

1 **Quantifying the response of water and carbon balances to land**  
2 **cover and climate extremes across Germany.**

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12

13 **Abstract.** Land cover and extreme weather events are closely connected to ecosystem services like water yield and  
14 carbon sequestration. Understanding how carbon and water respond to human disturbances is critical for managing  
15 these resources and realize desired ecosystem services at the national level. The monthly scale ecosystem model,  
16 Water Supply Stress Index (WaSSI), was tested and applied across Germany for mapping carbon and water balances  
17 from 2001 to 2019. We estimated that ecosystems in Germany generate 84.86 billion m<sup>3</sup> of water yield and sequester  
18 106.03 Tg of carbon annually on average. Most of the precipitation was lost as evapotranspiration in eastern states  
19 that were comparatively drier in river flows than the rest of the country. Croplands, urban areas and Evergreen Needle  
20 Forests (ENF) provide 82.5% of the national water yield, while the forest lands share the majority (56.3%) of land  
21 carbon sequestration altogether. Our simulation results highlight the importance of sparse land covers (e.g. wetlands)  
22 in carbon sequestration. Findings also suggest that national water yield and carbon balances are sensitive to extreme  
23 events such as the floods in 2002 and 2013 and the extreme drought in 2003 and 2018. We found that hydrologic  
24 buffers from the previous year played an important role in mitigating negative impacts on both carbon and water  
25 availability. This study highlights that, when integrated with local data, a relatively simple modelling approach is  
26 adequate to quantify the coupled water and carbon responses to climatic and land cover variability at a large scale.  
27 We conclude that land management of both forests and croplands is vital to sustain ecosystem services under a  
28 changing climate at regional to national levels.

## 29 1. Introduction

30 Ecosystem services such as water yield and carbon sequestration are intimately linked with land cover and climate  
31 extremes. The two key ecosystem services support life and economic activity (Morales et al., 2005). The tightly  
32 coupled links between water and carbon cycles through parameters such as precipitation, temperature,  
33 evapotranspiration (ET), and ecosystem services are well recognized (Beer et al., 2007; Sun et al., 2011). However, it  
34 is still unclear how changes in land cover and climate extremes have impacted these services in Germany at a national  
35 level. These services are challenging to measure directly, but an ecosystem services model can be applied to estimate  
36 them across the German landscape at a sub-basin scale.

37 Changes in land cover are driven by multiple interconnected reasons, two of them are improving living standards and  
38 population growth (Allan et al., 2022). Studies have shown that land cover change greatly reduces ecosystem services,  
39 but the impact varies spatially and temporally (Hasan et al., 2020). According to Pandey & Ghosh (2023), and Salerno  
40 et al. (2018), urbanization disrupts regulating service for e.g., water purification, soil retention, and climate regulation.  
41 On the other hand, Arowolo et al. (2018) and Cui et al. (2021) observed that expansion of cropland often increases  
42 goods from provisioning services such as food, fodder and water yield. A recent survey in 2022 from the German  
43 national forest inventory found that since 2017, the German forest has become a source of carbon dioxide, instead of  
44 being a sink. The reason behind the change in ecosystem functions is the high loss of living biomass due to climate  
45 change and low forest growth (Fourth Federal Forest Inventory 2022, 2024).

46 Another environmental phenomena that impact ecosystem services are extreme climate events (e.g. droughts &  
47 extreme precipitation). Catastrophic weather events not only made countries in the Global South but also in Global  
48 North vulnerable. Germany's 2021 summer flood resulted in a loss of 220 lives and US\$ 40 Billion (Schumacher,  
49 2022); the incurred damages from the 2003 drought, primarily on agriculture, were approximately US\$13 Billion  
50 across Europe (Eisenreich, 2005). Germany has seen an increase in the intensity and frequency of heavy rainfall, more  
51 in winter than in summer. The air temperatures are also projected to rise by 1.6 to 3.8°C by 2080 (Schröter et al.,  
52 2005). A shift in precipitation season has been observed, which will potentially increase the risks of floods during  
53 winter and decrease the water supply during summer periods (Schröter et al., 2005). The extreme events are changing  
54 due to climate change. Their impacts may reduce terrestrial carbon uptake or gross primary productivity (GPP)  
55 (Williams et al., 2014), which negatively affects other factors within the co-evolved processes of carbon-water cycle  
56 in an integrated terrestrial system (Zhang et al., 2018). Potentially leading to adverse effects on regional food and  
57 livelihood security.

58 Although ecosystem services are essential and well-recognized in Germany, national-scale studies on both carbon and  
59 water yield are still lacking. There are multiple studies that focus on a specific land cover type or specific ecosystem  
60 services at the European, national or subnational scales. For example, Potter & Pass (2024) estimated the changes in

61 net primary productivity (NEP or carbon sequestration) for Western Europe, including Germany. Gutsch et al. (2018)  
62 assessed German forest ecosystem services under climate change and different management scenarios. Their results  
63 showed that climate change has negative impacts on water percolation and positive impacts on carbon sequestration.  
64 Using agricultural long-term field experiments, carbon sequestration was projected to increase in the southern parts  
65 of Germany, indicating higher productivity, and decrease in central and east Germany where poor soil will further  
66 reduce the productivity (Donmez et al., 2024). Other studies used regional analysis to assess water or carbon cycles  
67 (Al-Qubati et al., 2023; Prescher et al., 2010; Ungaro et al., 2021; Wu et al., 2021). The lack of integrated water-  
68 carbon cycles assessment hampers deriving national or regional adaptive land management strategies to alleviate the  
69 adverse impacts resulting from environmental and climate change, particularly in the long term.

70 Furthermore, we observed a varied response of the coupled water-carbon cycle to changes in land cover and climate  
71 (Cheng et al., 2017; Jung et al., 2017; Zeng et al., 2018). The variation is manifested by the coupled mechanisms  
72 occurring at multiple timescales. These may be short-term leaf-gas exchanges, monthly or annual ET and carbon  
73 accumulation, and long-term water yield and species composition. This emphasises that a single type of observation  
74 is not sufficient to provide the robust validation needed to address the response of water and carbon cycles to  
75 environmental disturbances or climate shocks (Margulis et al., 2006). Gentine et al. (2019) argued that terrestrial  
76 water-carbon cycles must be investigated as an integrated system. They recognized the importance of incorporating  
77 multiple observations on different timescales from various sources to better validate model simulations, which may  
78 reduce uncertainties, mitigate bias, and provide better predictions. Unfortunately, the suggested approach is seldomly  
79 applied in hydrological modelling (e.g. G. Sun et al., 2011, 2023; J. Zhang et al., 2022; Y. Zhang et al., 2016). Thus,  
80 impeding the improvement of our predictive ability to quantify the potential water-carbon changes and consequences  
81 that are vital to effective policy decision-making for developing climate adaptation and mitigation strategies.  
82 Therefore, we integrated multi-timescale observations and information sources in our model to validate simulated  
83 water yield and carbon sequestration. We used gauged river discharge (Q), in-situ measured ET and GPP from eddy  
84 flux towers, and remotely sensed ET and GPP data for model validation.

85 In this study, WaSSI, an ecosystem service model, was applied on a monthly and subbasin (804) resolution to simulate  
86 the water and carbon processes across the different land covers within Germany (Sun et al., 2011). The model has  
87 been used globally for various purposes and under different climatic and socioeconomic conditions (Averyt et al.,  
88 2011; Caldwell et al., 2011, 2014, 2012; N. Liu et al., 2020; G. Sun et al., 2011; S. Sun et al., 2015; McNulty et al.,  
89 2016;) in countries like the United States of America, Rwanda, Australia, Turkiye, Nepal and China (Chen et al., 2024;  
90 Jin et al., 2025; Liu, 2017; Liu et al., 2013; McNulty et al., 2016; Sun et al., 2011). By validating the WaSSI model,  
91 we aim to have an improved understanding of the response of water-carbon cycles on German land cover with climate  
92 variability at a watershed scale. Furthermore, we focus on three questions: (i) How did ET, water yield and NEP vary  
93 over time and space? (ii) How did different land cover contribute to water yield and carbon sequestration? and (iii) to  
94 what extent and how sensitive are the two ecosystem services to extreme weather events?

## 95 **2. Methodology and Data**

96 The WaSSI model merges the water and carbon cycle using water use efficiency (WUE) parameters estimated from  
97 global eddy flux observations. It is made up of two components: a hydrological and a carbon sub-model. The required  
98 inputs are precipitation, temperature, digital elevation model, land cover, fractional impervious cover, leaf area index  
99 (LAI), and soil parameters, while the outputs are Q, ET, GPP, and net ecosystem exchange (NEE) (Liu, 2017).  
100 Transboundary inflows and outflows were not accounted in this study; therefore, watersheds close to Germany's  
101 boundary, which accumulated their flow across the border, were not considered.

