than their potential evaporation.

2.1.5 Leaf Area Index

Leaf Area Index (LAI) is the ratio of green leaf area to ground area (in m^2 m^{-2}). We used LAI derived from the MODIS data product MCD15A3H.006 (Myneni et al., 2015). This algorithm derives 4-day composite LAI values on 500 m spatial resolution from the Terra and Aqua satellites and is available for 2003 onwards. Within this 4-day period, the best pixel is selected from the MODIS sensors located on the Terra and Aqua satellite for the calculation of LAI. The LAI calculation algorithm uses a Look-up-Table that was generated using a 3D radiative transfer equation (Myneni et al., 2015). Heinsch et al. (2006) compared the MODIS data product with ground measurements at FLUXNET sites and concluded that 62.5% of the MODIS LAI was well estimated, but that MODIS LAI overestimated ground measured LAI for the other sites. Despite this overestimation, MODIS LAI was used, because it has a long record length, good (and free) data availability, good spatial coverage, and high temporal resolution. The overestimation and saturation of the signal at high LAI could introduce noise in the LAI data. We do however not expect this noise to change the conclusions of our analysis. The resolution of the LAI data product is 500 m, compared to a typical flux tower footprint length of 100 to 1000 m (Kim et al., 2006). The exact size and location of the footprint of flux towers however varies with among others wind direction and wind speed, surface roughness, and flux measurement height (Kim et al., 2006; Barcza et al., 2009). For our analyse~~i~~s, we selected the one nearest LAI pixel for each flux tower. Data were filtered to remove clouds, using the with the product delivered quality label. To smoothen outliers, the moving mean LAI was calculated for three consecutive data points. Monthly mean values were calculated if at most one data point was missing. Site-year ~~mean~~ average LAI was calculated when no monthly data were missing.

2.2 Methodology

To study the link between LAI and surface fluxes, we performed a linear regression between LAI and the surface fluxes. We calculated the correlation coefficient for 1) site-year data, 2) multi-year average data (spatial variability) and 3) yearly data for a few specific sites (temporal variability). Afterwards, to study if the link between LAI and fluxes changed with aridity, all site-years within one ecosystem type were ranked by aridity, from most arid to most humid. For each consecutive 30 site-years in this ranking, we performed a linear regression between LAI and the fluxes. For some site-years, part of the data was missing that was needed to calculate the regression. Within each window of 30 site-years, the slope of the regression was calculated if at least 15 complete site-years were available (Figure 3).

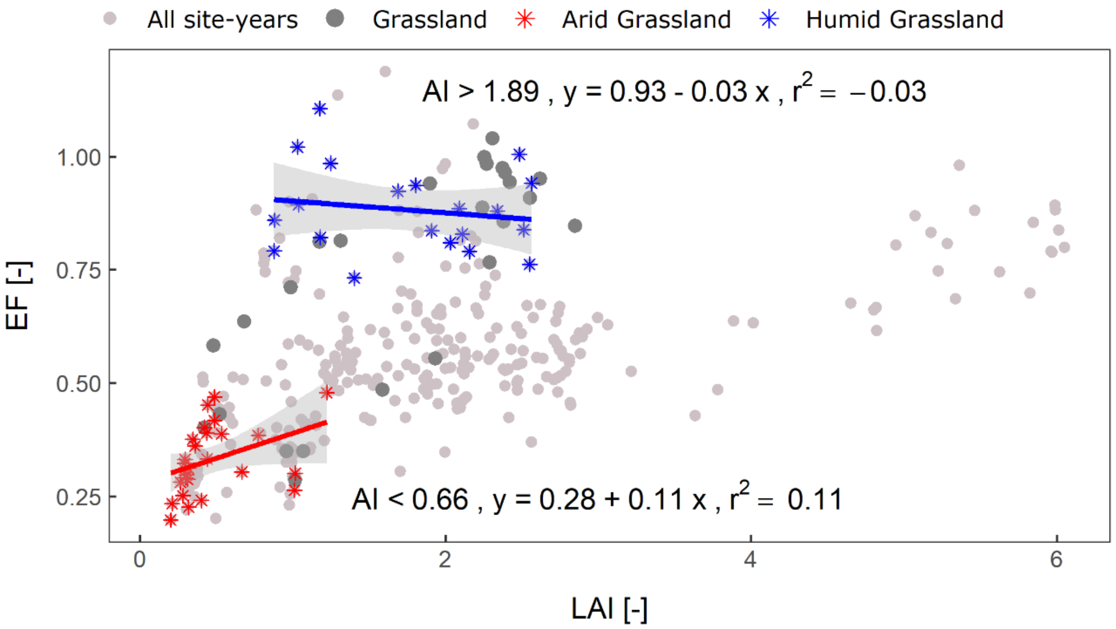


Figure 4 Illustration of the applied methodology. The correlation coefficient between leaf area index (LAI) and evaporative fraction (EF) is calculated for 30 site-years for grassland over a moving window of aridity index. In the illustration, the correlation has a significant positive slope at p = 0.056 for the 30 most arid grassland sites, while for the 30 most humid grassland sites, the slope is nearly flat and not significant (p = 0.49).

Table 1 A list of all included site-years for the 93 sites. For each site, mean yearly leaf area index (LAI) and aridity index (AI) are calculated for all years included in the dataset~~For each site, mean yearly leaf area index (LAI) and aridity index (AI) are calculated for the included site-years~~.

