Spatial optimization of carbon-stocking projects across Africa integrating stocking potential with co-benefits and feasibility

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Carbon (C) offset projects through forestation are employed within the emissions trading framework to store C. Yet, information about the potential of landscapes to stock C, essential to the design of offset projects, is often lacking. Based on data on vegetation C, climate and soil we quantify the potential for C storage in woody vegetation across tropical Africa. The ability of offset projects to produce co-benefits for ecosystems and people is then quantified. When co-benefits such as biodiversity conservation are considered, the top-ranked sites are sometimes different to sites selected purely for their C stocking potential, though they still possess up to 92% of the latter's C stocking potential. This work provides the first continental-scale assessment of which areas may provide the greatest direct and indirect benefits from C storage reforestation projects at the smallest costs and risks, providing crucial information for prioritization of investments in C storage projects.

The primary aim of C stocking projects is to reduce atmospheric C concentrations to mitigate anthropogenic climate change; therefore a central component in feasibility assessments of C stocking projects is their potential to store C[1]. Storing C in vegetation constitutes an important focus for C stocking projects, because human land-use often results in vegetation C storage that is less than its potential maximal value under prevailing environmental conditions. Notably, forest degradation due to logging, grazing and fuel wood collection, or deforestation from conversion of forests to agricultural land, may result in decreases in C storage, with forest C sinks converted to C sources[2,3]. Deforestation is the second-largest source (15%) of greenhouse gas release into the atmosphere, a trend that is expected to continue due to human population increases and ongoing land-use changes, while climate change may lead to additional forest losses and release of greenhouse gases[4-6]. Other natural and anthropogenic disturbances such as herbivory[2] and more frequent or intense fires[3], may also decrease vegetation C storage. Understanding the difference between potential and actual C storage is therefore essential for assessing the scope for C stocking in vegetation.

While vegetation C stocking projects focus on reducing atmospheric C concentrations, they may have secondary benefits for biodiversity, ecosystem services and local economies. For example, C stocking projects can provide payments to the local communities in which they are based[7]. Biodiversity conservation can also be promoted through, for example, habitat restoration[8] or conservation of species[9], and reforestation and restoration of degraded vegetation can contribute to ecosystem services like water flow regulation, soil protection, flood regulation and the provision of food and other non-timber forest products[9,10]. Such co-benefits are often overlooked when establishing C stocking projects[11]. In fact, in the voluntary market, 40% of forest C projects use exotic species[12]. Since many C stocking projects constitute monocultures and may involve the transformation of natural grasslands to exotic plantations, they can harm biodiversity and other ecosystem services[9]. While monocultures of fast-growing species can have the advantage of rapidly storing significant amounts of C, they may cause problems such as altering water supply and driving species loss, and some exotic plantation species can become invasive, with further-reaching ecological and economic consequences[13]. In sum, it is advantageous to consider biodiversity and other ecosystem co-benefits in C forest projects to not only avoid unintended adverse effects, but also to ensure sustainability of such projects by enhancing their value to local people and attracting more and diverse potential investors[14].

Within the developing world, Africa is underrepresented in terms of forest-based C stocking projects and projects in Africa tend to be geographically biased, with the majority located in East Africa[9]. However, Africa is one of the fastest growing regions for the voluntary C market, with much of the growth driven by consumer demand for projects geared toward sustainability[15]. Many of the recent C projects in Africa have been certified by high-quality standards[15], which, amongst others, assess carbon storage, audit projects, ensure transparency, and evaluate multiple benefits of carbon projects. Given these positive trends, and the apparent demand in the C market for benefits other than C storage, Africa holds promise for further and more integrated C stocking projects. Yet, for C stocking projects that have been initiated in Africa, information on the ability of landscapes to stock C has often been missing prior to initiating stocking projects[9]. To ensure the long-term sustainability of these projects and to provide the desired returns, it is crucial to establish more systematic identification of the areas with the potential to store significant amounts of C, while also considering their potential co-benefits.

Recent advances in data availability have made such systematic approaches feasible. For example, aboveground C storage has been quantified across broad spatial scales using remote sensing, enabling the generation of maps of aboveground C storage for continental regions[16,17]. These broad-scale maps, coupled with an understanding of the factors that affect vegetation C storage, can be used to estimate the potential of regions to store C by means of forestation programs. In addition, spatial prioritization techniques developed for systematic conservation planning provide powerful tools for choosing sites that offer the best solutions to multiple criteria such as co-benefits and costs. To help guide international investments in C storage, we develop and test such a systematic approach to the prioritization of investments in C storage projects across tropical Africa.

We quantify the potential for above-ground C stocking in forests in the absence of human disturbance for tropical Africa to identify where C stocking through forestation might provide the greatest benefits. A spatial prioritization technique is subsequently employed to identify areas where C stocking projects could also provide other benefits and reduce costs.

Results

Generation of maps showing potential for C stocking. Maps of C stocking potential, i.e. additional C that could be stored in vegetation if disturbances were eliminated, were produced for tropical Africa. Different C stocking potential maps were produced based on two available maps of above-ground C storage: that by Saatchi et al.[16] and Baccini et al.[17] (Fig. 1, Supplementary Fig. S1, Supplementary Table S1). We also employed two different modeling methods, 90% quantile regression (QR) and ordinary least square (OLS) regression analyses, to generate maximum C biomass maps, which were used to produce the C stocking potential maps. The coefficients of the QR and OLS models are presented in Supplementary Table S2. These coefficients were similar to coefficients produced from 2000 set of analyses that were run on random subsets of the dataset, for both Saatchi- and Baccini-produced maximum C biomass maps, though confidence was higher for the former than the latter (Supplementary Tables S2 and S3). A map of model uncertainty per planning unit (PU) for maximum C biomass is given in Supplementary Fig. S2. There was geographic variation in uncertainties between areas, but variation in estimates remained small, indicating low uncertainty. We also evaluated how well the predicted maximum C biomass corresponded to actual values of C biomass in undisturbed forests. There was a positive relationship between the two (except for the 98% QR maps based on the Saatchi dataset, Supplementary Table S4 and Supplementary Fig. S3). The r^2 values between the field data and the predicted C biomass were not much different from those between the field data and the original C biomass maps, though the latter had slopes closer to one (Supplementary Table S4, Supplementary Fig. S3). The Baccini-generated maximum C biomass map better matched the field data than that of the Saatchi map did (Supplementary Table S4, Supplementary Fig. S3). Nevertheless, due to the above-mentioned higher confidence in the Saatchi dataset, and because the two original maps by Saatchi and Baccini are highly correlated for the study area (87%, Supplementary Table S5) we focus on the analyses based on the more recently produced Saatchi dataset, though most analyses were repeated on the Baccini-based data (Supplementary Figs. S1, S4 and S5). Carbon stocking potential maps produced by QR and OLS analyses were highly correlated (>92%, Supplementary Table S5). For this reason, and because the human influence index[18] on which the OLS analyses were based (Supplementary Methods) may not be an altogether accurate measure of vegetation degradation[18], we here report the results from the QR analysis, while OLS results are presented in Supplementary Figs. S1, S4 and S5.

The areas with the greatest C stocking potential were the western Upper Guinean rainforest, the Lower Guinean rainforest (both particularly predicted by the computations based on the Saatchi map, Fig. 1), pockets north and south of the Congolian rainforests, and the area around Lake Victoria (especially predicted by the computations based on the Baccini map) (Figs. 1, 2 and Supplementary Fig. S4f). In contrast, the Congolian rainforests (for the Saatchi data only the western sections) and the Sahel exhibited low levels of C stocking potential. The total additional woody biomass that could be stored in vegetation across the entire region amounted to 8.90×10^{10} T (Fig. 1c, i.e. based on 90% QR analyses conducted on Saatchi C map). The total additional woody biomass that could be stored in vegetation across the entire region amounted to 1.06×10^{11} T when C storage was calculated using 90% QR models based on the Baccini C map, and 3.93×10^{10} T or 4.40×10^{10} T when C storage was calculated using OLS models based on the Saatchi and Baccini C maps respectively.

For some PUs the C stocking potential exceeded the maximum C storage values given in the original C biomass maps obtained from Saatchi et al.[16] and Baccini et al.[17]. We do not purpose that the potential C stocking values we obtained are absolute values – they are more likely to provide indications of relative values. On the other hand, there are indications that the maximum C biomass for Africa that is provided by both original C biomass maps are actually surpassed in the tropical forests of Africa[19-21] (e.g. 596 T x ha-1, recorded in Cameroon[19]), indicating that it is not impossible that there are regions with the higher C stocking potential values we obtained in our models. Therefore, the C stocking potential values should be interpreted more as relative, rather than absolute values.

Identifying where C stocking projects would have co-benefits. Next, we assessed which PUs not only possess high C stocking potential, but would also hold co-benefits and have lower costs associated with them. When biodiversity measures, groundwater recharge, and socioeconomic factors were considered along with C stocking potential to select PUs for C stocking (Fig. 2, Supplementary Fig. S4a-e), the top 5% highest-ranked PUs differed from those ranked only by their C stocking potential (Fig. 2, Supplementary Fig. S4f), except when C stocking potential in the multi-criteria selections was weighted particularly high with respect to the other features, resulting in similar prioritizations. This indicates that the PUs identified as most suitable for C stocking were not always most beneficial in terms of co-benefits, costs, and risks (Fig. 2, Supplementary Fig. S4a-e vs. S4f). The distribution of high-ranking PUs also differed depending on the cell removal rule used (Supplementary Fig. S4, 'ABF' vs. 'BCZ' method).

The ranking of PUs differed between runs with different weightings for C stocking potential (Fig. 2). Though similar contiguous areas with a concentration of highly ranked PUs were usually identified in analyses with different C stocking potential weightings, their size and extent changed as the importance of C stocking potential varied (Fig. 3, Supplementary Fig. S5). As the weighting of C stocking potential decreased, and the other factors thus gained in importance, there were fewer highly ranked sites around Lake Victoria and north and south of the Congolian rainforests (with the exception of the Batéké Plateau), while there was an increasing concentration of highly ranked sites in the Lower Guinean rainforests. As expected, runs with more similar weightings of C stocking potential showed more overlap in the top 5% rankings of PUs (Supplementary Table S6), and showed less change in overall rankings (Supplementary Table S7) than runs with more dissimilar rankings.