102 The WaSSI model estimates land cover-specific water yield (mm per month), which can be aggregated as flow volume  
103 downstream ( $\text{m}^3$  per month) for any individual watersheds. The hydrologic fluxes estimated are snow melt, snow  
104 accumulation, soil storage, surface flow, base flow, routed flow accumulation, and ET (Sun et al., 2011). The model  
105 employs a conceptual method (McCabe & Wolock, 1999) that uses the monthly average temperature and mean average  
106 elevation of a watershed to partition precipitation into rainfall and snowfall, estimate the rate of snow melt, and  
107 calculate the mean monthly snow water equivalent for each watershed (Caldwell et al., 2012). The Sacramento Soil  
108 Moisture Accounting (SAC-SMA) model was used for soil and runoff parameters, which runs infiltration, baseflow,

109 surface runoff, and soil moisture processes, while also constraints ET estimates based on soil water content. For ET  
110 estimations, we used the Type II regression model from (Fang et al., 2015), where the ET model was developed using  
111 quality-controlled global data from more than 200 eddy flux sites (Pastorello et al., 2020), incorporating the three most  
112 commonly available biophysical parameters precipitation (P), potential ET (PET) (Temperature based) and LAI in the  
113 following equation:

$$ET = -4.79 + 0.75PET + 3.92LAI + 0.04P \quad (1)$$

114 WaSSI estimates three main components of the carbon cycles: (i) GPP or total carbon uptake, (ii) ecosystem  
115 respiration (Re) representing carbon loss, and (iii) Net Ecosystem Productivity (NEP) or negative Net Ecosystem  
116 Exchange (NEE) or carbon sequestration:

$$NEP = -NEE = -(Re - GPP) \quad (2)$$

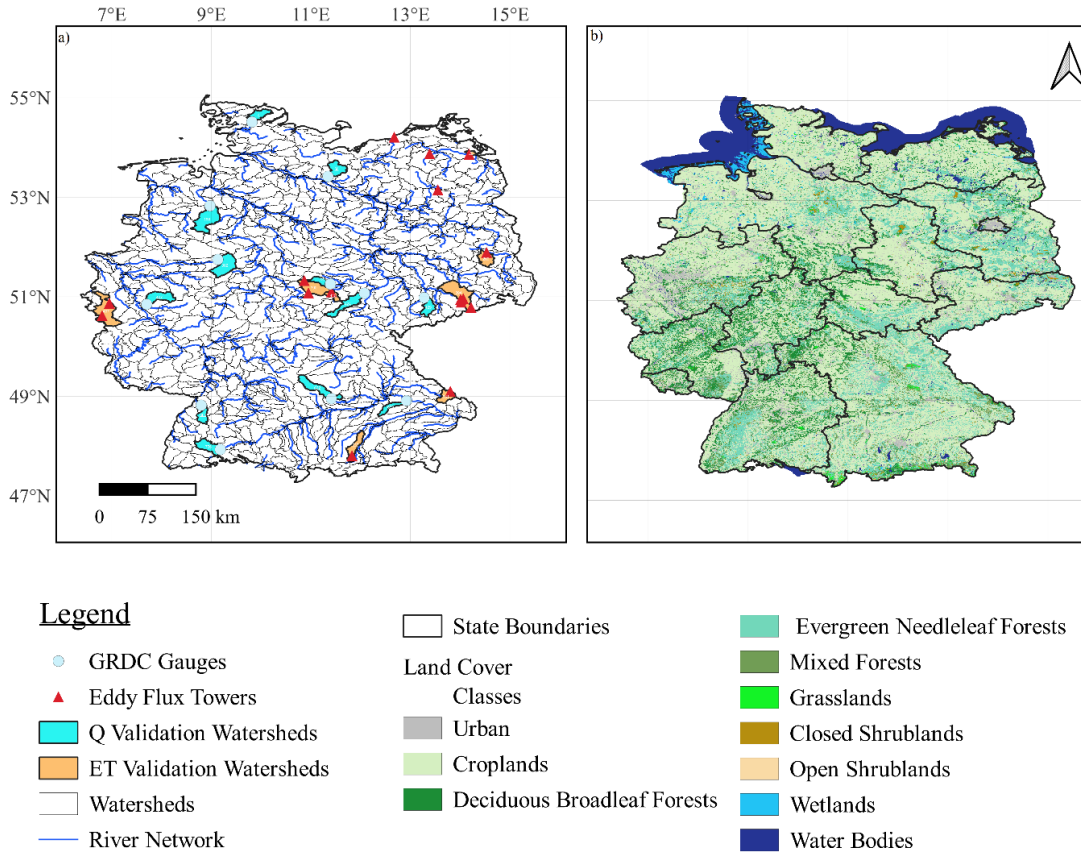
117 Furthermore, a closely coupled relationship between ET and GPP has been found in multiple studies (Law et al., 2002;  
118 Sun et al., 2011), as presented in Equation 3. In the WaSSI model, according to G. Sun et al., (2011), the relationship  
119 of monthly GPP with ET was estimated using linear regression for each land cover. Furthermore, land cover-specific  
120 WUE parameters were used, which were estimated using 142 eddy flux tower data (Zhang et al., 2016). Similarly, the  
121 Re from heterotrophic and autotrophic bacteria can be estimated using Equation 4, where regression coefficients are  
122 estimated from eddy flux data. The coefficient (a, m, and n) values used in this study are provided in Table S1.

$$GPP = a \times ET \quad (3)$$

$$Re = m + n \times GPP \quad (4)$$

## 123 2.1. Model Validation

124 We validated the model outputs using both in-situ observed data (e.g., stream discharge data from gauge stations and  
125 ET eddy flux data) and remotely sensed data (e.g., ET and GPP estimates from satellites). The temporal resolution of  
126 the WaSSI model output was monthly. The discharge was validated for twelve upstream watersheds across Germany  
127 (Fig. 1). The chosen upstream stations were selected to ensure spatial coverage across Germany, representing the  
128 country's major climatic zones, land use, and land cover types. Stations with long and continuous discharge records  
129 were prioritised. The performance criteria to determine the accuracy of outputs are model bias (%), coefficient of  
130 determination ( $R^2$ ), scatter plots, Nash-Sutcliffe efficiency (NSE), and Kling-Gupta efficiency (KGE). The estimated  
131 ET was validated against data on different timescales. Simulated ET was compared with daily data from multiple eddy  
132 flux towers, monthly ET from Moderate Resolution Imaging Spectroradiometer (MODIS) (MOD16A2GF) (Running  
133 et al., 2019b), and watershed-specific water balance values, which were calculated by subtracting discharge from  
134 precipitation, on a monthly and annual timescale. Depending on the validation datasets, values were summed to either  
135 monthly or annual timesteps. For carbon, we compared the GPP estimates with GPP measurements from eddy flux  
136 towers, MODIS GPP (MOD17A2HGF) and Copernicus Global Land Service (CGLS) GPP (Running et al., 2019a;  
137 Smets et al., 2019). A monthly land cover-specific validation was conducted between modelled GPP and observed  
138 GPP. Where observed GPP estimates were developed using the daytime partitioning method (GPP\_DT\_VUT\_REF).  
139 Further details for each validation dataset are provided in the following section 2.3. Since the observed data from the  
140 gauge stations and eddy flux towers did not overlap, therefore, joint evaluation at the same subbasin for both Q and  
141 ET was not possible in this study.



142

143 **Figure 1:** A map of the study area presenting **a)** Germany's boundaries with all the 804 watersheds delineated, Global  
 144 Runoff Data Center's (GRDC) gauge station locations, major rivers, eddy flux tower sites and representative  
 145 watersheds for streamflow (Q) and evapotranspiration (ET) validation and **b)** Germany's land cover and state  
 146 boundaries.

## 147 2.2. Input Data

### 148 2.2.1. Study Area

149 Germany, with an area of 357,168 km<sup>2</sup>, consists of sixteen states. Approximately 83.5 million people reside across  
 150 five major river basins that fall within Germany (Rhine, Danube, Elbe, Weser, and Ems). Due to cross-boundary flows,  
 151 Germany has bilateral water treaties with all of its neighbours. The climatic conditions span from maritime to  
 152 continental. The annual mean temperature ranges from 9 to 11°C, and the annual precipitation ranges from 450 mm  
 153 to 970 mm (Kosanic et al., 2019). The land use is dominated by agriculture (61%) and forests (29%). Furthermore,  
 154 the built-up area (6%) is continuously expanding as cities grow due to urbanization. Socio-economically there is a  
 155 clear divide between the Eastern and Western states due to the Soviet-era policies. In this study, Germany was  
 156 delineated into 804 subbasins as the modeling units using a high-resolution digital elevation model (Fig. 1).

### 157 2.2.2. Climate Data

158 Climate data (i.e., precipitation and temperature) is sourced from Germany's national meteorological service (DWD,  
 159 2018). Datasets have a spatial resolution of 1km and a temporal resolution of months. The gridded data are prepared  
 160 by estimating monthly deviations for each station, which are then interpolated using inverse squared distance weighted  
 161 interpolation and transformed back into real values using reference grids (Kaspar et al., 2013).

### 162 2.2.3. Land cover classification

163 CORINE land cover (CLC) map of 2018 with a 100 m spatial resolution was used in this study (EEA, 2021). Validation  
164 studies showed that it can capture land cover with an accuracy of 85% (Büttner et al., 2021; Keil, 2017). This study  
165 reclassified land cover into 10 major classes. Table S2 shows the range of CLC classes that were merged along with  
166 their percentage across Germany. The selection of 10 classes was based on the availability of water-use efficiency  
167 (WUE) parameters. These 10 classes encompass all dominant ecosystem types across the study.