FLUXNET-ID	Country	Years included	mean LAI	mean AI	Vegetation	DOI
AT_Neu	Austria	2002-2012	2.31	1.78	GRA	10.18140/FLX/1440121
AU_Ade	Austria	2008	1.19	0.96	Woody SAV	10.18140/FLX/1440193
AU_Cow	Australia	2009-2018	5.78	3.83	EBF	102.100.100/14244
AU_Cpr	Australia	2011-2013	0.47	0.29	SAV	10.18140/FLX/1440195
AU_Ctr	Australia	2010-2018	5.39	3.80	EBF	102.100.100/14242
AU_Cum	Australia	2013-2014	1.34	0.49	EBF	10.18140/FLX/1440196
AU_DaP	Australia	2008, 2010	1.71	1.11	GRA	10.18140/FLX/1440123
AU_DaS	Australia	2008-2010, 2012-2014	1.34	0.87	SAV	10.18140/FLX/1440122
AU_Dry	Australia	2012, 2014	1.26	0.52	Woody SAV	10.18140/FLX/1440197
AU_Emr	Australia	2012, 2013	0.76	0.51	GRA	10.18140/FLX/1440198
AU_Gin	Australia	2014	0.96	0.34	Woody SAV	10.18140/FLX/1440199
AU_GWW	Australia	2013	0.37	-	SAV	10.18140/FLX/1440200
AU_How	Australia	2003, 2008, 2010-2014	1.83	1.09	Woody SAV	10.18140/FLX/1440125
AU_Rig	Australia	2011-2012, 2014	1.56	0.47	GRA	10.18140/FLX/1440202
AU_Rob	Australia	2014	5.82	1.43	EBF	10.18140/FLX/1440203
AU_Stp	Australia	2010, 2012, 2014	0.52	0.53	GRA	10.18140/FLX/1440204
AU_Tum	Australia	2002-2003, 2005-2009, 2011, 2013-2014	4.62	0.97	EBF	10.18140/FLX/1440126
AU_Whr	Australia	2012-2014	1.12	0.34	EBF	10.18140/FLX/1440206
AU_Wom	Australia	2011-2012	5.10	1.07	EBF	10.18140/FLX/1440207
AU_Ync	Australia	2013	0.45	0.58	GRA	10.18140/FLX/1440208
BR_Sa3	Brazil	2001-2003	5.94	0.96	EBF	10.18140/FLX/1440033
CA_Man	Canada	1995, 2001	1.07	0.64	ENF	10.18140/FLX/1440035
CA_NS1	Canada	2003-2004	1.10	-	ENF	10.18140/FLX/1440036
CA_NS3	Canada	2002-2004	0.75	-	ENF	10.18140/FLX/1440038
CA_NS5	Canada	2004	1.10	0.48	ENF	10.18140/FLX/1440040
CA_NS6	Canada	2002-2004	0.76	0.49	ENF	10.18140/FLX/1440041
CA_NS7	Canada	2003-2004	0.32	0.66	ENF	10.18140/FLX/1440042
CA_Qfo	Canada	2004-2009	0.87	1.82	ENF	10.18140/FLX/1440045
CA_SF1	Canada	2004-2005	1.34	1.08	ENF	10.18140/FLX/1440046
CA_SF2	Canada	2003-2004	1.06	0.73	ENF	10.18140/FLX/1440047
CA_SF3	Canada	2003-2005	0.66	0.98	ENF	10.18140/FLX/1440048
CH_DAV	Switzerland	1997, 1999-2004, 2006-2014	0.94	1.46	ENF	10.18140/FLX/1440132
CH_Fru	Switzerland	2007-2008, 2011-2014	1.88	2.67	GRA	10.18140/FLX/1440133
CH_Oe1	Switzerland	2005-2008	1.27	2.41	GRA	10.18140/FLX/1440135
CN_Cng	China	2008-2009	0.41	0.75	GRA	10.18140/FLX/1440209
CN_Dan	China	2004-2005	0.11	1.14	GRA	10.18140/FLX/1440138
CN_Din	China	2003, 2005	3.30	1.49	EBF	10.18140/FLX/1440139
CN_Du2	China	2007-2008	0.45	0.52	GRA	10.18140/FLX/1440140
CN_HaM	China	2003-2004	0.41	1.21	GRA	10.18140/FLX/1440190
CN_Qia	China	2003-2005	2.95	1.30	ENF	10.18140/FLX/1440141
CN_Sw2	China	2011	0.25	0.32	GRA	10.18140/FLX/1440212
DE_Gri	Germany	2004-2010, 2012-2014	2.40	1.93	GRA	10.18140/FLX/1440147
DE_Hai	Germany	2000-2009, 2011-2012	2.65	1.60	DBF	10.18140/FLX/1440148
DE_Lkb	Germany	2011-2012	0.84	2.53	ENF	10.18140/FLX/1440214
DE_Obe	Germany	2009-2014	2.47	1.96	ENF	10.18140/FLX/1440151
DE_RuR	Germany	2012-2014	2.58	1.97	GRA	10.18140/FLX/1440215
DE_Tha	Germany	1997-2014	2.59	1.53	ENF	10.18140/FLX/1440152
DK_Sor	Denmark	1997-2004, 2006-2010, 2012	2.30	1.93	DBF	10.18140/FLX/1440155
FI_Hyy	Finland	1997-1999, 2001-2014	1.79	1.44	ENF	10.18140/FLX/1440158
FI_Sod	Finland	2003-2011, 2013-2014	0.56	2.27	ENF	10.18140/FLX/1440160
FR_Fon	France	2006-2013	2.67	1.10	DBF	10.18140/FLX/1440161
FR_LBr	France	1998, 2001-2008	1.61	0.88	ENF	10.18140/FLX/1440163
FR_Pue	France	2001-2010, 2013-2014	2.02	1.20	EBF	10.18140/FLX/1440164
GF_Guy	French Guiana	2004, 2006-2014	5.24	1.89	EBF	10.18140/FLX/1440165
IT_CA1	Italy	2012, 2014	1.23	-	DBF	10.18140/FLX/1440230
IT_CA3	Italy	2012, 2013	1.16	1.03	DBF	10.18140/FLX/1440232
IT_Col	Italy	2007, 2009, 2011, 2014	2.32	1.53	DBF	10.18140/FLX/1440167