As the weighting of C stocking potential increased in Zonation analyses, the C stocking potential of sites increased (Fig. 3 and Supplementary Fig. S5a-e), while the performance of ecosystem services and economic risks and costs suffered reductions (Fig. 3, see also Supplementary Fig. S5). The performance of features showed more consistent trends for all features when the added benefit function (ABF), rather than the basic core zonation (BCZ), cell removal rule was used. The performance of the various features was erratic for analyses conducted using BCZ. For example, for the 90% QR analyses based on the Saatchi data the performance potential C stored was lower for analyses weighted 12 than 6 (Supplementary Fig. S5), though one would have expected the reverse pattern. Therefore, our interpretations were entirely based on analyses conducted using the ABF cell removal rule. For ABF analyses, benefits other than C stocking potential predictably decreased and penalties increased with increasing C stocking potential weightings (Figs. 3 and Supplementary Fig. S5a-e). (Only the effects of increasing the C stocking potential weighting on biodiversity were somewhat dependent on whether species richness was averaged per PU or summed across the entire landscape (Fig. 3). Species richness summed across the landscape performed as expected – it tended to decrease with increasing C stocking potential, while mean species richness per PU did not always show consistent trends. This is because species richness summed across the landscape better represents the conservation objectives of the site selection method used here: highly ranked sites should support different subsets of species, rather than purely harbor high species richness.)

Since the primary aim of this study was to identify regions with potential for C stocking that would also, secondarily, benefit ecosystem services at minimal socioeconomic cost and risk, we focused on the ranking of PUs in which C stocking potential was assigned the sum of the weights of all other factors, i.e. 12 (Fig. 2c). This strategy ensured that C stocking potential was neither down-weighted by, nor dominant over, the other features in the PU selection process. Indeed, the amount of C that could be stored in the 5% highest-ranked PUs of this procedure (90% QR Saatchi ABF analyses) was 92% of that of the 5% highest-ranked PUs based on C stocking potential only, while total mammal, reptile and amphibian species richness were 56%, 89% and 28% higher respectively; groundwater recharge and governance were 8% and 3%

higher respectively and total land value 5% lower than if sites had been chosen based on C stocking potential only (Fig. 3). (See Supplementary Fig. S5 for results of other analyses.)

Three large contiguous areas emerged as having high C stocking potential and co-benefits (Fig. 2c, yellow areas): the Upper and Lower Guinean Forests and the Batéké Plateau. As mentioned, other regions surrounding the Congolian rainforests and the areas around Lake Victoria showed high potential for C stocking alone, but did not perform as strongly when other factors were taken into consideration (Fig. 2, Supplementary Fig. S4).

Connectivity parameters were included and varied to identify larger contiguous areas of high ranking during the site selection process (Supplementary Fig. S6). As expected, the larger the connectivity parameter used, the larger were the contiguous patches of highly ranked PUs (Supplementary Fig. S6), though the total C stocking potential and other benefits in the top ranked sites generally decreased, with some variation (Supplementary Fig. S7). Again, the mean biodiversity richness per PU increased with connectivity in some cases, but the biodiversity at landscape scale decreased with higher connectivity; therefore, while more species per PU might have been included in the highest ranked sites of higher connectivity, fewer unique species were conserved across the landscape. Maps with the highest connectivity measures were uninformative (Supplementary Fig. S6). Overall, including connectivity in analyses served to further highlight the previously mentioned regions where carbon stocking potential would also benefit biodiversity and ecosystem services while taking socioeconomic factors into consideration (Fig. 2, Supplementary Fig. S6).

Discussion

It is well established that Africa has great potential for C offset projects by reforestation[1,9]. There is, however, a need to pinpoint areas that are predicted to produce particularly high returns through C stocking by reforestation, avoid unintended costs and reap additional benefits for local communities, biodiversity conservation and other beneficiaries; knowledge that would be invaluable for estimating the benefits of C projects prior to their establishment [1,9]. Our investigation fills a major knowledge gap by producing the first map of C stocking potential by reforestation for tropical Africa, or any other similarly large region, and indicating where such reforestation projects would provide substantial co-benefits.

We identified areas where high productivity and high landscape disturbance or degradation overlap, and where C stocking projects would thus bring high returns (Figs. 1, 2), notably the Upper and Lower Guinean rainforests, the regions surrounding the Congolian rainforests and the shores of Lake Victoria. These all occur in the equatorial belt with high rainfall and warm temperatures, and thus high potential productivity, but have been subjected to considerable degradation[22-25]. In contrast, much of the Congolian rainforests, which also receive high rainfall, exhibited relatively low levels of C stocking potential due to their comparatively low levels of degradation[24], while the Sahel's low potential for C stocking could be attributed to its low rainfall.

There have been several calls to consider biodiversity, ecosystem services and socioeconomic in the planning carbon offset projects[9,11,26]. Several studies have included *existing* C biomass as one of several factors that should be considered as a trade-off for identifying sites conservation purposes or under the Reducing Emissions from Deforestation and Forest Degradation (REDD) scheme[27-30]; however, there is a lack of concomitant information on how C stocking by forestation or forest restoration, i.e. *potential* C biomass, could be traded off with such co-benefits. We assess where C stocking projects should be placed to optimize positive synergies with other factors such as species conservation, ecosystem services and socioeconomic factors (Fig. 2c, yellow areas).

Generally, highly ranked areas when co-benefits were considered were similar to areas identified solely on the basis of C stocking potential (Figs. 2, S4). However, there were moderate shifts in geographic emphasis when co-benefits were considered. More extensive regions of the Upper and Lower Guinean rainforests were highly ranked; these regions thus not only have high C stocking potential, but also higher degrees of governance and levels of biodiversity (Supplementary Fig. S8). They support several restricted-range species [31,32] but have, especially in West Africa, been extensively degraded, resulting in extensive local losses of forest species[23,33,34].

The Batéké Plateau was also identified as a high priority area, as it possesses high groundwater recharge, low land value and a relatively high governance index (Supplementary Fig. S8). The Batéké Plateau is an extensive mosaic of savanna and gallery forests, some heavily degraded, stretching across central Congo (Brazaville) with a climate suitable for extensive forests[35]. Debate exists as to whether the savannas in this area are secondary[36], or whether they reflect earlier Holocene climate change[35]. Therefore, while reforestation in the region is possible, given the uncertainty of the "natural" state of the savanna vegetation, specifically selecting recently degraded areas for reforestation would be advantageous.

An area that was identified as having high C stocking potential, but became less highly ranked when other factors were considered, is the region around Lake Victoria. It has seen a human population explosion since the 1930s due to improved accessibility and health conditions[22,37], resulting in extensive deforestation and soil degradation[22,38]. Thus, while much of this region achieved top priority in terms of C stocking potential alone, its high population density and intense agricultural productivity underlie substantial land values. The area also does not support particularly high terrestrial biodiversity (Supplementary Fig. S8). Therefore, the region around Lake Victoria did not emerge as a top-priority area when biodiversity, ecosystem services benefits, and costs of C stocking projects were also considered.

Other regions of high C stocking potential, but lower co-benefits, were several pockets North and South of the Congolian rainforest. Despite their high C stocking potential, these regions tend to have low governance, and do not support exceptional levels of biodiversity (Supplementary Fig. S8). The latter can probably be attributed to past climate changes which are thought to have resulted in the extinction or range contractions of species that previously occurred here[39,40].

Identifying areas with high C stocking potential (with or without co-benefits) constitutes only the first step in setting up C stocking projects by reforestation, and a number of considerations and uncertainties. Caution should be taken that C projects by reforestation should not extensively conflict with existing land uses such as agriculture, as loss of agricultural activity on land earmarked for C stocking projects could result in leakage, where C stocking in one area results in agricultural increases – and therefore loss of C stocks – in other areas[13]. Also, for reforestation projects to succeed in developing countries, surrounding communities must obtain benefits from forests and be actively involved in their management[41,42]. A number of co-benefits have been shown to improve the success of C stocking projects. These include improved livelihoods which address local needs, increased incomes, the creation of employment opportunities, and markets for e.g. non-timer forest products that could be harvested from within the reforested patch[41]. Future climate change comprises a further consideration for reforestation projects. Trees are long-lived organisms. The success of reforestation projects, and the ability of reforested areas to build up and maintain their C stocks may be influenced by whether and how climate change will affect the ability of plants to grow in novel climates[43]; the African tropics may be especially prone to such effects[43]. Some of the areas under consideration in this study are likely to experience climates not currently experienced anywhere on Earth[43], making it difficult to predict climate change effects. In addition, future climate change predictions for these areas have high uncertainty[44], further complicating predictions of climate change effects on the vegetation and species of the region. Increases in atmospheric CO_2 are a further factor – they are likely to benefit tree growth due to CO_2 fertilization effects[45], allowing even higher tree biomass, and thus C biomass, than predicted from our models to be sequestered in C stocking forests. Finally, a number of uncertainties in analyses such as our inevitably exist. These may, for example, arise due to the large scale at which the project was conducted, which brings about uncertainties in the input data which have usually been generated by a form of interpolation and/or on the basis of indirect remote sensing data. In addition, C stocking potential may be affected by factors other than those that we used in our analyses, but might be difficult to obtain at large spatial scales, or might only act locally. The identification of potential sites for C stocking by forestation using methods such as ours should thus only serve as a first step in planning the location of potential sites. Subsequently integrating a wide range of expertise in site assessment, project identification, planning and execution is essential for ensuring the wider benefits of such projects. This integration would empower the description of existing ecological and socioeconomic conditions and promote the development of a detailed strategy that not only maximizes C stocking potential, but also considers ecosystem processes and features, monetary and managerial constraints and could examine uncertainties at a local level.