### 168 2.2.4. Leaf Area Index

169 Climate Data Record's (CDR) Vegetation (VGT) sensor LAI was used. The data is available from 2001 to 2014, with  
170 a 10-day temporal and 1km spatial resolution. All pixels with an invalid LAI status were removed during quality  
171 control. Invalid LAI status refers to pixel values that do not fall within an expected range (Verger et al., 2018).  
172 Validation studies of this product showed that it underestimates ground data with a bias of 0.31 and a correlation of  
173 0.72, while against multiple satellite datasets, it overestimates with biases ranging between 0.03 (for MODIS) to 0.36  
174 (for GLOBCARBON) (Camacho & Cernicharo, 2014).

### 175 2.2.5. Fractional impervious cover and soil data

176 The fractional impervious cover is derived from the Global Man-made Impervious Surface (GMIS) dataset (Brown  
177 de Colstoun et al., 2017). It has a spatial resolution of 30m.

178 Digital soil map BUEK 200 was used to estimate eleven soil parameters following Y. Zhang et al. (2011) and Anderson  
179 et al. (2006). Land cover and soil properties were used to obtain the curve number (CN) that controls the partitioning  
180 of soil into upper and lower zones. The water allocation between tensed and free water storage is determined by soil  
181 composition. The final product has a spatial resolution of 500 m.

## 182 2.3. Validation Data

### 183 2.3.1. Stream Discharge Data

184 The discharge data used for validation are sourced from the Global Runoff Data Center (GRDC). Twelve upstream  
185 stations were identified from a large group of stations for validation of discharge in this work. The selection focused  
186 on upstream watersheds that have less anthropogenic influence (e.g. dams), thus representing natural processes  
187 reasonably well. Furthermore, these stations had continuous long-term discharge data, they represent different climatic  
188 zones in Germany, and they capture diverse land use and land cover types. The location of stations can be observed  
189 in Fig. 1, while their names and ID are provided in Table S3.

### 190 2.3.2. Eddy Flux ET and GPP

191 ET and GPP in-situ measurements were acquired from the FLUXNET2015 database (Pastorello et al., 2020). The data  
192 available is quality-controlled. The gaps within the data are filled and corrected following standardised  
193 FLUXNET2015 procedures, which apply algorithms to ensure temporal continuity and consistent flux measurements.  
194 Furthermore, the energy balance closure correction factors (EBC\_CF) were used to correct these datasets. The  
195 EBC\_CF were estimated using three different methods each assuming that the Bowen ratio holds true. In this study,  
196 monthly latent heat turbulent flux (LE) was converted to ET with and without energy closure corrections and GPP  
197 was calculated using the daytime partitioning method (Pastorello et al., 2020).

### 198 2.3.3. MODIS ET and GPP Data

199 The MODIS ET product MOD16A2GF is employed in this work (Running et al., 2019b). The remote sensing data is  
200 used to compare the spatial variation of model output. MODIS has a spatial resolution of 500m and a temporal  
201 resolution of 8-day. The ET estimation follows the Penman-Monteith equation (Running et al., 2019b). The product  
202 has been comprehensively validated in multiple studies (Kim et al., 2012; Liu et al., 2015; Trambauer et al., 2014;  
203 Velpuri et al., 2013) and used to evaluate the output of hydrological models (Sun et al., 2011). This study used a  
204 monthly sum of ET values and spatial average calculated on a sub-watershed scale.

205 The gap-filled GPP product employed in this study is MOD17A2HGF, with a spatial resolution of 500m and a  
206 temporal resolution of 8-day (Running et al., 2019a). It follows Monteith's logic and uses land cover specific light  
207 use efficiency ( $\epsilon$ ), fraction of absorbed photosynthetically active radiation (FPAR), incident photosynthetically active  
208 radiation (IPAR), the deficit of vapor pressure, and minimum air temperature (Running et al., 2019a). Insights on the  
209 application and validation of MODIS-GPP are provided in multiple studies (Liu et al., 2015; Sun et al., 2011; Turner  
210 et al., 2006; Wang et al., 2017; Zhu et al., 2018).

211 CGLS GPP are derived from the Gross Dry Matter Productivity (GDMP) values (Smets et al., 2019). We used the  
212 version 2 product from SPOT/VGT and PROBA-V satellites to evaluate the model GPP estimates for the period of  
213 2001 – 2019. The GDMP product has a spatial and temporal resolution of 1-km and 10-day. It represents the additional  
214 gross dry biomass stored in vegetation, which could be converted into gross carbon uptake by multiplying it with a  
215 scaling factor of 0.45 gC/gDM (Smets et al., 2019):.

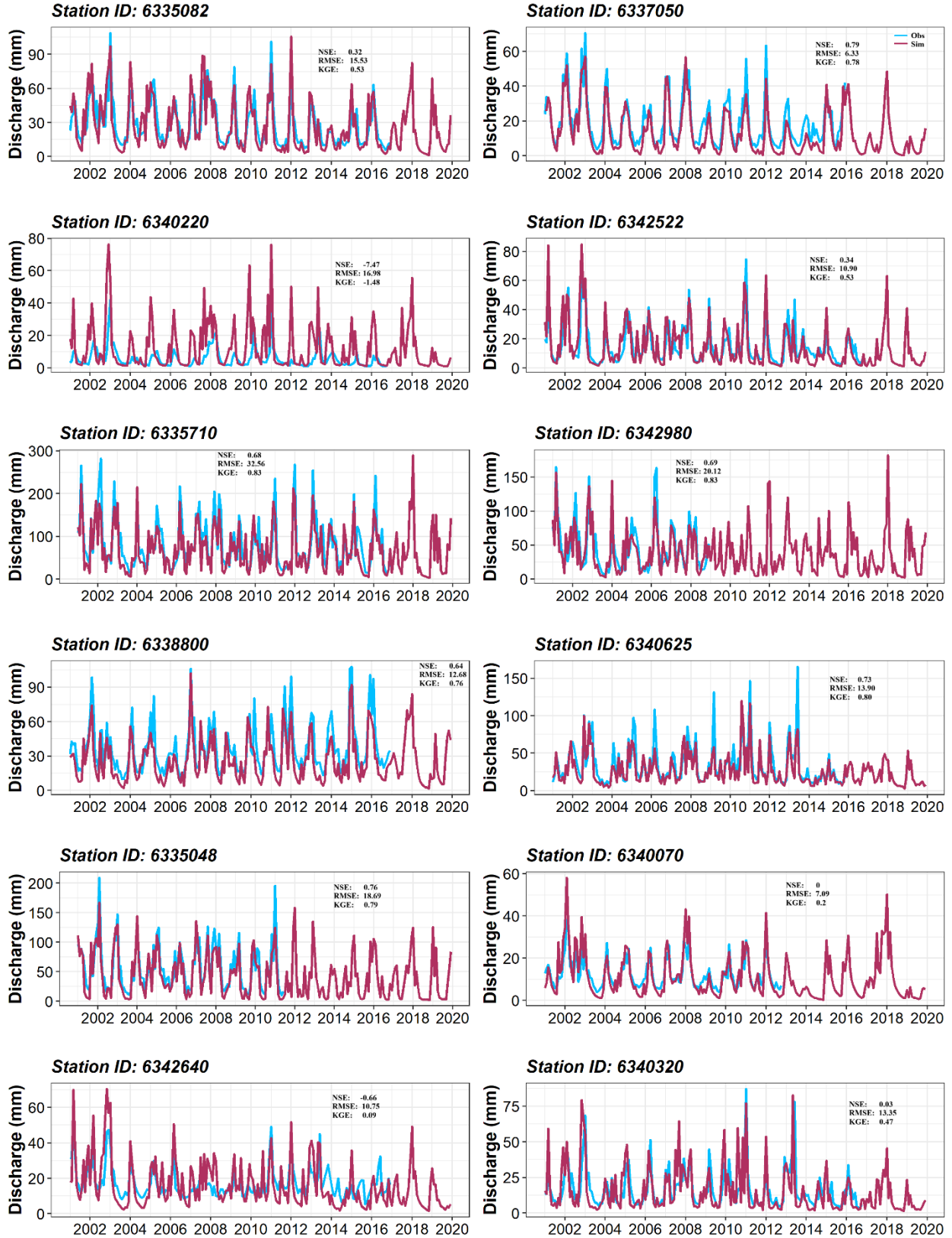
$$GPP (gC m^{-2} day^{-1}) = GDMP (kg DM ha^{-1} day^{-1}) * 0.45 * 0.1 \quad (5)$$

## 216 3. Results

### 217 3.1. Model Validation

#### 218 3.1.1. Discharge Validation

219 The hydrograph plots reveal that the model, in general, is able to simulate the monthly flows reasonably well (Fig. 2).  
220 Furthermore, the model discharge validated on a monthly scale gives KGE for eight out of the twelve watersheds  
221 above 0.5 and NSE for six out of twelve watersheds greater than 0.6, as shown in Table S3. While on an annual scale  
222 the values of model bias (%) for eleven out of the twelve stations are between -25% to 25% and for  $R^2$  ten out of  
223 twelve stations are above 0.60, as presented in Table S4. The scatter plot between modelled and observed discharge,  
224 across the twelve watersheds on both annual and monthly scales, is presented in Fig. S1. The plot shows high  
225 correlation between the two datasets suggesting the model performs reasonably well. Except for the Wasserthaleben  
226 station, where the model performance is weak with bias equal to 131.8 % and annual  $R^2$  of 0.18.