IT_Cp2	Italy	2013	3.84	0.93	EBF	10.18140/FLX/1440233
IT_Cpz	Italy	2003, 2006, 2007	3.12	0.89	EBF	10.18140/FLX/1440168
IT_Isp	Italy	2013, 2014	1.66	2.41	DBF	10.18140/FLX/1440234
IT_Lav	Italy	2003-2013	2.55	1.74	ENF	10.18140/FLX/1440169
IT_MBO	Italy	2003-2013	1.16	2.41	GRA	10.18140/FLX/1440170
IT_PT1	Italy	2003	0.81	0.77	DBF	10.18140/FLX/1440172
IT_Ren	Italy	2003, 2005-2013	1.53	1.60	ENF	10.18140/FLX/1440173
IT_Ro1	Italy	2002-2006	-	0.91	DBF	10.18140/FLX/1440174
IT_Ro2	Italy	2002-2007, 2012	1.99	0.83	DBF	10.18140/FLX/1440175
IT_SR2	Italy	2013	2.12	1.38	ENF	10.18140/FLX/1440236
IT_SRo	Italy	1999-2004, 2006-2007, 2009, 2012	2.05	0.70	ENF	10.18140/FLX/1440176
IT_Tor	Italy	2010-2014	0.98	2.54	GRA	10.18140/FLX/1440237
NL_Hor	Netherlands	2004-2005, 2007-2008, 2010	1.81	2.01	GRA	10.18140/FLX/1440177
NL_Loo	Netherlands	1996-1997, 2000-2013	2.09	1.20	ENF	10.18140/FLX/1440178
RU_Fyo	Russia	1999-2014	2.09	1.19	ENF	10.18140/FLX/1440183
SD_Dem	Sudan	2008	0.34	0.12	SAV	10.18140/FLX/1440186
SN_Dhr	Senegal	2012	0.61	0.27	SAV	10.18140/FLX/1440246
US_AR1	United States	2010-2011	0.57	0.68	GRA	10.18140/FLX/1440103
US_AR2	United States	2010-2011	0.54	0.59	GRA	10.18140/FLX/1440104
US_Blo	United States	2000-2006	1.94	1.26	ENF	10.18140/FLX/1440068
US_Ha1	United States	1992, 1994-2001, 2004, 2006, 2009, 2011	2.58	1.91	DBF	10.18140/FLX/1440071
US_Me2	United States	2002, 2004-2005, 2007, 2009-2010, 2012-2014	1.97	0.65	ENF	10.18140/FLX/1440079
US_Me6	United States	2014	0.82	-	ENF	10.18140/FLX/1440099
US_MMS	United States	1999-2014	2.71	1.28	DBF	10.18140/FLX/1440083
US_NR1	United States	1999-2014	1.32	1.02	ENF	10.18140/FLX/1440087
US_Prr	United States	2011	-	0.92	ENF	10.18140/FLX/1440113
US_SRG	United States	2009-2014	0.41	0.42	GRA	10.18140/FLX/1440114
US_SRM	United States	2004-2014	0.35	0.31	Woody SAV	10.18140/FLX/1440090
US_Ton	United States	2002-2006, 2008-2014	1.02	0.50	Woody SAV	10.18140/FLX/1440092
US_UMB	United States	2000-2014	2.14	0.95	DBF	10.18140/FLX/1440093
US_UMd	United States	2008-2013	1.90	1.09	DBF	10.18140/FLX/1440101
US_Var	United States	2001-2004, 2006-2014	1.07	0.70	GRA	10.18140/FLX/1440094
US_WCr	United States	2000-2003, 2005, 2011, 2013-2014	2.00	1.40	DBF	10.18140/FLX/1440095
US_Wkg	United States	2005-2014	0.28	0.35	GRA	10.18140/FLX/1440096
ZA_Kru	South Africa	2002, 2010	1.08	0.38	SAV	10.18140/FLX/1440188
ZM_Mon	Zambia	2008	1.62	0.49	DBF	10.18140/FLX/1440189

~~2.2 Method~~

~~To study if the link between LAI and fluxes changes with aridity, we performed a linear regression between the fluxes and LAI for each consecutive 30 site-years (with a minimum of 15 site-years for the lowest and highest aridity boundary), moving from a low AI to a high AI (Figure 3).~~

3 Results

3.1 The link between water, energy, and carbon fluxes versus LAI

LAI and LE were positively correlated in SAV, GRA, and EBF (Figure 4, Table 2). The slope of the correlation between the different vegetation types is different;~~:~~ the slope was steepest for SAV (slope = 46.1 W m^{-2}): a doubling in LAI (1 to 2) was associated with almost a doubling in LE (51 to 97 W m^{-2}), compared to a flatter slope in GRA (9.80 W m^{-2}) and EBF (13.0 W m^{-2}). In ENF and DBF, LAI and LE were not significantly correlated. LAI and H were negatively correlated in SAV, GRA and EBF, while there was no significant correlation in ENF and DBF. LAI and the EF were positively correlated in SAV, GRA and EBF, while no correlation was found in ENF and DBF. A positive slope indicates that, for a higher LAI, a higher fraction of the available energy is used for evapotranspiration of water, compared to surface heating. The slope between LAI and EF was steeper in SAV and GRA (slope = 0.27 for both) than in EBF (slope = 0.08). A positive correlation between LAI and GPP was found in all vegetation types (r = 0.47 - 0.97), with a very strong correlation coefficient for SAV (r = 0.97). The correlation followed a steep slope for SAV (slope = 3.37 gC m^{-2} d^{-1}) and GRA (slope = 2.17 gC m^{-2} d^{-1}), a similar slope in EBF (slope = 1.71 gC m^{-2} d^{-1}) and ENF (slope = 1.81 gC m^{-2} d^{-1}), and a less steep slope in DBF (slope = 0.76 gC m^{-2} d^{-1}). The correlation between LAI and NEE is negative in SAV, EBF, and ENF. This indicates that net carbon uptake increases with LAI. Among the different fluxes, GPP showed the strongest correlation with LAI for all vegetation types. Comparing the different vegetation types, the correlation between LAI and fluxes was strongest in SAV.