In conclusion, the primary aim of C offset projects is to reduce atmospheric CO_2 concentrations. Although biodiversity and other ecosystem services often indirectly benefit from C stocking projects[46], policies that promote C stocking do not always benefit conservation or ecosystem services, nor is it always realistic to establish projects in areas with the highest C stocking potential. Strategies that solely benefit C stocking may compromise biodiversity and water supply[30,47,48], come at the expense of agricultural production[13], negatively impact ecosystems[47,48] and local people[49], or have costs associated with high land value or poor governance. Therefore, much can be gained if the planning of C projects considers co-benefits, costs and risks. Here, we demonstrate how prioritization of C projects can integrate factors beyond C stocking, including biodiversity conservation, ecosystem services and political and socioeconomic risks and costs. Consideration of these factors may influence geographic priorities and serve as a useful initial decision-making tool to balance various factors to maximize the overall benefits of C offset projects. Our site-selection methods identify areas that should specifically benefit from restorative reforestation, e.g. by planting a complement of woody species indigenous to the area, while the indigenous fauna are allowed to persist or are reintroduced. Therefore, setting aside landscapes for C stocking purposes can make important contributions to mitigating climate change; and if the selection of such landscapes is performed within a larger framework, stocking projects may also result in wider benefits[50].

Methods

Assessing C stocking potential. This study focused on the potential of reforestation for C stocking. Due to data limitations (C estimates for non-woody vegetation, below-ground C and soil C are more difficult to attain[3]), we assessed the potential for C storage in terms of aboveground woody biomass (henceforth "biomass"). Two maps of biomass for tropical Africa were used, one by Saatchi et al.[16], the other by Baccini et al.[17] (Fig. 1, Supplementary Table S1, Supplementary Methods)[16,17]. The two maps are highly correlated (Supplementary Table S5). Main analyses were run using both datasets; however, we mainly represent the results from the more recent map by Saatchi et al.[16].

We quantified the maximum C biomass that could be stored per unit area using two methods: 1) 90th-percentile QR and 2) OLS regressions (Supplementary Methods). Biomass was used as response variable, and modeled in terms of four climatic variables[51] that are important for the distribution of vegetation types across Africa[52] and two soil variables[53] (Supplementary Methods). Confidence of model estimates was assessed, and the predicted maximum C biomass compared to above-ground C biomass measured in undisturbed forests across tropical Africa (Supplementary Methods).

Two sets of maps of the difference between potential and actual C storage were created by subtracting the original biomass maps[16,17] from the maximum biomass calculated by 1) QR and 2) OLS. The resulting maps ("C stocking potential" maps) represent alternative representations of the amount of biomass that each PU (i.e. raster grid-cell) should be able to support under optimal conditions (no disturbances such as forest clearing or fire that could reduce woody biomass). The values of PUs with negative C stocking potential (i.e. where predicted maximum C stocking potential was lower than the C biomass of original biomass maps) were changed to zero – this was 11% (QR) and 33% (OLS) of PUs in Saatchi analyses, and 6% (QR) and 26% (OLS) in Baccini analyses.

Carbon stocking potential maps produced using 90% QR and OLS, based on both the Saatchi and Baccini data, were compared using Pearson's product-moment correlation analyses.

We chose to run QR models using 90% quantiles to prevent models from overestimating potential carbon storage. However, to ensure that running the analyses using higher quantiles would not result in different patterns of projected C stocking potential , QR analyses were repeated using 98% quantiles

(Supplementary Methods). These results are referred to in the supplement; except if otherwise stated, “QR” here refers to 90% quantile regressions. Maps of C stocking potential which had been produced using 90% and 98% QR were also compared using Pearson’s correlation analyses.

Selecting regions for C stocking. We used the spatial prioritization technique Zonation[54] version 3.1.2 to select areas where C stocking potential could be optimized while also maximizing conservation potential, an ecosystem service, and considering socioeconomic factors. Zonation identifies areas of high conservation priority by iteratively removing PUs that contribute least to the conservation targets from the full landscape, while taking other specified cost factors into consideration[55]. Analyses were run at 10-km resolution (Supplementary Methods).

Zonation analyses were mainly run using the added benefit function (ABF) cell removal rule, though for comparative purposes analyses were repeated using the basic core zonation (BCZ) cell-removal technique[54] (Supplementary Methods).

Optimal areas for C stocking projects were selected based on the occurrence and abundance of a number of features: carbon stocking potential, biodiversity richness, groundwater recharge, governance and land value (Supplementary Fig. S8). PUs with higher values for these features (lower values for land value), and complementarity to previously chosen features for species, had a higher probability of being selected.

Species distribution and richness are perhaps the most basic, but also of the most important measures of diversity, and they constitute an important measure of conservation importance[56]. Therefore, as representatives of biodiversity features, distribution maps for all species of mammals, reptiles and amphibians were obtained from the IUCN[31] and included in analyses as separate layers. (A total of 979 mammals, 142 reptiles and 671 reptiles were recorded for the region.) We used species distributions rather than species richness maps, as this allowed PUs to be selected on both the number and rarity of their species [54].

Groundwater recharge, the amount of water that filters from the earth's surface to replenish groundwater supplies, is an important ecosystem service[57]. Since groundwater is protected from surface pollution and experiences less fluctuation in levels than surface water sources, lack of groundwater recharge can limit sustainable groundwater usage[57]. Therefore, a map of groundwater recharge[57] was used as a feature layer in our analyses. Areas with high groundwater recharge were considered to be of high value.

Socioeconomic factors were also included as features in our analysis. Land cost is a constraining factor in setting aside land for C stocking. Although prices for C credits vary widely between projects, it is essential that the benefits of stocking are profitable[12]. Naidoo and Iwamura[58] mapped global land value as a function of crop productivity, livestock density and consumer prices of crops and livestock to calculate gross economic rents of the land. In addition to land value, this index is also representative of agricultural productivity. Land value was included in our assessment with negative weighting, i.e. areas with low land value were preferentially selected.

Governance is essential to ensuring that incentives with co-benefits for communities or biodiversity are successful[59], as the lack of capacity to manage and ensure the success of such incentives may lead to their failure. Therefore, PUs were positively selected if they were associated with a higher Ibrahim Index of African Governance[60]. This index is produced on national scale as a function of four categories: safety and rule of law, participation and human rights, sustainable economic opportunity and human development[60]. Including this index in our site-selection process did not mean that areas with poor governance would not be selected; however, a higher cost was associated with poor governance.

Landscapes unsuitable for C stocking projects were excluded from analyses (Supplementary Methods).

Features can be weighted differently in Zonation analyses so that some features are prioritized over others. Here, all features were equally weighted[27]: groundwater recharge and governance received a weighting of three, and land value weighted negative three. For species richness, each taxonomic group carried a weight of one so that the final weight carried by faunal biodiversity also summed to three. Each species was weighted as a function of the number of species in their taxonomic class in the region considered here[27], with each mammals species weighted at 1/979, reptile species at 1/142 and amphibian species at 1/671. Finally, since we focused on C stocking potential, its weight was varied in separate runs (weights of 3, 6, 12, 24, and 48). These weightings reflect different prioritizations of C stocking potential, ranging from being equal to each of the other factors, to being assigned four times the weight of the other factors combined. For comparative purposes, Zonation models were run where only C stocking potential was included as a feature. This analysis identified the PUs that would be selected based on C stocking potential alone. All these prioritization runs thus span strategies in which C stocking is considered as one of several equally important factors in landscape planning, to strategies in which C stocking is the primary goal.

The output of prioritization maps included maps ranking each PU in terms of the features and their weightings that were specified in the analyses. Highest ranked PUs were most favorable for the conditions that were specified during the prioritization runs. The performance trade-offs of using different weightings for C stocking potential were calculated for the top 5% highest ranked PUs and for all PUs (Supplementary Methods). In addition, two-tailed Spearman rank correlation were used to compare different prioritization runs, i.e. the order in which PUs were removed during Zonation analyses for different cell removal methods and different datasets (Supplementary Methods).

Finally, Zonation analyses where connectivity of sites was accounted for[55] were run using different boundary length parameters (Supplementary Methods). Increasing connectivity among sites reduces fragmentation of high priority sites in the landscape, and thus identifies larger contiguous regions where carbon sequestration would be beneficial considering the other features taken into account here.

An outline of which of the two C datasets were used for which combination of analyses to calculate C stocking potential, and to create maps of the trade-off between C stocking potential and other factors are presented in Supplementary Table S1.

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Author contributions

M.G. and J.C.S. designed the study with contributions from B.R and A.M.L. ; M.G. analyzed the data and wrote the paper with significant contributions from all authors.

Additional Information

Competing financial interests: The authors declare no competing financial interests.