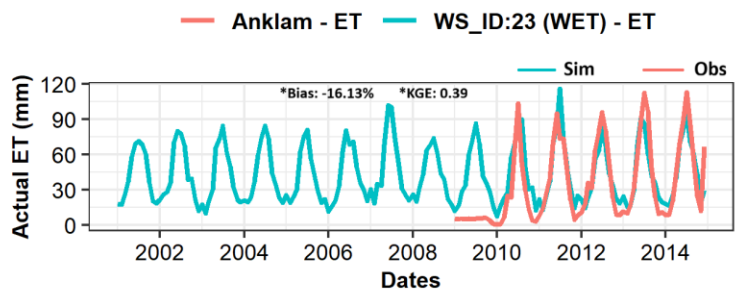
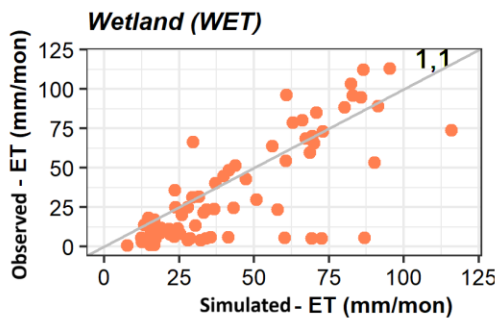
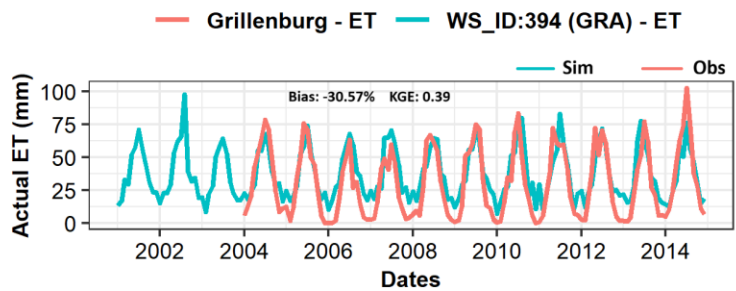
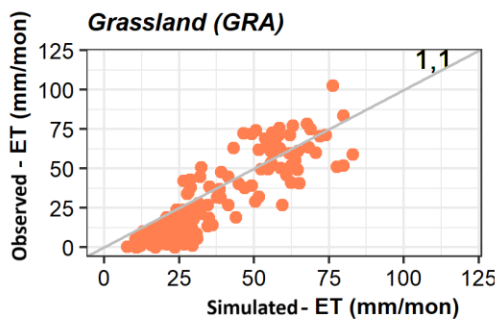
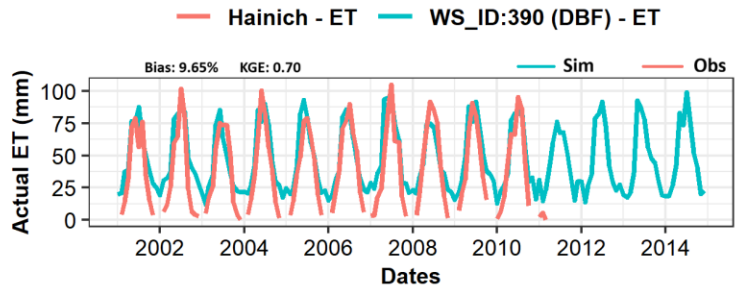
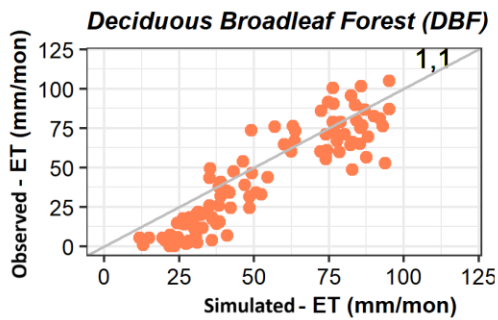
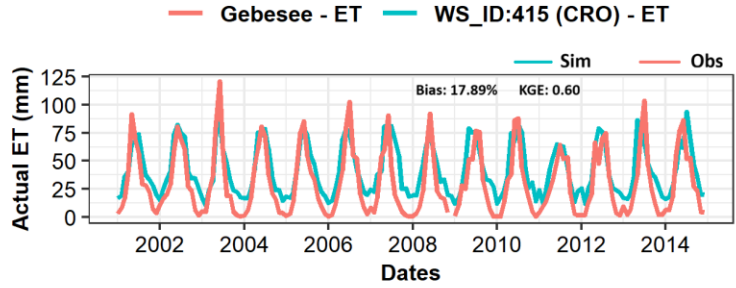
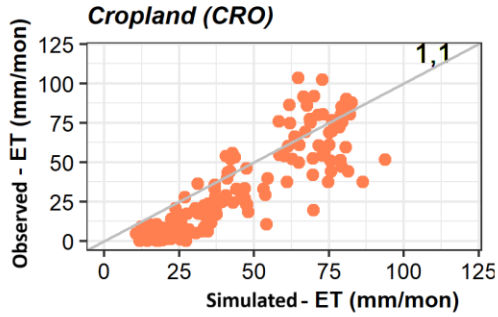
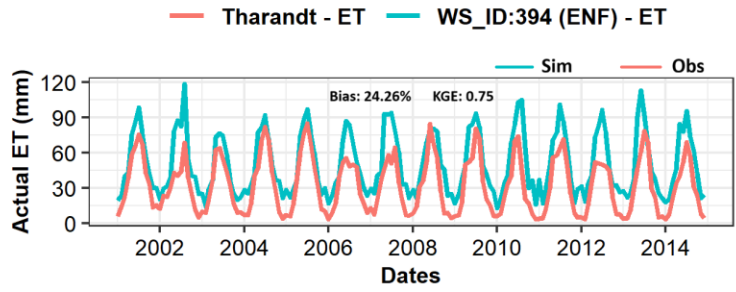
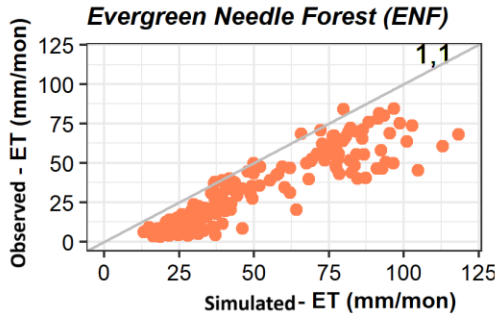


228 **Figure 2:** Monthly discharge time series from WaSSI simulation in mm (maroon) plotted against observed gauge  
229 station flow in mm (blue) during 2000-2020.

### 230 3.1.2. ET Validation

231 Monthly land cover specific validation of simulated ET against EC ET is presented in Fig. 3. The ET estimates are  
232 captured reasonably well by the model as the points in the scatter plot generally stayed close to the 1:1 line except for  
233 Grassland. The detailed validation results are provided in Table S5. Ten out of eleven watersheds have an  $R^2$  value  $>$   
234 0.6 and a correlation  $>$  0.75. Seven out of eleven watersheds have a model bias (%) between -25% to 25%, and KGE  
235 estimate  $\geq$  0.6. Discrepancies are found in Lackenberg station with a bias of 52.4 %, and in general we observed that  
236 WaSSI model tends to slightly overestimate ET during winter. Overall, the model is able to capture ET values  
237 reasonably well across different land covers within Germany (Fig. S2a).

238 WaSSI ET on an interannual scale showed that it can satisfactorily simulate the variability of ET captured by MODIS  
239 across Germany, as shown in Fig S2b-c. The model mostly underestimated ET in southern and northwestern Germany,  
240 while slightly overestimating the ET in mid-western and eastern Germany. When the simulated ET is assessed against  
241 ET estimates as precipitation minus observed discharge ( $P-Q_{\text{observed}}$ ) interannually, the mean annual biases for all the  
242 twelve watersheds are within  $\pm 25\%$  threshold. Eight out of the twelve watersheds have biases within  $\pm 10\%$ , indicating  
243 a very good model performance (Table S6).



245 **Figure 3:** Land cover specific simulated ET validation (WS\_ID) against corrected eddy flux ET data. The line running  
 246 diagonally through the scatter plot is a 1:1 line. The performance metrics provided were calculated using corrected  
 247 ET for all stations except for Anklam (wetland).

248 **3.1.3. GPP Validation**

249 The results showed that nine out of fourteen watersheds have a model bias within  $\pm 25\%$ , twelve had  $R^2 > 0.6$ , seven  
 250 had  $NSE > 0.5$ , six have  $KGE > 0.5$ , and all the watersheds have a correlation  $> 0.6$ , as shown in Table 1. Furthermore,  
 251 the results show that simulated GPP from WaSSI are higher compared to the remotely sensed GPP estimates from  
 252 Copernicus and MODIS satellite by approximately 7% and 16%, respectively. The difference, correlation and  
 253 regression between simulated GPP and remotely sensed GPP is shown in Fig. S3.