Using multi-year average~~d~~ data reduced the number of data points to only 5 to 16 sites per ~~land-cover~~vegetation type~~ and it does not include year-to-year variability~~. Nevertheless, ~~multi-year data gave similar results as compared to using site-year data~~the spatial correlation (site-to-site variability) between LAI and surface fluxes is very similar to the spatio-temporal correlation (Figure 5, Table 2). For SAV, GRA, and ENF, the slope and strength of the correlation were similar when compared with the site-year data. For the EBF, for the site-year data, the correlation with LE and EF was only significant at $p \leq 0.1$ and the correlation was not significant for H and NEE.~~ Given the similarity in results, the site-year data were used in the further analysis, because this averaging method created a larger data set and provided the opportunity to study year-to-year variability.~~

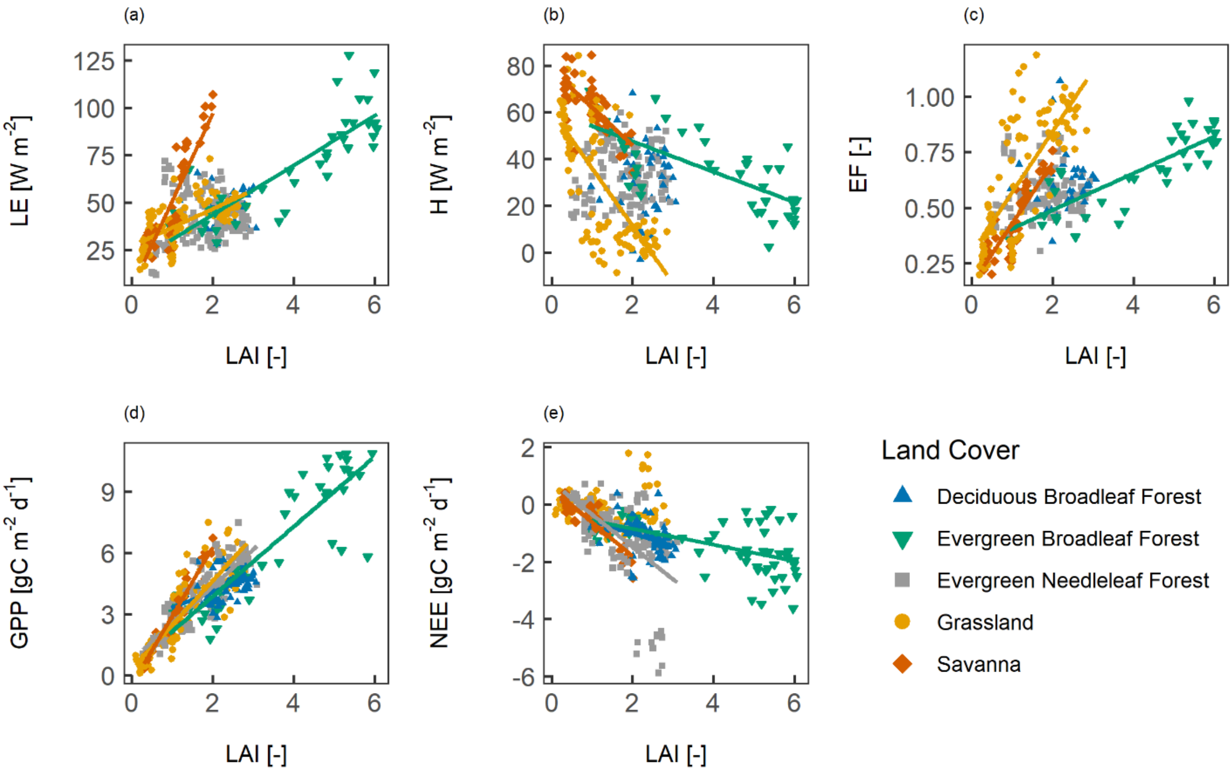


Figure 5 The spatio-temporal correlation between ~~site- year~~ surface fluxes and leaf area index (LAI). Panels show (a) the latent heat flux (LE), (b) the sensible heat flux (H), (c) the evaporative fraction (EF), (d) gross primary productivity (GPP), and (e) net ecosystem exchange (NEE). A line indicates a significant correlation at $p < 0.05$.

Table 2 Strength and significance of the correlation between LAI versus surface fluxes for site-year and multi-year average data. The correlation coefficients are shown for significant correlations at $p \leq 0.05$ (*) or at $p \leq 0.1$ (·). A - indicates that the correlation was not significant.

	Site-years					Multi-year average				
	LE	H	EF	GPP	NEE	LE	H	EF	GPP	NEE
Savanna	0.88*	− 0.72*	0.89*	0.97*	− 0.89*	0.94*	− 0.96*	0.95*	0.99*	− 0.90*
Grassland	0.65*	− 0.71*	0.74*	0.86*	-	0.68*	− 0.80*	0.79*	0.84*	-
Evergreen Broadleaf Forest	0.84*	− 0.69*	0.83*	0.88*	− 0.51*	0.87·	-	0.87·	0.96*	-
Evergreen Needleleaf Forest	-	-	-	0.84*	− 0.58*	-	-	-	0.89*	− 0.57*
Deciduous Broadleaf Forest	-	-	-	0.47*	− 0.33*	-	-	-	0.65·	-

Temporal (year-to-year) variability in LAI and surface fluxes was smaller than spatial (site-to-site) variability (Figure 1). For both SAV sites, and one of the two GRA, EBF, and DBF sites, LAI and LE were positively correlated in time. For H, one EBF site showed a significant negative correlation with LAI, and for EF, and one of the two SAV, GRA, EBF, and DBF sites showed a positive correlation with LAI ($p \leq 0.1$ or $p \leq 0.05$). For GPP and NEE, one of the SAV, GRA, EBF, and ENF sites showed a positive correlation, and for NEE. Overall, the temporal correlations between LAI and surface fluxes was of similar direction as the spatio-temporal and spatial