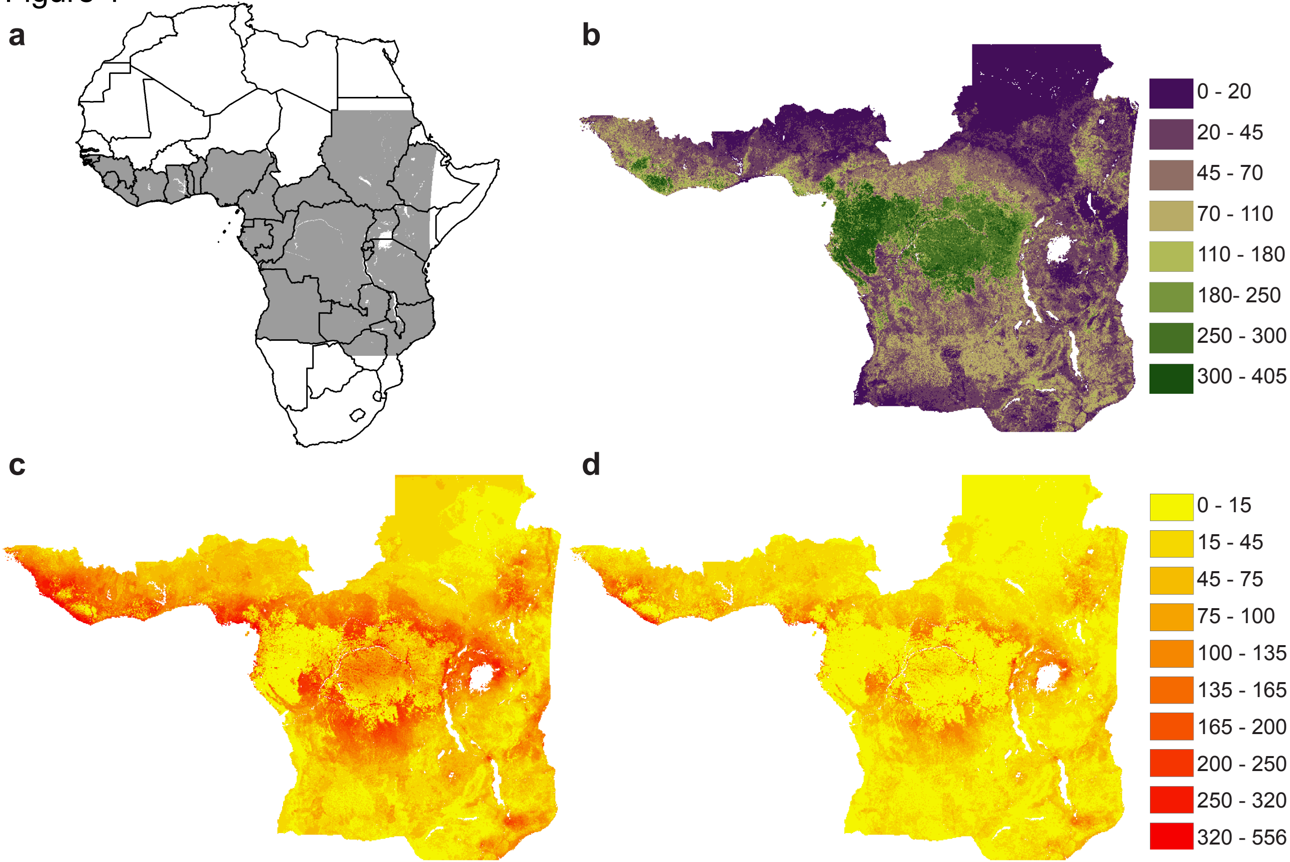
Figure Legends

Figure 1. Saatchi carbon maps. (**a**) Map of extent of study area. (**b**) Woody biomass (mapped from ref. 16); and C stocking potential (the difference between the potential woody biomass and the actual woody biomass) as calculated by (**c**) 90% quantile regressions and (**d**) ordinary least square regressions with human influence set to zero. Carbon values were taken from Saatchi et al[16].

Figure 2. Priority rank maps of tropical Africa based on quantile regression C maps. Priority rank maps based on Zonation analyses, showing the areas that would be most suitable for carbon sequestration projects while also benefitting biodiversity, groundwater recharge, land value and governance. Maps a-e represent different analyses, where the weighting of carbon stocking potential was altered between 3 (**a**), 6 (**b**), 12 (**c**), 24 (**d**) and 48 (**e**), while the weight of all other features was kept constant. Map (**f**) represents the carbon only map, which was generated using C stocking potential alone, and did not consider any other benefits or costs; it is thus a ranking of sites in terms of the C stocking potential. Yellow areas indicate the 5% highest ranked planning units and are thus deemed high priority, whereas red areas indicate the lowest ranked planning units and are deemed low priority. Carbon stocking potential was calculated from the Saatchi map using 90% quantile regressions. The ABF cell removal rule was used in Zonation analyses.

Figure 3. Performance plots at different weightings of C stocking potential weightings. The performance of the 5% top-ranked planning units (yellow areas in Fig. 2) when the C stocking potential was differently weighted (3, 6, 12, 24, 48, Carbon only; x-axis) in Zonation analyses is shown. (**a**) 'Potential Carbon' – the total additional C biomass that could be stored in all 5% top-ranked planning units. (**b-d**) Biodiversity 'Mean Richness' – the mean richness per 5% top-ranked planning unit. (**e-g**) Biodiversity 'Total Richness' – the taxon richness summed across all 5% top-ranked planning units. (**h**) Groundwater recharge, (**i**) land use value and (**j**) governance were averaged across all 5% top-ranked planning units in the landscape. The C stocking potential map was generated by 90% QR on the Saatchi dataset, and the ABF cell removal rule was used in Zonation analyses.

Figure 1



a
b
0 - 20
20 - 45
45 - 70
70 - 110
110 - 180
180- 250
250 - 300
300 - 405
c
d
0 - 15
15 - 45
45 - 75
75 - 100
100 - 135
135 - 165
165 - 200
200 - 250
250 - 320
320 - 556

Figure 2

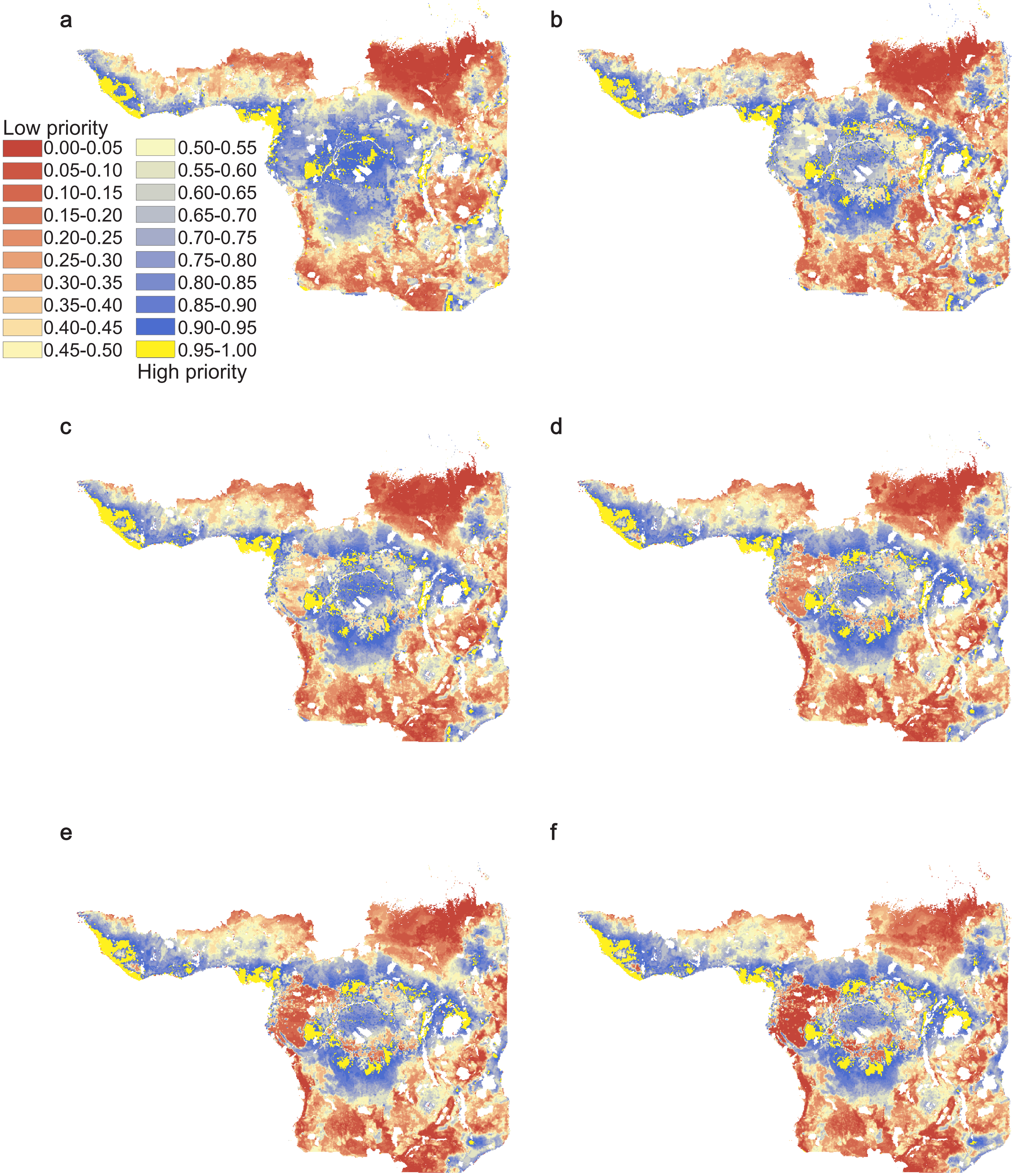
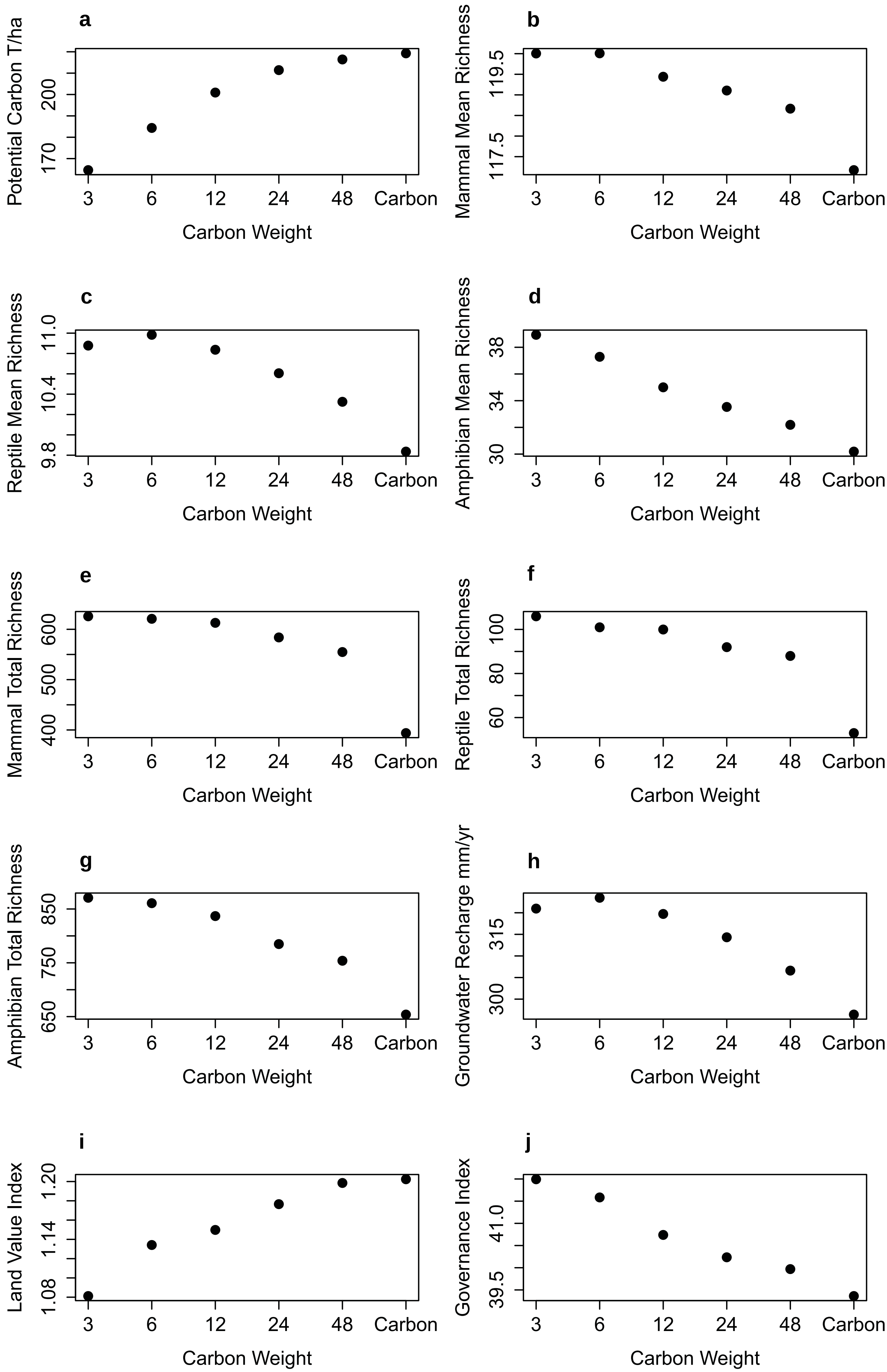