254 **Table 1:** Monthly validation of WaSSI-GPP against EC-GPP. Stations are grouped for different land covers e.g.  
 255 cropland (CRO), deciduous broadleaf forest (DBF), ENF, grassland (GRA) and wetland (WET).

256

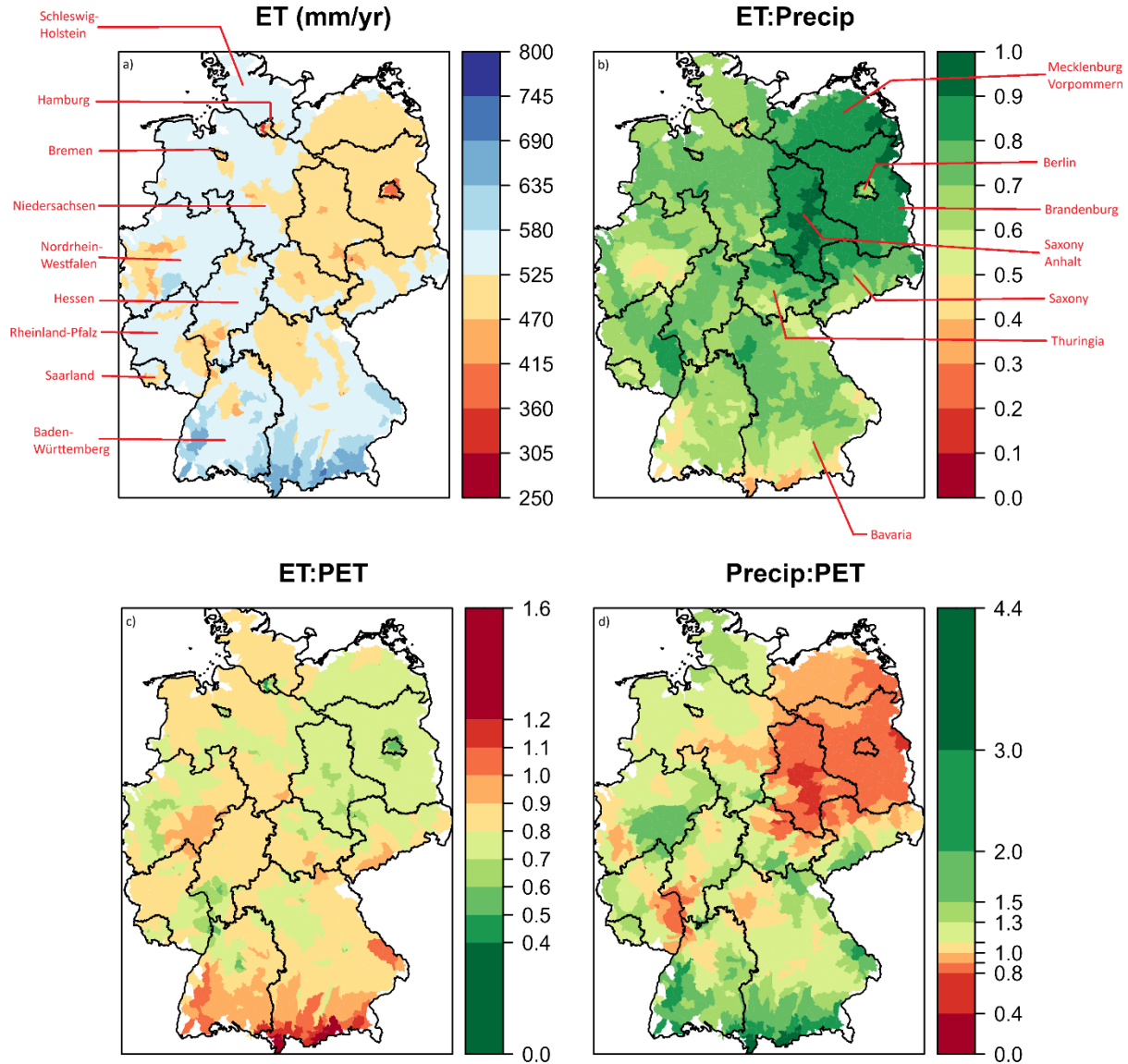
Eddy Flux Tower	Watershed ID	Land cover	Model bias %	$R^2$	Corr	NSE	KGE
Selhausen Juelich	457	CRO	-15.94	0.65	0.81	0.45	0.33
Klingenberg	394		8.34	0.38	0.62	0.37	0.37
Gebsee	415		13.54	0.48	0.69	0.41	0.35
Hainich	390	DBF	8.28	0.84	0.92	0.73	0.57
Leinefelde	390		3.19	0.87	0.93	0.75	0.57
Lackenberg	631		224.09	0.83	0.91	-5.82	-1.51
Oberbärenburg	394	ENF	-13.4	0.86	0.93	0.74	0.59
Tharandt	394		-19.7	0.89	0.94	0.73	0.59
Grillenburg	394	GRA	-35.42	0.75	0.87	0.37	0.3
Rollesbroich	457		-26.79	0.81	0.9	0.55	0.49
Schechenfilz Nord	737		2.61	0.68	0.83	0.67	0.82
Spreewald	269	WET	-50.54	0.82	0.91	0.18	0.16
Zarnekow	38		21.62	0.84	0.92	0.77	0.7
Anklam	23		-40.91	0.63	0.79	0.28	0.2

257

258 **3.2. Understanding the water-carbon coupling across Germany**

259 **3.2.1. Spatial variation of ET from 2001 - 2019**

260 Over a nineteen-year period, the mean annual ET across Germany ranges between 250 to 800 mm yr<sup>-1</sup> and has a spatial  
261 mean and standard deviation of 530 ± 49.5 mm yr<sup>-1</sup>. Eastern Germany (Saxony Anhalt, Brandenburg, Mecklenburg  
262 Vorpommern, Saxony, and Thuringia) have lower ET than the spatial mean, while the South and West has higher ET,  
263 as shown in Fig. 4a. On an annual scale, Bavaria and Lower Saxony experiences significant ET losses. The absolute  
264 losses are 39.5 billion m<sup>3</sup> yr<sup>-1</sup> in Bavaria and 25.7 billion m<sup>3</sup> yr<sup>-1</sup> in Lower Saxony. Bavaria has a smaller fraction of  
265 its precipitation lost as ET (0.3 to 0.9) compared to Lower Saxony (0.5 to 0.9). Across Germany, the eastern states  
266 lost the largest share of their precipitation as ET (0.8 – 1.0), leading to a very limited available water supply in the  
267 region, shown in Fig. 4b. Furthermore, to understand whether ET is limited by energy or water availability, we  
268 estimated ET:PET ratio across Germany. PET is the atmospheric evaporative demand under ideal conditions (i.e., no  
269 soil water stress) and acts as an upper limit of ET. The actual ET of watersheds near the Alps exceeds the PET due to  
270 high precipitation, saturated soils and land cover type. These watersheds receive more precipitation compared to the  
271 rest therefore energy limits the ET values, while for the rest parts of Germany the water availability limits ET (Fig.  
272 4c). Lastly, eastern states and some watersheds in Rhineland-Pfalz and Hessen are drier with relatively high-water  
273 scarcity as they receive less precipitation compared to their PET (Fig. 4d).

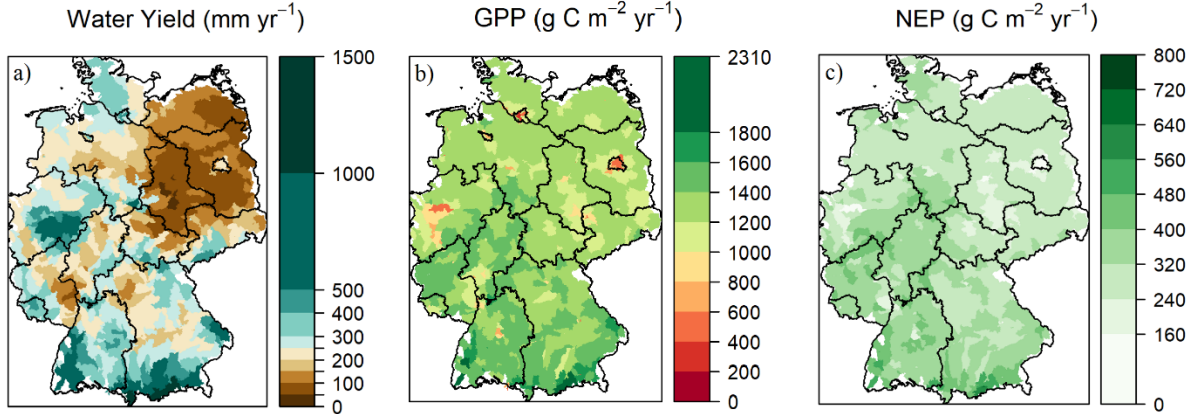


274

275 **Figure 4:** Modelled parameters presenting ET dynamics on a watershed scale across Germany over state boundaries  
 276 within the period of 2001 - 2019. The separate sections show a) mean annual actual ET (mm yr<sup>-1</sup>), b) ratios between  
 277 ET and precipitation, c) ratios between ET and potential ET and d) ratios between precipitation and potential ET.