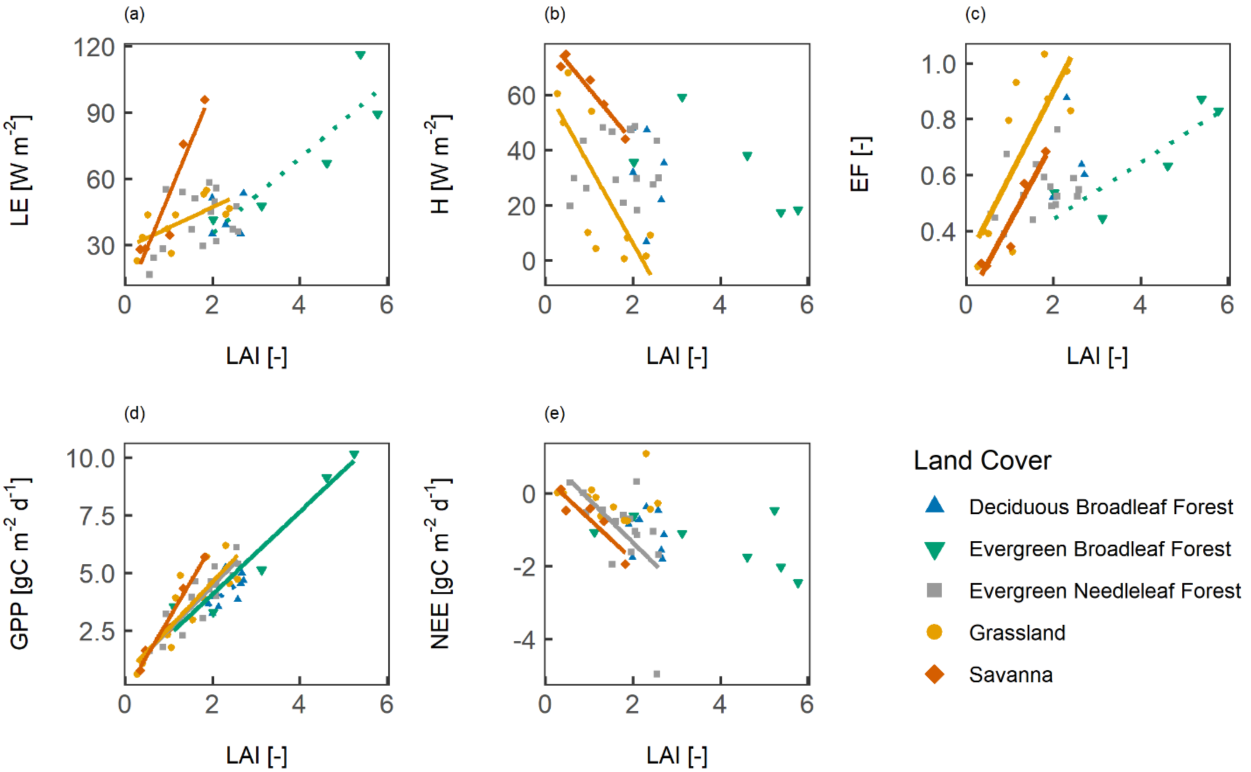


Figure 6 The spatial correlation between ~~multi-year average~~ surface fluxes and leaf area index (LAI). Panels show (a) the latent heat flux (LE), (b) the sensible heat flux (H), (c) the evaporative fraction (EF), (d) gross primary productivity (GPP), and (e) net ecosystem exchange (NEE). All sites are included that have at least three years of LAI and flux data available. A line indicates a significant correlation at $p < 0.05$ and a dashed line indicates a significant correlation at $p < 0.1$. ~~The similarity with figure 4 indicates that including year-to-year variability did not influence the results.~~

correlations. For more than half of the sites in Figure 1, however, year-to-year variability in LAI and surface fluxes was low and variability in fluxes was not significantly correlated with variability in LAI.

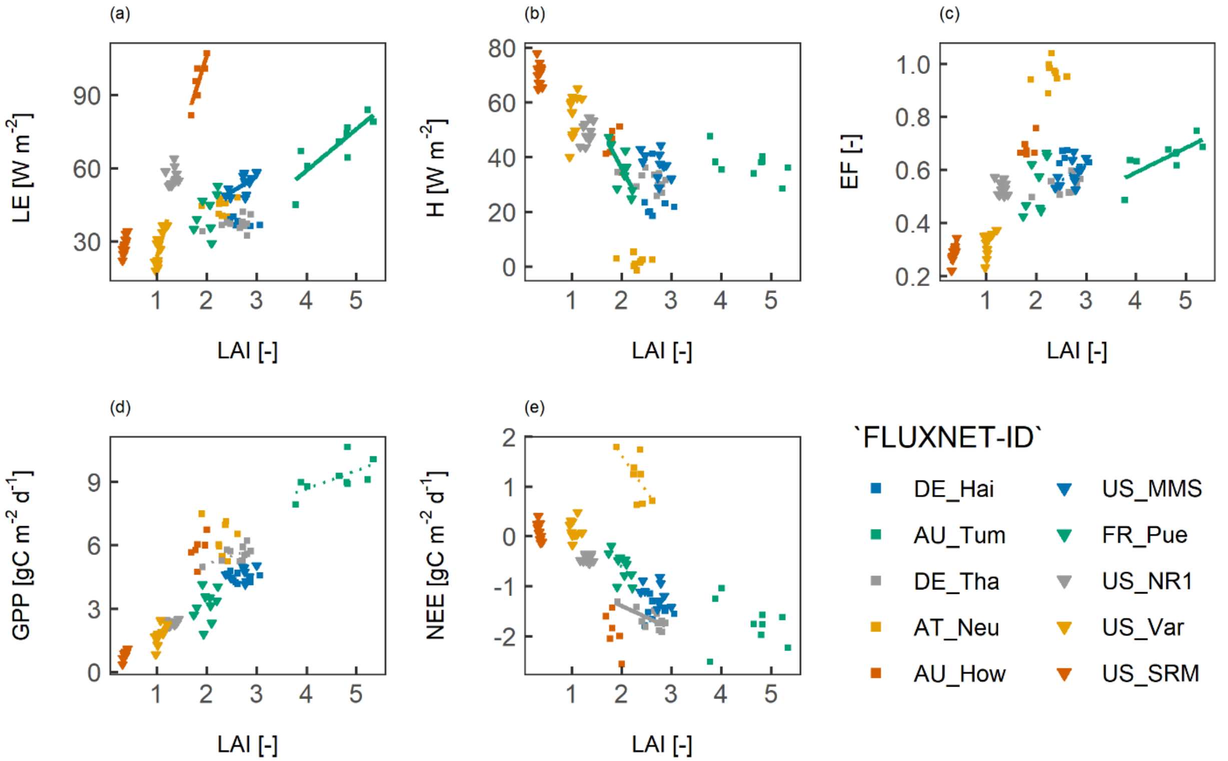


Figure 7 An illustration of the temporal correlation between yearly average surface fluxes and leaf area index (LAI). For each land cover type, two sites were selected that had the highest number of available data. The colours of the symbols indicate the land cover type as in Fig 4 and Fig 5. Panels show (a) the latent heat flux (LE), (b) the sensible heat flux (H), (c) the evaporative fraction (EF), (d) gross primary productivity (GPP), and (e) net ecosystem exchange (NEE). A line indicates a significant correlation at $p < 0.05$ and a dashed line indicates a significant correlation at $p < 0.1$.