a
b
Low priority
0.00-0.05
0.05-0.10
0.10-0.15
0.15-0.20
0.20-0.25
0.25-0.30
0.30-0.35
0.35-0.40
0.40-0.45
0.45-0.50
0.50-0.55
0.55-0.60
0.60-0.65
0.65-0.70
0.70-0.75
0.75-0.80
0.80-0.85
0.85-0.90
0.90-0.95
0.95-1.00
High priority
c
d
e
f

Figure 3



a
Potential Carbon T/ha
170
200
b
Mammal Mean Richness
117.5
119.5
c
Reptile Mean Richness
9.8
10.4
11.0
d
Amphibian Mean Richness
30
34
38
e
Mammal Total Richness
400
500
600
f
Reptile Total Richness
60
80
100
g
Amphibian Total Richness
650
750
850
h
Groundwater Recharge mm/yr
300
315
i
Land Value Index
1.08
1.14
1.20
j
Governance Index
39.5
41.0
3
6
12
24
48
Carbon
Carbon Weight

Supplementary Table S1. Overview of all analyses that were run for this study. Two different datasets of above-ground carbon biomass were used to calculate C stocking potential – Saatchi et al.[16] and Baccini et al.[17]. Furthermore, maximum C biomass, from which C stocking potential was derived, was calculated using quantile regressions (QR) or ordinary least square (OLS) regressions. QR analyses were normally run using the 90% quantile; however, in one instance they were also run using the 98% quantile, to test the sensitivity of the analyses to using different quantiles. The C stocking potential maps were used to run Zonation analyses, in which site selection was conducted based on planning units' ability to maximize carbon storage and have gains or cut losses of several other factors. Zonation analyses were run using two different methods: added benefit function cell removal (ABF) and basic core area Zonation cell removal (BCZ). For all these analyses, the weighting of C stocking potential varied (three, six, 12, 24, 48), while the weighting of the other factors remained constant at three, except for the 'carbon only' analyses where site selection was based purely on C stocking potential, and all other factors were removed from analyses (see Methods). Finally, for one set of site selection analyses site connectivity was also altered by including a range of boundary length parameters (BLPs). The green cell represents the analyses that are represented in the main body of the paper, and which were mainly used for interpretation of data.

1. Carbon Dataset	Saatchi et al.[16]					Baccini et al.[17]			
2. Calculate Maximum C Biomass (to compute Carbon Stocking Potential)	90% QR			98% QR	OLS	90% QR			OLS
3. Site Selection (Zonation Analyses)	ABF		BCZ	ABF	ABF	ABF		BCZ	
4. Boundary Length Parameter	No BLP	BLP*	No BLP		No BLP	No BLP	BLP*	No BLP	

* For BLP analyses, the weighting of C stocking potential was kept at 12 and the other features at three, and only the BLP was varied between runs.

Supplementary Table S2. Coefficients for creation of potential woody biomass maps. Coefficients from quantile regression (QR) of woody biomass against several environmental variables, and of ordinary least square regressions (OLS) of the square-root of woody biomass against the environmental variables and human influence. The variables of the OLS were scaled. The parameters of each of the models are presented in italics in the last rows of the table. Abbreviations: **p < 0.01, ***p < 0.001; Mean Temp: mean annual temperature, Precipitation: annual precipitation, Temp Seas: temperature seasonality; Prec Driest ¼: precipitation of the driest quarter

	90% QR-Saatchi	98% QR-Saatchi	OLS-Saatchi	90% QR-Baccini	OLS-Baccini
Intercept	1.97×10^{5}***	1.92×10^{5}***	7.44×10^{1}***	2.14×10^{4}***	8.45×10^{1}***
$(\text{Mean Temp})^2$	4.10×10^{-1}***	6.20×10^{-1}***	2.35×10^{1}***	8.40×10^{-1}***	3.42×10^{1}***
$(\text{Mean Temp})^4$	-3.70×10^{-6}***	-5.40×10^{-6}***	-2.70×10^{1}***	9.20×10^{-6}***	-3.94×10^{1}***
√Precipitation	-3.34×10^{2}***	5.51×10^{2}***	2.24×10^{1}***	6.63×10^{2}***	1.31×10^{1}***
Precipitation	1.38×10^{1}***	2.03×10^{1}***	-6.86×10^{1}***	-2.20**	
log(Temp Seas)	-1.45×10^{4}***	8.15×10^{3}***	7.22×10^{1}***	1.71×10^{4}***	-6.51***
$(\log(\text{Temp Seas}))^2$	9.83×10^{2}***	-5.95×10^{2}***	1.48×10^{1}***	-1.59×10^{3}***	
log(Prec Driest ¼)	-1.60×10^{3}***	1.14×10^{3}***	-4.04×10^{1}***	-1.02×10^{3}***	-2.63×10^{1}***
$\log(\text{Prec Driest ¼})^2$	7.00×10^{2}***	9.17×10^{1}***	3.58×10^{1}***	4.31×10^{2}***	3.92×10^{1}***
√Soil pH	-4.05×10^{4}***	-5.96×10^{4}***	2.18×10^{1}***	-8.31×10^{3}***	-1.14×10^{1}***
Soil pH	2.46×10^{3}***	3.55×10^{3}***	-2.51×10^{1}***	4.16×10^{2}***	6.84*
Bulk Density	2.42×10^{2}***	3.25×10^{2}***	-5.28***	-6.67×10^{2}***	-1.02×10^{1}***
$(\text{Bulk Density})^2$	-8.80×10^{-1}***	-1.20***	-2.00***	2.32***	9.50***
Human Influence			7.44×10^{1}***		-1.43***
$(\text{Human Influence})^2$			2.35×10^{1}***		-8.42***
Akaike Weight	*1.000*	*1.000*	*1.000*	*0.996*	*0.526*[#]
R^2			*0.687*		*0.526*
F			*29154****		*8312****
DF			*159694*		*96636*

[#]The OLS model also including $(\log(\text{Temp Seas}))^2$ had an Akaike weight of 0.208. However, because that model contained one more predictor variable than the OLS presented in Table 2, the model presented here was used for calculating potential C storage.

Supplementary Table S3. Confidence intervals of coefficients for calculating potential woody biomass. Mean and standard deviations (StDev) of coefficients of the 90% quantile regression models based on the Saatchi and Baccini maps. Means and standard deviations were obtained by running 2000 models on randomly selected subsets of the entire dataset. The size of the subset was 80% of the total sample size (i.e. the total number of planning units). The Saatchi columns here are an indication of the uncertainty of the coefficients of the "90% QR-Saatchi" column in Supplementary Table S2, and the Baccini columns of the "90% QR-Baccini" column in Supplementary Table S2.

	Saatchi		Baccini	
	Mean	StDev	Mean	StDev
Intercept	1.97×10^{5}	7.74×10^{3}	2.09×10^{4}	1.21×10^{4}
(Mean Temp)^2	4.08×10^{-1}	1.46×10^{-2}	8.48×10^{-1}	4.24×10^{-2}
(Mean Temp)^4	-3.71×10^{-6}	1.26×10^{-7}	-9.29×10^{-6}	3.64×10^{-7}
√Precipitation	-3.35×10^{2}	2.20×10^{1}	6.54×10^{2}	1.01×10^{2}
Precipitation	1.39×10^{1}	4.44×10^{-1}	-2.03	1.29
log(Temp Seas)	-1.44×10^{4}	1.20×10^{3}	1.71×10^{4}	1.56×10^{3}
(log(Temp Seas))^2	9.78×10^{2}	8.00×10^{1}	-1.59×10^{3}	1.17×10^{2}
log(Prec Driest ¼)	-1.60×10^{3}	5.73×10^{1}	-1.04×10^{3}	1.02×10^{2}
log(Prec Driest ¼)^2	6.99×10^{2}	1.71×10^{1}	4.34×10^{2}	1.71×10^{1}
√Soil pH	-4.04×10^{4}	1.72×10^{3}	-8.25×10^{3}	2.28×10^{3}
Soil pH	2.46×10^{3}	1.06×10^{2}	4.13×10^{2}	1.48×10^{2}
Bulk Density	2.42×10^{2}	1.57×10^{1}	-6.65×10^{2}	6.01×10^{1}
(Bulk Density)^2	-8.76×10^{-1}	5.18×10^{-2}	2.32	2.13×10^{-1}

Supplementary Table S4. Relationship between measured and predicted C biomass. Results from regression analyses between measured carbon biomass in undisturbed forest plots taken from the Afritron dataset[66] and predicted maximum/original map carbon biomass as calculated from two datasets (Saatchi and Baccini), using 90% quantile regressions (90% QR), 98% quantile regression (98% QR, calculated only for Saatchi) and ordinary least regressions (OLS). The relationship between the Afritron data and the original maps ('Original') produced by Saatchi et al. and Baccini et al. are also displayed. Degrees of freedom = 76 for all analyses.