### 278 3.2.2. Ecosystem services across Germany throughout 2001 – 2019.

279 The mean annual water yield across Germany ranges between 31.8 – 1477.5 mm yr<sup>-1</sup>, has a spatial average of 259 ±  
 280 173.5 mm yr<sup>-1</sup> and generates a total discharge of 84.86 billion m<sup>3</sup> per year (Fig. 5a). In eastern states the water yield  
 281 is lower than the spatial average, while in southern states it is higher. The mean annual GPP estimates (Fig. 5b) are  
 282 found between 0 – 2046.5 g C m<sup>-2</sup> yr<sup>-1</sup> with a spatial average of 1278.8 ± 237.7 g C m<sup>-2</sup> yr<sup>-1</sup> and a total national carbon  
 283 uptake of 441.54 Tg C yr<sup>-1</sup>. The mean annual NEP values (Fig. 5c) are observed between 0 – 665.5 g C m<sup>-2</sup> yr<sup>-1</sup> with  
 284 a spatial average of 308.3 ± 78.2 g C m<sup>-2</sup> yr<sup>-1</sup> and a total national carbon sequestration of 106.03 Tg C yr<sup>-1</sup>.

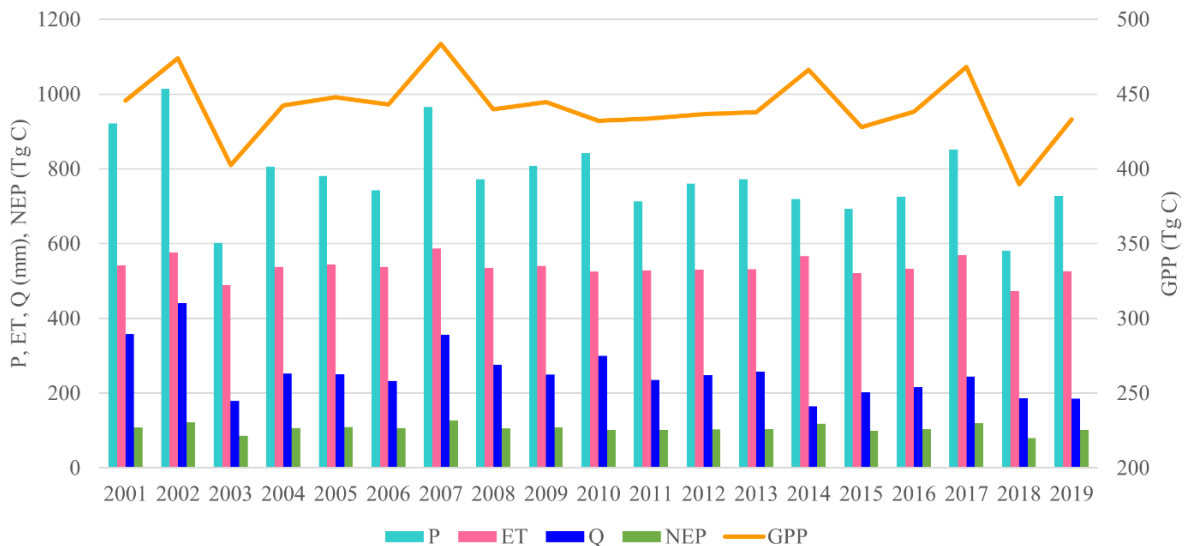


285

286 **Figure 5:** Spatial distribution of model simulated **a)** mean annual total water yield (mm yr<sup>-1</sup>), **b)** mean annual GPP (g C  
287 m<sup>-2</sup> yr<sup>-1</sup>), and **c)** mean annual NEP (g C m<sup>-2</sup> yr<sup>-1</sup>).

288 **3.2.3. Temporal variability of ecosystem services and the control of land cover on these services.**

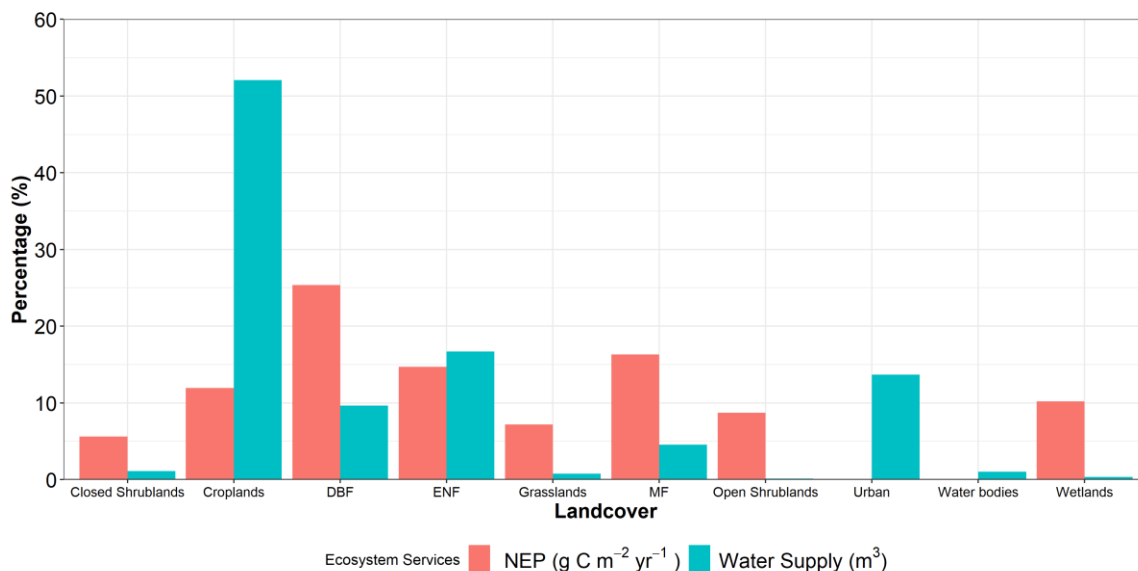
289 The mean annual precipitation for the period 2001–2019 is estimated at  $779 \pm 106.2$  mm/year. Notably, 2002 and  
290 2007 are identified as the two wettest years within this timeframe. Precipitation in 2002 exceeded the mean by 30.2%,  
291 while in 2007 it was 24% higher than the mean. Conversely, the driest years are 2003 and 2018, with rainfall falling  
292 below the mean by 22.7% and 25.5%, respectively. There are relatively high variations in Q and NEP during these  
293 wet and dry years, indicating that these two fluxes are sensitive to changes in precipitation compared to ET and GPP.  
294 In 2018, which is the driest year in the study period, we observed that compared to the mean there is 25.5% less  
295 precipitation. This is accompanied by 11.7% less ET, a 26.8% reduction in Q, 11.7% less GPP and 24.7% lower NEP.  
296 Alternatively, during 2002, the wettest year in our study, we found 30.2% more precipitation compared to mean.  
297 Which may have lead to 7.4% more in ET, 73.4% higher Q, 7.3% more GPP, and 15.5% rise in NEP, relative to mean.  
298 An annual overview for temporal variation is presented in Fig. 6.



299

300 **Figure 6:** Simulated annual ecosystem fluxes evapotranspiration ET (mm), Net ecosystem productivity NEP (Tg C)  
301 ), Gross Primary Productivity GPP (Tg C), discharge Q (mm) and precipitation P (mm) across Germany simulated  
302 by the model during 2001 - 2019.