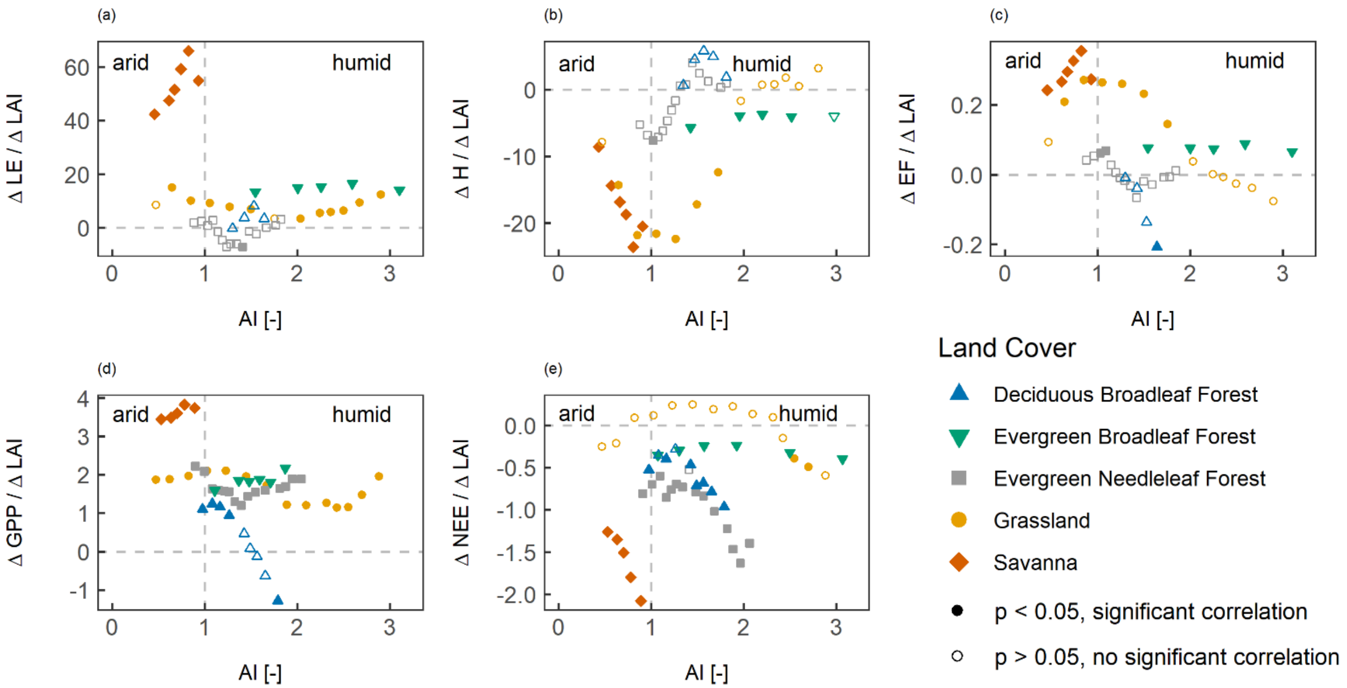


Figure 8 The effect of aridity on the relation between surface fluxes and leaf area index (LAI). The slope of the correlation between LAI and surface fluxes is shown for different aridity values for (a) the latent heat flux (LE), (b) the sensible heat flux (H), (c) the evaporative fraction (EF), (d) gross primary productivity (GPP), and (e) net ecosystem exchange (NEE). Each dot indicates the slope value for the 30 closest aridity values. The filled symbols indicate that the correlation was significant at $p < 0.05$, while the empty symbols indicate a non-significant correlation.

3.2 The effect of climatological aridity on the link between LAI and surface fluxe~~s and LAI~~s

Figure 7 shows the steepness and significance of the correlation between LAI and surface fluxes for different aridity values. In dry vegetation types or regions, the correlation between LAI and fluxes~~ and LAI~~ was significant and had a steeper slope, while in the more humid vegetation types or regions, the slope was ~~lower~~ relatively horizontal and the correlation was often not significant. In SAV, GRA, and EBF, the correlation between LAI and LE was significant ~~over~~ for the whole range of aridity values. In arid ~~grassland~~GRA, the correlation had a steeper slope, as compared to humid GRA. For LAI versus H and LAI versus EF, the slope was steep and significant for SAV. For GRA, the correlation was strong and significant in the arid regions, and insignificant for the humid regions. For EBF, the slope and significance of the correlation did not change with aridity. For LAI and GPP, the slope and significance of the correlation did not change with aridity for SAV, GRA, EBF, and ENF. For DBF, the ~~relationship~~ correlation between LAI and GPP was negative at higher aridity, but these results were strongly influenced by one site with an above average LAI for all the site-years. For LAI versus NEE, a steep slope with negative correlation was found in arid SAV and humid ENF. In other humid regions, the correlation was less steep.