	R square	Intercept	Slope
Saatchi 90% QR	0.056	245***	0.184*
Saatchi 98% QR	0.025	331***	0.122
Saatchi Original Map	0.098	96*	0.515**
Saatchi OLS	0.095	146***	0.206**
Baccini 90% QR	0.222	186***	0.309***
Baccini OLS	0.152	108***	0.312***
Baccini Original Map	0.160	34	0.572***

Supplementary Table S5. Correlations between maps used in analyses. Correlations between 1) different above-ground carbon maps used in analyses, 2) different potential carbon storage maps generated, and 3) different sets of Zonation ranking maps generated by selecting planning units based on their performance in sequestering carbon but also taking biodiversity, groundwater recharge, land value and governance into account. In Zonation analyses, carbon stocking potential was weighted 12 and all features three. The set of analyses that the datasets belonged to are indicated by the 'Level' column, which corresponds to the numbering in the first sentence, also given by the number in the first column of Supplementary Table S1. True Skills Statistic (TSS) scores measuring the coincidence between the top 5% cells (yellow cells in Fig. 2 and Supplementary Fig. S4) of the different sets of Zonation analyses were also calculated. Abbreviations: cor: correlation coefficient; 95% CIs: 95% confidence intervals; PC: Pearson's product-moment correlation; SC: Spearman's rank correlation; QR: quantile regression; OLS: ordinary least square regressions; ABF: added benefit function cell removal; BCZ: basic core area Zonation cell removal; ***: $p < 0.001$

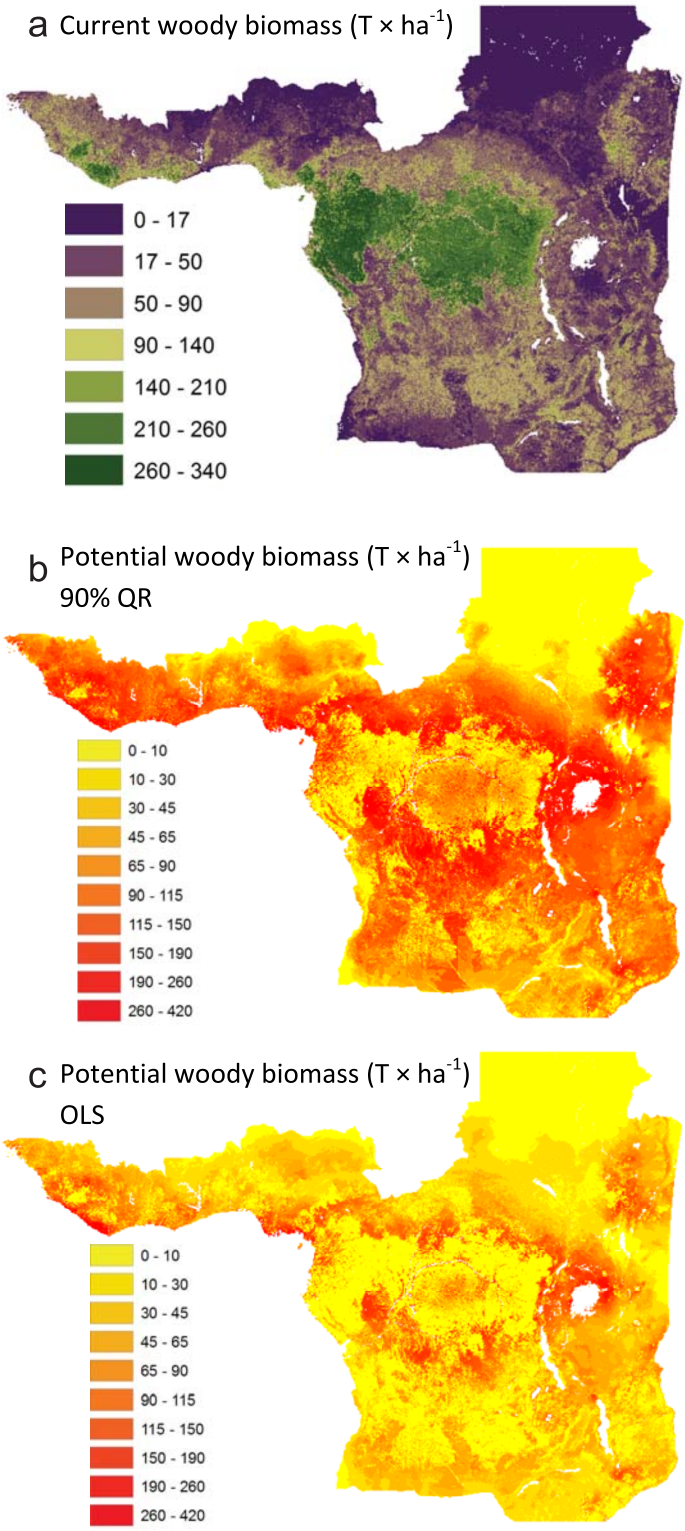
Level	Correlation Comparison	Test	Cor	Rho	t	S	df	95% CIs		TSS
1	Original Saatchi vs. Baccini C maps	PC	0.865***		697.8		163262	0.864	0.867	
2	Saatchi Potential C: 90% QR vs. OLS	PC	0.923***		961.8		159705	0.923	0.924	
2	Saatchi Potential C: 90% QR vs. 98 %QR	PC	0.939***		1091.7		159705	0.938	0.940	
2	Baccini Potential C: 90% QR vs. sqrt(OLS)	PC	0.968***		1546.6		159705	0.968	0.969	
2	Saatchi vs. Baccini Potential C: 90% QR	PC	0.538***		254.9		159705	0.534	0.541	
2	Saatchi vs. Baccini Potential C: OLS	PC	0.319***		134.5		159705	0.315	0.324	
3	Zonation Saatchi 90% QR vs. OLS ABF	SC		0.926***		2.0×10^{-13}				0.813
3	Zonation Saatchi 90% QR: ABF vs. BCZ	SC		0.742***		6.9×10^{-13}				0.089
3	Zonation Baccini 90% QR ABF vs. BCZ	SC		0.882***		3.2×10^{-13}				0.081
3	Zonation Saatchi vs. Baccini 90% QR ABF	SC		0.821***		4.8×10^{-13}				0.588

Supplementary Table S6. Correlations between top-ranked sites of prioritization runs with different weights for carbon stocking potential. True Skills Statistic (TSS) measuring the coincidence between the top 5% planning units of Zonation prioritization analyses when the carbon stocking potential weight was adjusted. TSS scores vary between 0 (low) and 1 (high). During Zonation analyses, the weights of the other features was kept constant at a value of three, except in the 'Carbon' analyses, where sites were ranked only on their carbon stocking potential and no other features were included in the prioritization. Analyses were run based on the 90% QR dataset using ABF analyses (Supplementary Table S1) based on the Saatchi carbon dataset (yellow) and the Baccini dataset (blue).

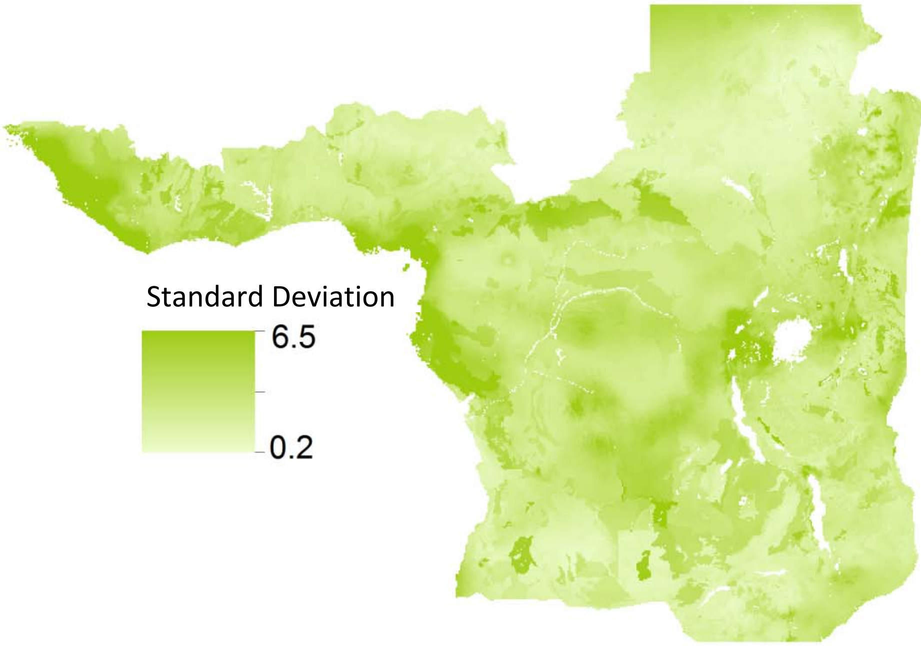
Weights	3	6	12	24	48	Carbon
3	1	0.826	0.619	0.449	0.340	0.216
6	0.843	1	0.779	0.598	0.482	0.351
12	0.699	0.845	1	0.814	0.693	0.560
24	0.588	0.726	0.877	1	0.878	0.746
48	0.514	0.647	0.796	0.919	1	0.866
Carbon	0.421	0.550	0.699	0.822	0.903	1

Supplementary Table S7. Changes in rankings between prioritization runs with different weights of carbon stocking potential. The mean ± standard deviation of the change in the ranking of all planning units during Zonation runs when the weighting of carbon was altered (as indicated in the column titles); the change in ranking was calculated as the absolute value of the difference in ranking between respective analysis and the analysis where carbon was given a weighting of 12. The change is expressed as a percentage change in ranking, and thus varies between 0 and 1. During Zonation analyses, the weights of the other features was kept constant at a value of three, except in the 'Carbon' analyses, where sites were ranked only on their carbon stocking potential and no other features were included in the prioritization. Analyses were run based on the 90% QR dataset using ABF analyses (Supplementary Table S1) based on the Saatchi carbon dataset (yellow) and the Baccini dataset (blue).