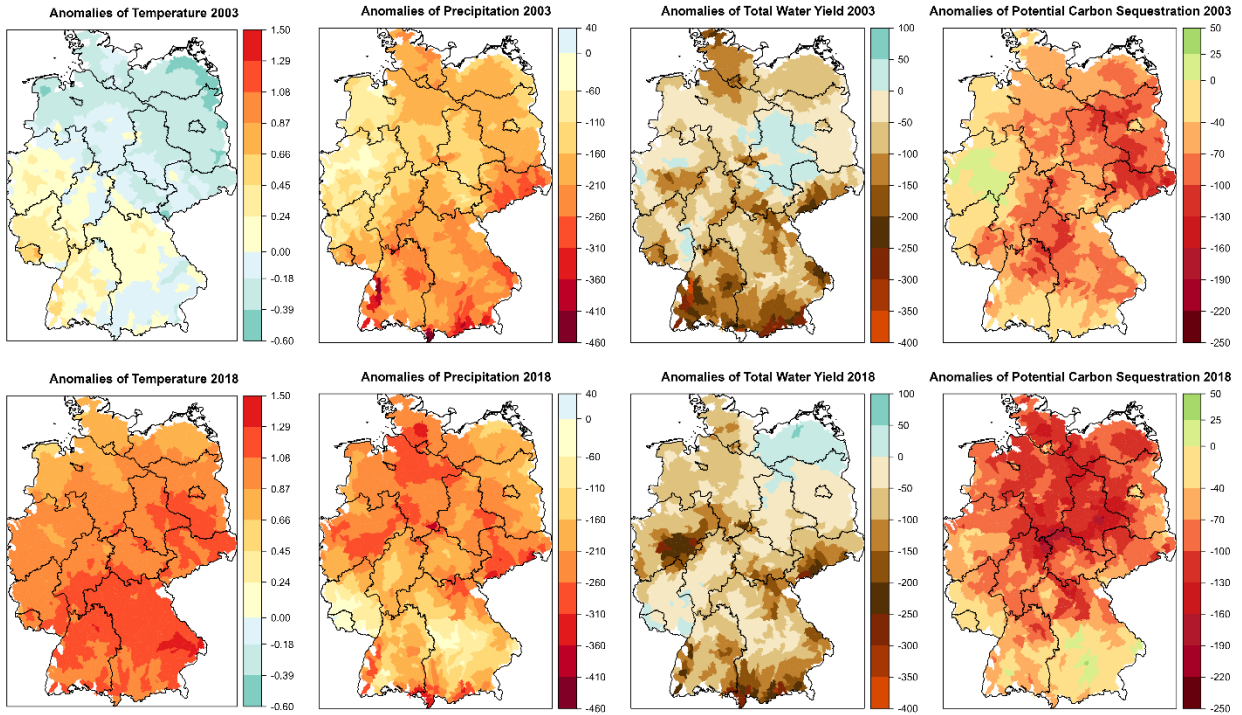
303 To evaluate the role of land cover in water yield and carbon sequestration, we estimated the share of ecosystem services  
 304 provided by the ten different land cover classes. The most essential land covers that provide the largest share of water  
 305 across Germany are Cropland (52.1%), ENF (16.7%), and Urban (13.7%); they supply 82.5% of the water in total.  
 306 Furthermore, forest sequester most of the carbon DBF (25.3%), mixed forest (MF) (16.3%), and ENF (14.7%). They  
 307 contribute 56.3% of carbon sequestered in Germany while only accounting for 30.5% of the land cover. Lastly, we  
 308 would like to highlight that a small portion of land covers, such as wetlands, open shrubland, closed shrubland, and  
 309 grasslands cover less than 2% of German territory; however, they regulate > 30% of the total carbon sequestered in  
 310 Germany, indicating the high importance of conserving these ecosystems, as shown in Fig. 7.



311 **Figure 7:** Simulated mean percentage or share of carbon sequestration and water supply originating from different  
 312 land covers across Germany.  
 313

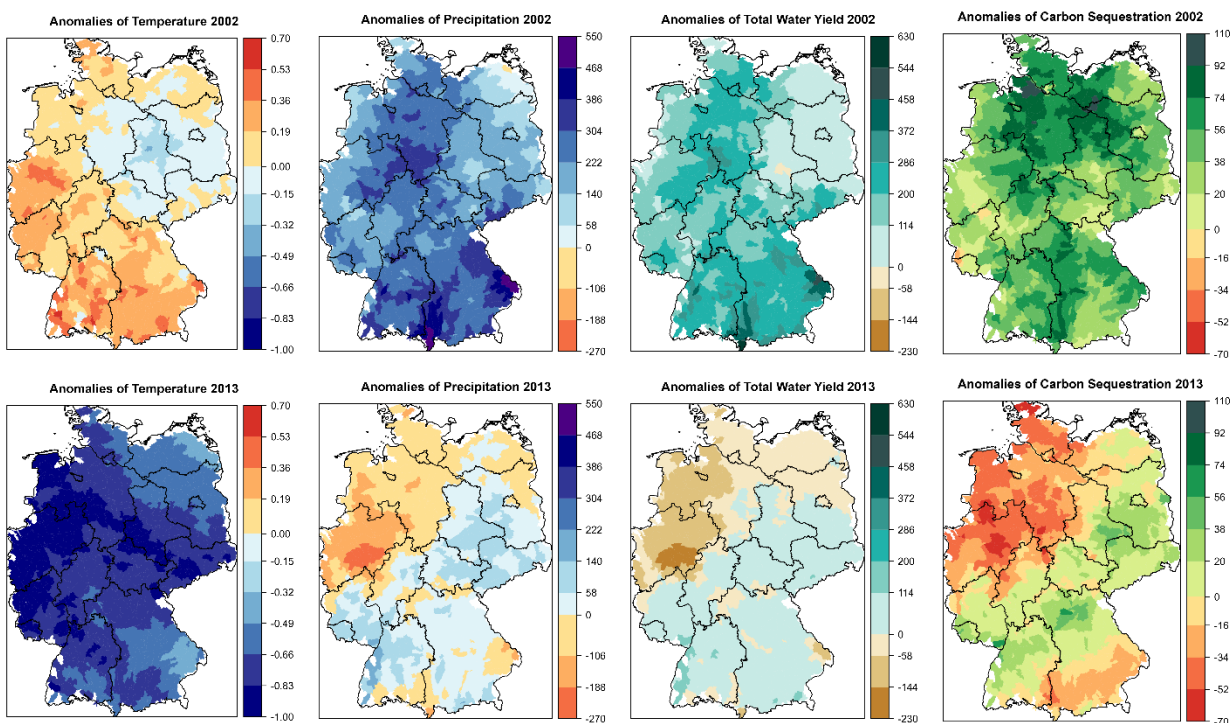
### 314 3.2.4. Spatial variability of ecosystem services during extreme weather events

315 To understand the impact of droughts and extreme precipitation on ecosystem services, we examined the droughts for  
 316 the year 2003 & 2018 and the extremely wet years 2002 and 2013. During 2003, precipitation was 22.7% less than its  
 317 average and only western states had close to average precipitation. The total water yield was 29.6% less than average.  
 318 The carbon sequestration was 18.5% lower than average. While western states had close to average carbon  
 319 sequestration the rest experienced significantly reduced levels. Compared to 2003, the pattern and intensity of the  
 320 2018 drought was more severe. During this event, Germany cumulatively received 25.5% less precipitation, had a  
 321 26.8% lower water yield, and had 24.7% less carbon sequestration. The total water yield was 62.13 billion m<sup>3</sup>, total  
 322 carbon uptake was 389.77 TgC, and total carbon sequestration was 79.82 TgC. The variations in ecosystem services  
 323 due to both drought events are presented in Fig. 8. On the other hand, during the extremely wet year of 2002, Germany  
 324 received 30% more precipitation than annual mean. The water yield and carbon sequestration were 70% and 15.5%  
 325 higher than the mean, respectively. The second wet year of 2013 suffered from severe regional floods. The regions  
 326 that received higher precipitation had a larger water yield and sequestered more carbon. Interestingly, northwest  
 327 Germany was drier than the mean, as a result, the overall ecosystem services for 2013 were close to the mean estimates.  
 328 The variations in ecosystem services during both years are presented in Fig. 9.



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**Figure 8:** The response of ecosystem services, water yield (mm) and carbon sequestration ( $\text{g C m}^{-2}$ ), during two drought events (2003 and 2018). Both drought events had different spatial patterns and intensities, thus the response from the ecosystem varied spatially. The anomalies in the figure were estimated by subtracting the mean annual values for the period 2001 – 2019 from the estimates of the individual drought years 2003 and 2018 on a watershed scale. The temperature anomalies ( $^{\circ}\text{C}$ ) are also provided for understanding the events.



335  
 336 **Figure 9:** The response of ecosystem services, water yield (mm) and carbon sequestration ( $\text{g C m}^{-2}$ ), during two  
 337 extreme precipitation events (2002 and 2013). Both events had different spatial patterns and intensities, thus the  
 338 response from the ecosystem varied spatially. The anomalies in the figure were estimated by subtracting the mean  
 339 annual values for the period 2001 – 2019 from the estimates of the individual years 2002 and 2013 on a watershed  
 340 scale. The temperature anomalies ( $^{\circ}\text{C}$ ) are also provided for understanding the events.

341 **4. Discussion**

342 This study explores the response of water-carbon cycle to land cover and extreme events across Germany on watershed  
 343 scale. The WaSSI model performs reasonably well in this region and is estimated to generate 84.86 billion  $\text{m}^3$  of  
 344 discharge and 106.03 TgC of carbon sequestration per year. The results (Figure 7) also highlight the importance of  
 345 sparse landcovers (e.g. wetlands, open shrubland, closed shrubland, and grasslands) in regulating carbon sequestration.  
 346 Furthermore, the study shows that ecosystem services are quite sensitive to droughts and extreme precipitation events,  
 347 but buffers developed from the previous year can play a significant role in mitigating this effect. As shown in Figure  
 348 8, we observe low but positive water yield anomalies during drought years in parts of Germany. Buffers can help delay  
 349 the onset of hydrological droughts in the region.

350 The model validation results successfully demonstrate that the model can be applied across Germany. Furthermore,  
 351 due to the common climatic and hydrological regime, we believe the model can potentially be applied to a broader  
 352 central European region. The simulated discharge had small model bias percentage and high regression values.  
 353 Furthermore, the spatial and temporal variability of the discharge was modelled reasonably well with high NSE, KGE,  
 354  $R^2$  and low P-bias for most watersheds (Table S3 - S4). Except for station Wasserthaleben, which had very high flow  
 355 values leading to a P-bias equal to 131.8%, KGE of -1.48, and annual  $R^2$  of 0.18. The poor performance of this  
 356 individual station could be attributed to several possible reasons, including its relatively small surface area, the  
 357 uncertainty of input data (soil parameters or climate data), underestimation of losses to groundwater, simplification of  
 358 physical processes that estimate surface runoff, or the presence of prevalent unidentified dams in the watershed  
 359 (Caldwell et al., 2012).