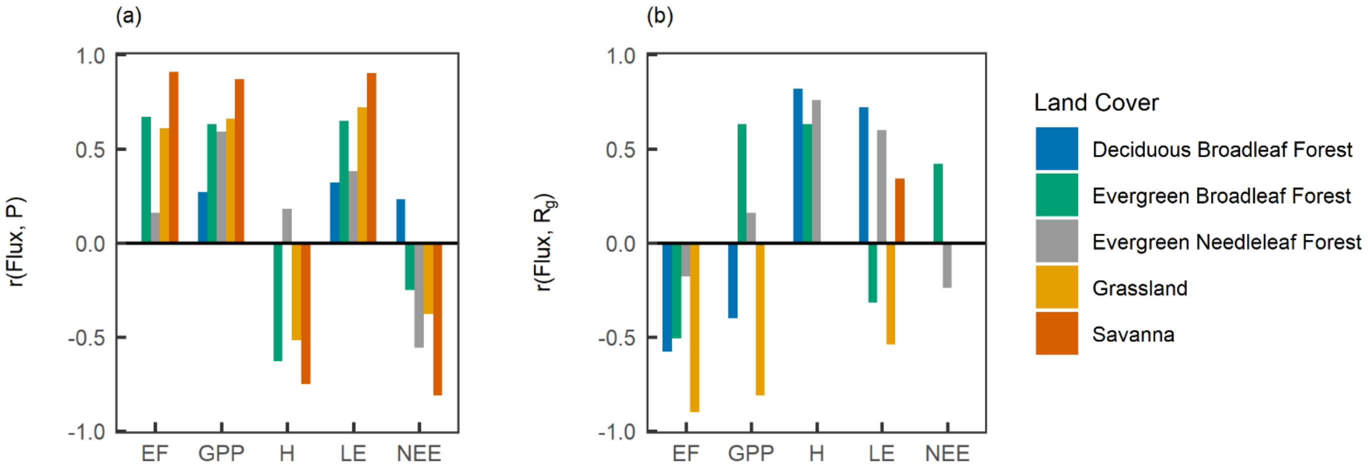


Figure 9 Water and energy control on surface fluxes. The correlation coefficient between site-year surface fluxes versus (a) mean yearly precipitation (P) and (b) incoming shortwave radiation (Rg). Each bar indicates a significant correlation at $p < 0.05$.

To study how the correlations varied with climatic drivers of ~~ecosystem~~ surface fluxes, we calculated the correlation coefficient between the fluxes versus precipitation (P) and incoming shortwave radiation (Rg) (Figure 8). In SAV, GRA, and EBF, the water fluxes showed a strong correlation with P, indicating that water availability partly explained the spatio-temporal variability in ~~ecosystem~~ surface fluxes. In ENF and DBF, there was a weak or no correlation between LE and P, but a strong correlation with Rg. This indicates that available radiation was the primary driver of water and energy fluxes in these sites.

4 Discussion

The EBF site-years span a wide range of LAI values (LAI = 0.9 - 6.1) and aridity conditions (AI = 0.3 - 9.3), and both are a potential limitation of our analysis for the EBF ~~land cover~~vegetation type. The uncertainty of the LAI retrieval in dense vegetation is higher compared to other ~~land cover~~vegetation types due to saturation of the remotely sensed signal. The large range of climatic conditions indicates that our EBF site-years range from arid, water-limited conditions to humid conditions. Despite this high variability in site-years, the sites fell within one ~~land cover~~vegetation type.

The correlation between LAI versus water and energy fluxes (LE, H, and EF) varied with vegetation type and aridity. For the spatio-temporal and spatial variability, w~~W~~e found 1) strong (positive or negative) correlations and (partly) steep slopes for SAV and GRA, 2) a significant correlation, but less steep slope for EBF, and 3) no significant correlations for ENF and DBF. For the temporal variability, this pattern was similar for LE, but almost no significant correlations were found for LAI versus H and EF for SAV and GRA. Evapotranspiration is the sum of transpiration, soil evaporation and interception evaporation and the magnitude of each component depends on LAI. Transpiration increases with LAI at the cost of soil evaporation when there is sufficient moisture available (Gu et al., 2018; Wang et al., 2014). In arid climates, the transpiration component is higher compared to wetter climates (Gu et al., 2018) and the link between transpiration and LAI is particularly strong in these arid climates (Sun et al., 2019). When soil moisture is deficient and vegetation encounters a high evaporative demand, stomatal control is stronger (Mallick et al., 2016). This accelerates a strong stomatal coupling between LAI and LE and could explain the strong correlation between LAI versus LE, H, and EF that was found in SAV and arid GRA. Soil water deficiency and high evaporative demand leads to a high increase in LE, for a small increase in LAI, which could explain the steep(er) slope in arid GRA and SAV vegetation.

In forests, soil evaporation is low, while interception evaporation is large. The high interception evaporation is due to the large leaf area (both green leaves included in the LAI and brown leaves after leaf senescence)~~LAI~~ ~~and therefore~~with a high canopy water storage capacity~~,~~ and a high turbulence, enhancing fast evaporation (De Jong and Jetten, 2007). In EBF, interception evaporation contributes to up to 30% of total evapotranspiration (Wei et al., 2017; Gu et al., 2018). This could explain the strong correlation between LAI versus water and energy fluxes in EBF. A high interception evaporation was however also reported for temperate and boreal forest (Miralles et al., 2011), while for these forest types, we found no correlation between LAI and water and energy fluxes.~~ This is in agreement with an earlier study at smaller scale that did not found a link between vegetation and water fluxes in temperate forest ecosystem(Hoek van Dijke et al., 2019).~~ The ENF and DBF sites were found in humid regions, and fluxes were in the first place energy-limited. In these energy-limited sites, LAI played no, or a weak role in controlling surface fluxes. This indicates a weak or no vegetation control on surface water and energy fluxes in energy-limited sites. This is in line with ~~weak stomatal control found for humid conditions (Mallick et al., 2016), or~~ a low land-atmosphere coupling in energy-limited sites (Ferguson et al., 2012).