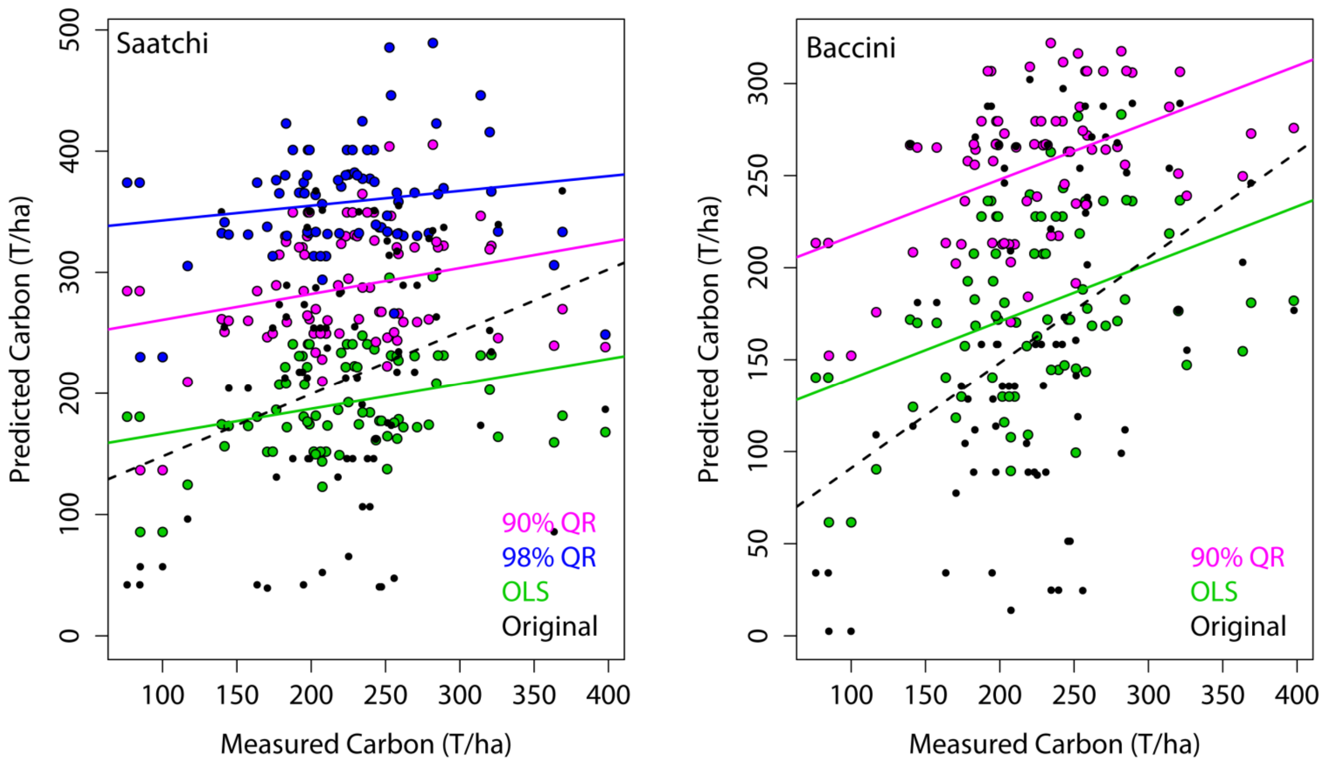
	3	6	12	24	48	Carbon
Saatchi	9.9 ± 8.9	6.6 ± 6.4	0 ± 0	4.1 ± 4.1	6.6 ± 6.6	9.4 ± 9.7
Baccini	12.1 ± 11	6.2 ± 6	0 ± 0	4.3 ± 4.2	6.6 ± 6.3	9.4 ± 8.8



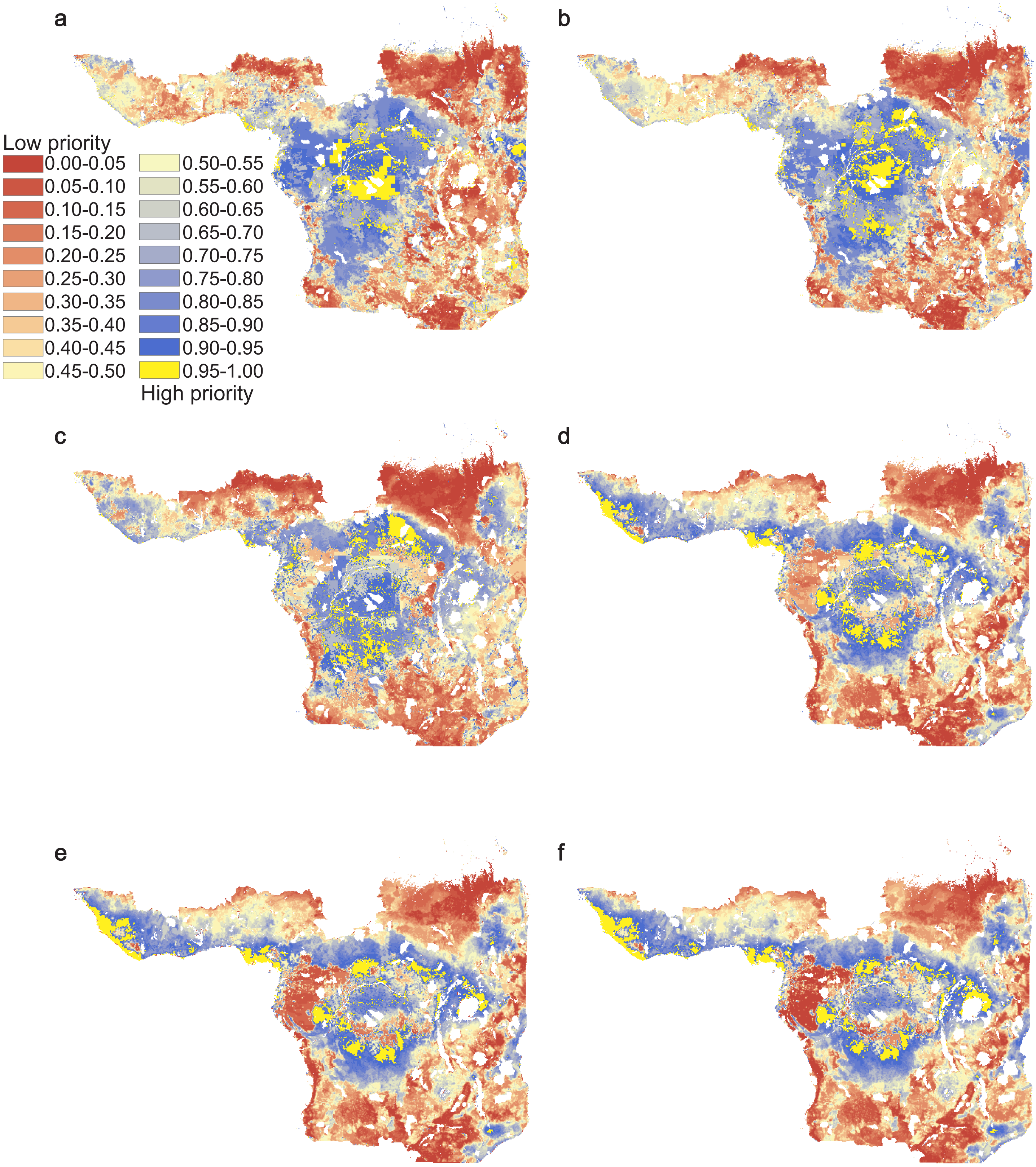
Supplementary Figure S1. Baccini carbon maps. (**a**) Woody biomass (mapped from Baccini et al.); and C stocking potential (the difference between the maximum potential woody biomass and the actual woody biomass) as calculated by (**b**) 90% quantile regression and (**c**) OLS regressions with human influence set to zero.



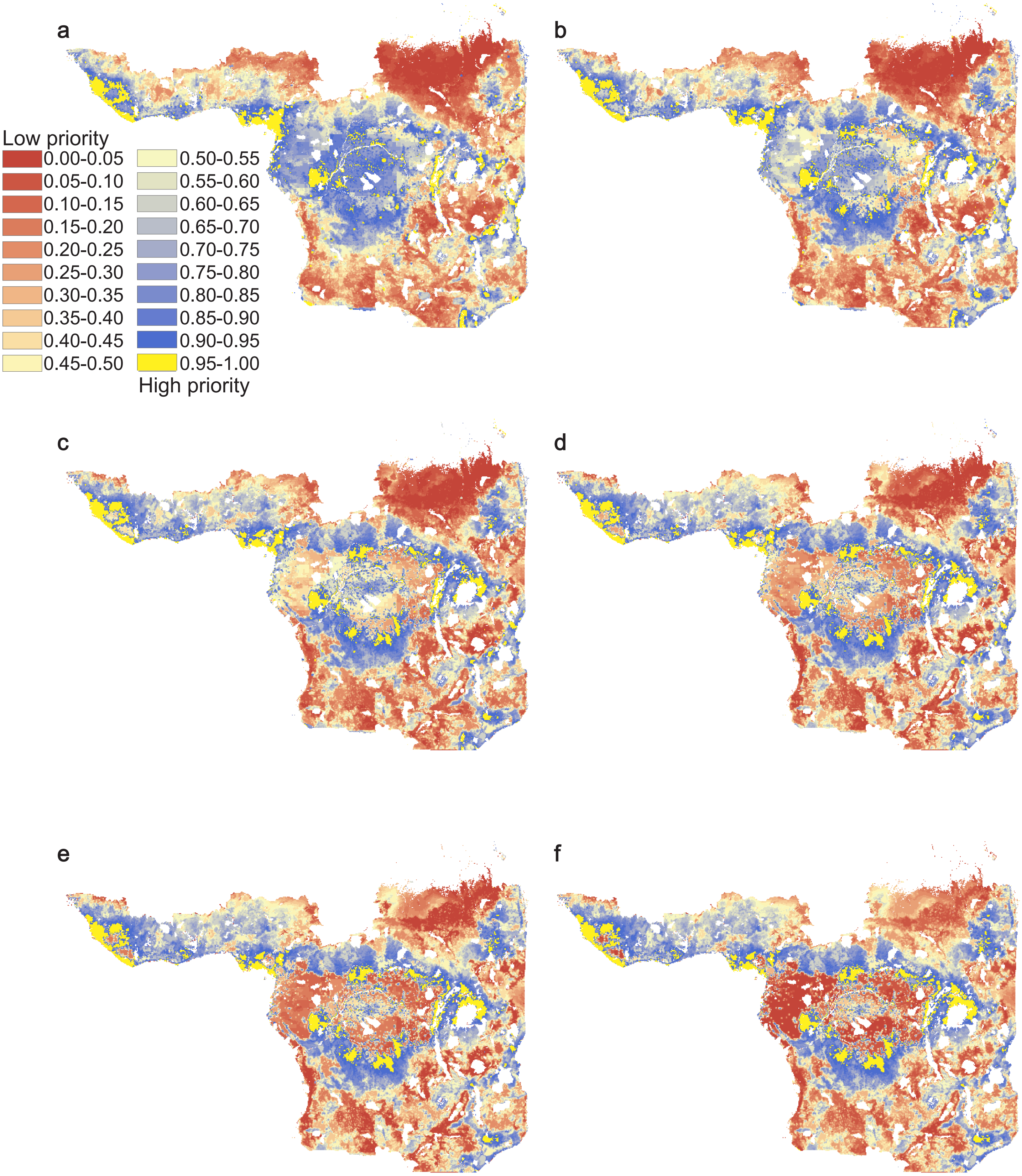
Supplementary Figure S2. Uncertainty map of potential maximum carbon biomass. Uncertainty was calculated for the 90% QR map generated from the Saatchi dataset. One thousand random datasets comprising 80% of the all data points were constructed, and 90% QR analyses run on each dataset. The coefficients of these quantile regressions were used to predict the maximum C biomass per planning unit 1000 times using regression analyses. This map shows the standard deviation of the maximum C biomass calculated for each planning unit using these regression analyses. (Units: $T \times ha^{-1}$)