360 Simulated ET validated reasonably well against data from different eddy flux towers across the study area (Fig. 3).  
 361 The largest discrepancy was found in Lackenberg station. Even though corrected ET values are used for validation,  
 362 there might be uncertainties in correction factor (Pastorello et al., 2020) and inaccuracies in the observed data due to

363 energy imbalance. For spatial analysis, the simulated ET was compared with MODIS data. The model values were  
364 low compared to MODIS ET in southern and northwestern Germany, but high in mid-western and eastern Germany.  
365 The discrepancies between MODIS-ET and WaSSI ET could be attributed to multiple factors, i.e. the intrinsic  
366 limitations of the different algorithms used by the model and MODIS to estimate ET, uncertainty from the  
367 misclassification of land cover between the two datasets, uncertainties in the model's input data, uncertainties in  
368 MODIS's input data, exclusion of waterbodies in ET estimation by MODIS, and the role of interception in MODIS-  
369 ET estimation (Kim et al., 2012; Trambauer et al., 2014).

370 Furthermore, the model performance across different land covers showed that simulated GPP estimates capture forest  
371 biomes significantly well, except for the station in Lackenberg Forest. The model performance for the rest of the land  
372 covers was less straightforward. For example, croplands had good model biases but low regression values; grasslands  
373 had poor model biases, but high regression estimates; wetlands are more multifaceted (see Table 1). The discrepancies  
374 in the results can be from 1) the model's inherent limitation i.e., lack of radiation in model PET leading to  
375 underestimation of GPP, 2) an insufficient number of eddy flux data for different land covers, and uncertainty in eddy  
376 flux GPP. The uncertainty of daily GPP can reach 15% to 20% (Falge et al., 2002; Hagen et al., 2006; Lasslop et al.,  
377 2010; Verma et al., 2014). Understanding uncertainties in eddy flux GPP is ongoing research. The mismatch of land  
378 cover and landscape heterogeneity at the evaluation sites between the model (watershed scale) and the eddy flux  
379 (single location) will reduce as more data becomes available with time (Verma et al., 2014). Lastly, the difference  
380 between spatial distribution of simulated GPP and remotely sensed GPP may be due to WUE parameters. They were  
381 derived from the global FLUXNET database, which might not have sufficient representation of certain ecosystems  
382 (e.g., wetlands and savannas) resulting in a bias of GPP estimation (Sun et al., 2011). Nevertheless, multiple studies  
383 have also shown that data from remote sensing tends to underestimate GPP (Liu et al., 2015; Wang et al., 2017; Zhu  
384 et al., 2018).

385 The simulated stocks and flows of ecosystem services across Germany by this study were similar to Zink et al. (2016)  
386 and Huang et al. (2010) who reported annual ET and water scarcity patterns at individual sites. The eastern region  
387 in Germany generally receives less precipitation, has high mean annual temperature, high ET from forests and low  
388 water yield, implying intense water use competition. The total water supply reported by German Environment Agency  
389 (UBA) was higher than the simulated results because WaSSI model does not consider transboundary flows (J. Arle et  
390 al., 2018). Furthermore, the southern region in Germany had slightly higher carbon uptake and sequestration values  
391 than the rest of the country. The distribution patterns of carbon sequestration were similar to carbon uptake because  
392 NEP and GPP have a linear relationship. Urban areas sequestered limited carbon but played a significant role in  
393 altering water balances. The distribution and management of land use and land cover determine how ecosystem  
394 services vary. To ensure adequate quantity and quality of services, like freshwater and natural sink of CO<sub>2</sub>, land use  
395 decision-making must incorporate the assessment of currently available stocks and their actual value according to  
396 regional and national priorities. Based on historical data, the available stocks quantified in this study provide evidence  
397 to relevant stakeholders of different regions. Furthermore, the significance of minor land covers or ecosystems in  
398 terms of proportional coverage, such as wetlands, is also highlighted. Germany aims to become CO<sub>2</sub> neutral by 2045;  
399 synergies and tradeoffs of ecosystem services can be used to design land use policy that align with Sustainable  
400 Development Goals. A science-based approach will be necessary to leverage the potential of natural C sink to fix and  
401 offset carbon emissions.

402 As the frequency and intensity of periodic dry and wet spells change due to global warming so does their impact  
403 through drought and extreme precipitation events. In this work, we, quantified the response of water yield and carbon  
404 sequestration to extreme drought and high precipitation events across Germany. During the drought events of 2003  
405 and 2018, the lack of precipitation, overall, had a direct negative impact on water yield and carbon sequestration. But  
406 it is interesting to see that soil has stored water from the previous years, acting as a buffer and provide limited relief  
407 during extreme drought events (Fig. 8). According to Ciais et al. (2005), a 30% reduction in carbon uptake was  
408 observed across Europe during the drought of 2003, while we estimated a reduction of around 8.8% for Germany.  
409 Europe-wide studies on the impacts of the 2018 drought event on carbon sequestration are presented by Thompson et  
410 al. (2020) and Smith et al. (2020). They found that the annual sequestration anomaly in 2018 across northern Europe  
411 was  $0.02 \pm 0.02$  PgC yr<sup>-1</sup> less compared to a 10-year European mean (Thompson et al., 2020). It was estimated that  
412 during the year 2018 an overall reduction in sequestration was around 57 TgC (Smith et al., 2020). However, a direct  
413 comparison between our research is difficult due to the difference in the spatial boundaries. In general, Germany has  
414 no shortage of water, however, a trend to have less precipitation during summer seasons or prolonged dry spells during

415 main vegetation growing months can have substantial adverse effects on both surface water and groundwater supply.  
416 Temporary seasonal rainfall deficiency can cause significant losses of surface water supply and carbon sequestration,  
417 leading to dry conditions that negatively affect the yields and products from the agriculture and forestry sectors. For  
418 example, low soil water availability weakens forest health and favors bark beetle infestation, resulting in huge  
419 economic losses of timber values and forest areas in Germany over the last few years (Lausch et al., 2013;  
420 Zimmermann & Hoffmann, 2020) and the situation continues to worsen. Therefore, land use transformation to adapt  
421 to climate change is indispensable to developing ecological resiliency based on an improved understanding of the role  
422 of various land covers in providing ecosystem services.

423 While this study provides valuable insights on response of water-carbon cycle to land cover and extreme events, it is  
424 limited by the scope of WaSSI Model. The monthly temporal resolution of the model prevents it from estimating peak  
425 flows accurately. The use of WUE to connect ET and carbon sequestration is limited due to insufficient eddy flux  
426 tower coverage. The lack of transboundary river flow and omission of crop rotation further limits the application of  
427 this model. In future, we plan to use WaSSI model across hydrological boundaries, apply projected climate data and  
428 projected landcover data to run simulations for different scenarios. The analysis will help us evaluate future changes  
429 in ecosystem services.

## 430 **5. Conclusions**

431 This study presents new insights into the relationship between water-carbon cycle and land cover, and the impacts of  
432 climate extremes across Germany. The model validation results holistically show that the simple water and carbon  
433 model could capture ecosystem services reasonably well at the national level. Furthermore, the spatial and temporal  
434 relationship between carbon and water highlighted that the eastern states of Germany are comparatively drier than the  
435 rest of the country because most of their precipitation is lost as ET. Nationally, ecosystems in Germany generates a  
436 total annual discharge of 84.86 billion m<sup>3</sup> and sequester 106Tg C yr<sup>-1</sup> carbon. Croplands supply the largest percentage  
437 of available water, while forests sequester the major share of carbon. Minor land covers (e.g. wetlands, open  
438 shrubland, closed shrubland, and grasslands) are also very important in providing ecosystem services for carbon  
439 sequestration. The extreme events in 2003 and 2018 had a significant impact on ecosystem services at the national  
440 level. Moreover, the severe flood of 2013 also played a major role on a regional scale in the Elbe and Danube River  
441 basins. This rigorously verified model provides confidence that the model can be used to strategic applications for  
442 developing Nature-based Solutions (NbS), which will be helpful for Germany to meet its net-zero carbon emissions  
443 by 2050.

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448 Forest Ecosystems for collaboration.

449 **7. Data Availability**

450 Model software (Liu, 2021), output data (Pyarali, 2024b) and corresponding watershed shapefile (Pyarali, 2024a) used  
451 and prepared in this study are available open source via figshare and can be access from the links in reference list.

452 **8. Author Contributions**

453 *Karim Pyarali*: Writing, review & editing manuscript, Methodology, Investigation, Data curation, Conceptualization.  
454 *Lulu Zhang*: Review, Supervision, Methodology, Funding acquisition, Conceptualization. *Ge Sun*: Review,  
455 Supervision, Methodology, Conceptualization. *Ning Liu*: Review, Data curation, Methodology. *Abdulhakeem Al-*  
456 *Qubati*: Review, Data curation, Methodology.

457 **9. Competing Interests:**

458 The authors declare that they have no known competing financial interests or personal relationships that could have  
459 appeared to influence the work reported in this paper.

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