In contrast to the results for water and energy fluxes, the spatio-temporal and spatial correlation between GPP versus LAI was strong across all ~~land cover~~vegetation types and (almost) all aridity gradients. A strong link between LAI and carbon uptake on yearly timescale over all vegetation types is expected, as plants try to optimize carbon gain and would generally not display leaves with a negative carbon balance. A strong link between LAI and mean yearly ~~mean~~ GPP ~~and LAI~~ was also shown by Hashimoto et al. (2012). Other studies however found a weak link between LAI and GPP for annual time scales (Law et al., 2002). In contrast to the spatial variability, year-to-year variability in GPP was only in part of the sites correlated to LAI. Water availability is an important driver for temporal variability in GPP ~~-~~(Williams and Albertson, 2004; Kutsch et al., 2008), and GPP is strongly reduced under drought conditions (Vicca et al., 2016). The effect of drought is also visible in reduced LAI, but on a longer time scale of one or two years in forest (Le Dantec et al., 2000; Kim et al., 2017).(Vicca et al., 2016; Aires et al., 2008) This different response time to water availability for forest LAI and GPP could partly explain the absence of a temporal correlation for part of the sites. The spatial correlation ~~link~~ between ~~NEE~~ LAI and ~~LAI~~ NEE was less strong as ~~for~~ compared to GPP, which is in agreement with results of Chen et al. (2019). NEE is the sum of carbon uptake by the vegetation (GPP) and carbon loss by ecosystem respiration. Ecosystem respiration ~~depends among others~~varies with ~~on~~ climate and soil carbon storage, which are not directly related with LAI. This could explain the absence of a correlation between LAI and NEE.

The results partly confirmed our hypothesis. As hypothesised, the correlation between LAI and surface fluxes was strong in arid regions for water and energy fluxes, and the correlation was absent in humid ENF and DBF. For humid EBF, however, we found a strong correlation between LAI and water and energy fluxes, and for GPP, the correlation with LAI was strong across all aridity gradients. ~~The difference between LE and H, and GPP can be explained.~~ While carbon uptake is the primary goal of vegetation, independent of the aridity gradient, ecosystem water loss comes inevitably with carbon uptake, but also depends on vapour pressure deficit, available radiation, and soil moisture, which are not directly linked to LAI.

Our statistical analysis cannot be used to study causality between LAI and surface fluxes, or to study vegetation control on the surface fluxes. The correlation between LAI and water fluxes is confounded by the effect of ~~water availability~~soil moisture, especially in arid and semi-arid ecosystems, where both canopy development and LE increase with water availability (Kergoat, 1998; Mallick et al., 2018). Similarly, precipitation is the main controller for spatial variability in both vegetation and GPP (Koster et al., 2014). Furthermore, LAI is related to vegetation properties, but not a direct measure of canopy conductance. ~~There are however~~Despite, there are similarities with previous studies showing the stomatal or vegetation control on surface fluxes. A strong vegetation control on water and energy fluxes in arid and semi-arid regions was shown on timescales of days or smaller (e.g. Mallick et al., 2016; Mallick et al., 2018) and also our study shows that, on large spatio-temporal scale, ~~vegetation~~ LAI versus water and energy fluxes show the strongest correlation in arid regions. For EBF however, we found a strong spatial correlation between vegetation versus water, and energy fluxes, while Padrón et al. (2017) showed that vegetation control in equatorial regions was absent. An interesting follow-up study would be ~~to investigate stomatal control for all different studied conditions by calculating the aerodynamic and canopy conductances, and~~ to link ~~this~~ stomatal control for different vegetation types (De Kauwe et al., 2017) to the canopy-scale ~~large-scale~~ pattern investigated in this study.

Our analyses give insight in how and when vegetation LAI is related to surface fluxes. The results show that LAI is a good predictor for spatial variability in GPP across different ~~land cover~~vegetation types and aridity gradients. ~~Also~~Furthermore, the analysis suggests that, in SAV, GRA, and EBF, LAI could be used to describe canopy-scale spatio-temporal variability water and energy fluxes. LAI is however not a good predictor for water and energy fluxes in ENF and DBF and ~~also~~ for NEE~~, LAI is not a suitable predictor in most land cover types~~. It is important to be aware of these limitations when using LAI to describe or estimate water, energy, and carbon fluxes in climate models or extrapolation methods.~~ Also, t~~ This study provides insight in the link between surface fluxes and LAI and could be used to improve predictions of the effects of land cover change on surface fluxes.

5 Conclusions

The objective of this study was to get an insight about the link between vegetation LAI and land-atmosphere fluxes for different vegetation types along an aridity gradient. We studied this link at large spatio-temporal scale~~s~~ using flux tower measurements of water, energy, and carbon, combined with satellite derived LAI data. The data analysis led to the following conclusions:

a) The link between LAI versus water and energy fluxes depends on vegetation type and aridity. The correlation between LAI versus water and energy fluxes is strong in SAV, GRA, and EBF. In DBF and ENF however, no significant correlation was found. Contrary to water and energy fluxes, the ~~link~~ spatial correlation between LAI versus GPP was strong~~ in all analysis~~, independent of vegetation type and aridity. ~~.~~This suggests ~~that the ability~~that usin~~ of~~g -LAI to model or extrapolate surface fluxes of water and energy is well possible in SAV, GRA, and EBF, but is limited in DBF and ENF.

b) As hypothesised, the ~~large-scale~~ link between LAI and water and energy fluxes was strong in arid, water-limited conditions and absent or weak for humid, radiation-limited conditions. ~~This is in agreement with earlier stomatal or vegetation control studies on smaller scales.~~ EBF, which was found over a high range of aridity conditions, but mostly in humid environments, forms an exception: the ~~link~~ spatial correlation between LAI versus water and energy fluxes was strong, despite the overall humid conditions.

This research – facilitated by the recent availability of large global datasets of remotely sensed LAI, flux tower data, and cloud-computing platforms – has added to the understanding of ~~large-scale~~ LAI interaction with surface fluxes and could help to improve ~~the representation of vegetation in land-atmosphere modelling~~modelling or extrapolating surface fluxes.

Author contribution

The data analyse~~i~~s ~~was~~ were done by AJHvD in close consultation with KM, MS, MM, MH, and AJT. AJHvD prepared the draft manuscript and all authors contributed to the discussions and writing of the manuscript.

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Competing interests

The authors declare that they have no conflict of interest.

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