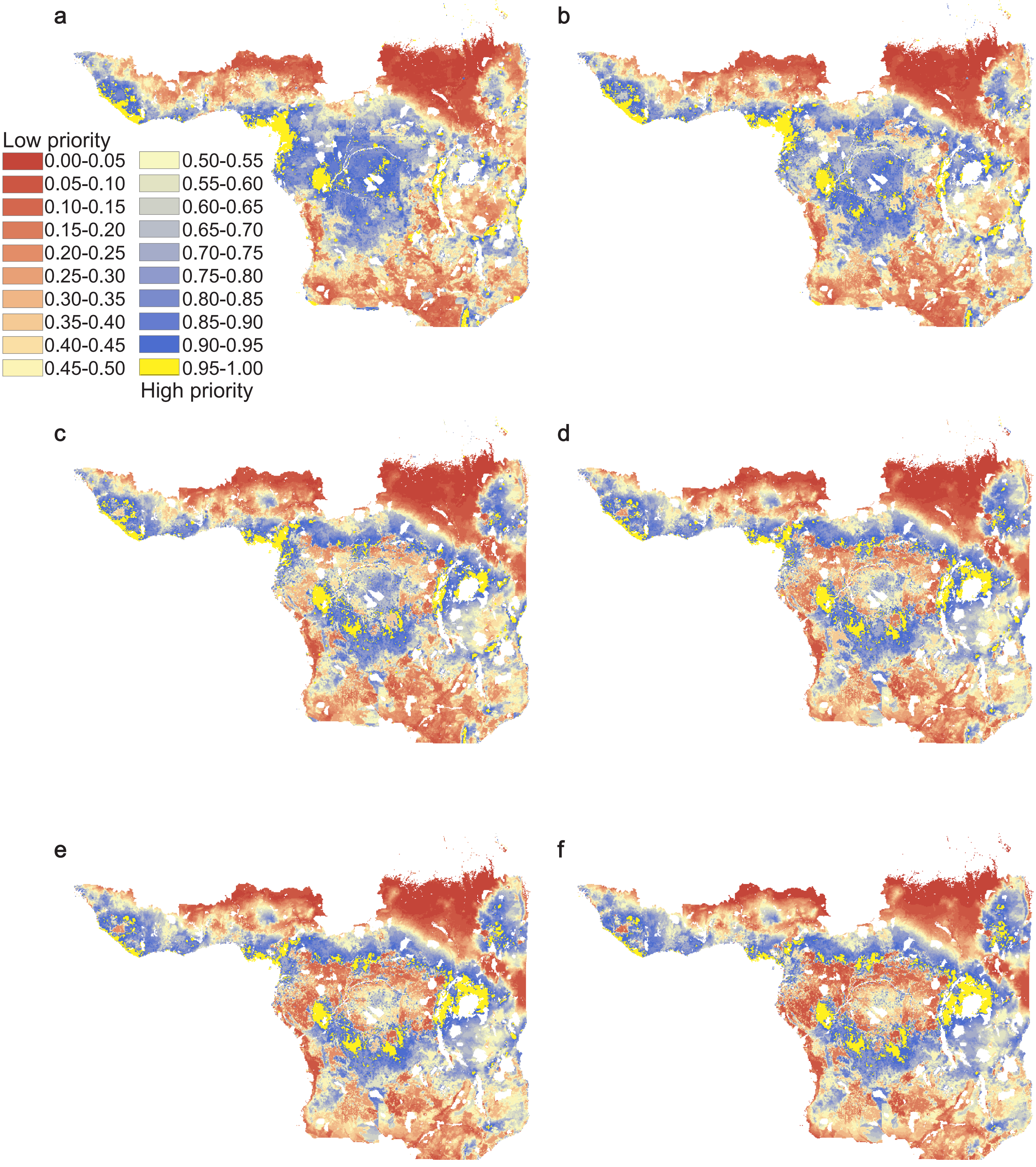
Supplementary Figure S3. **Relationship between measured and predicted carbon biomass.** Relationship between measured carbon biomass in undisturbed forest plots taken from the Afritron dataset[66], and predicted maximum carbon biomass as calculated from two datasets (Saatchi: left; Baccini: right), using 90% quantile regressions (90% QR - magenta), 98% quantile regression (98% QR - blue, calculated only for Saatchi) and ordinary least regressions (OLS - green). The relationship between the Afritron data and the original maps (‘Original - black) produced by Saatchi et al. and Baccini et al. are also displayed. The results from regression analyses between the measured and predicted maximum/original map carbon biomass are shown in Table S4. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.



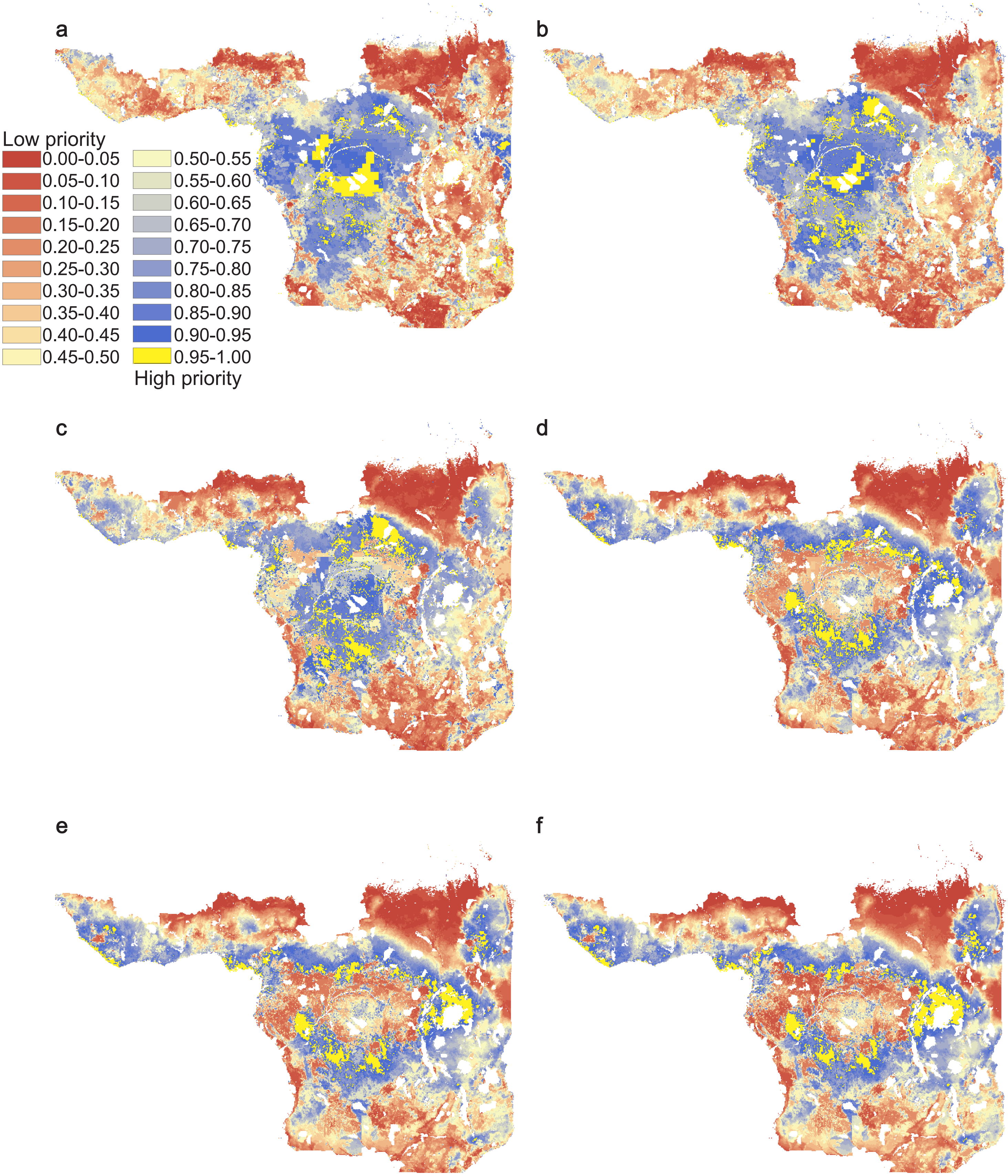
Saatchi - 90% QR - BCZ



Saatchi - OLS - ABF

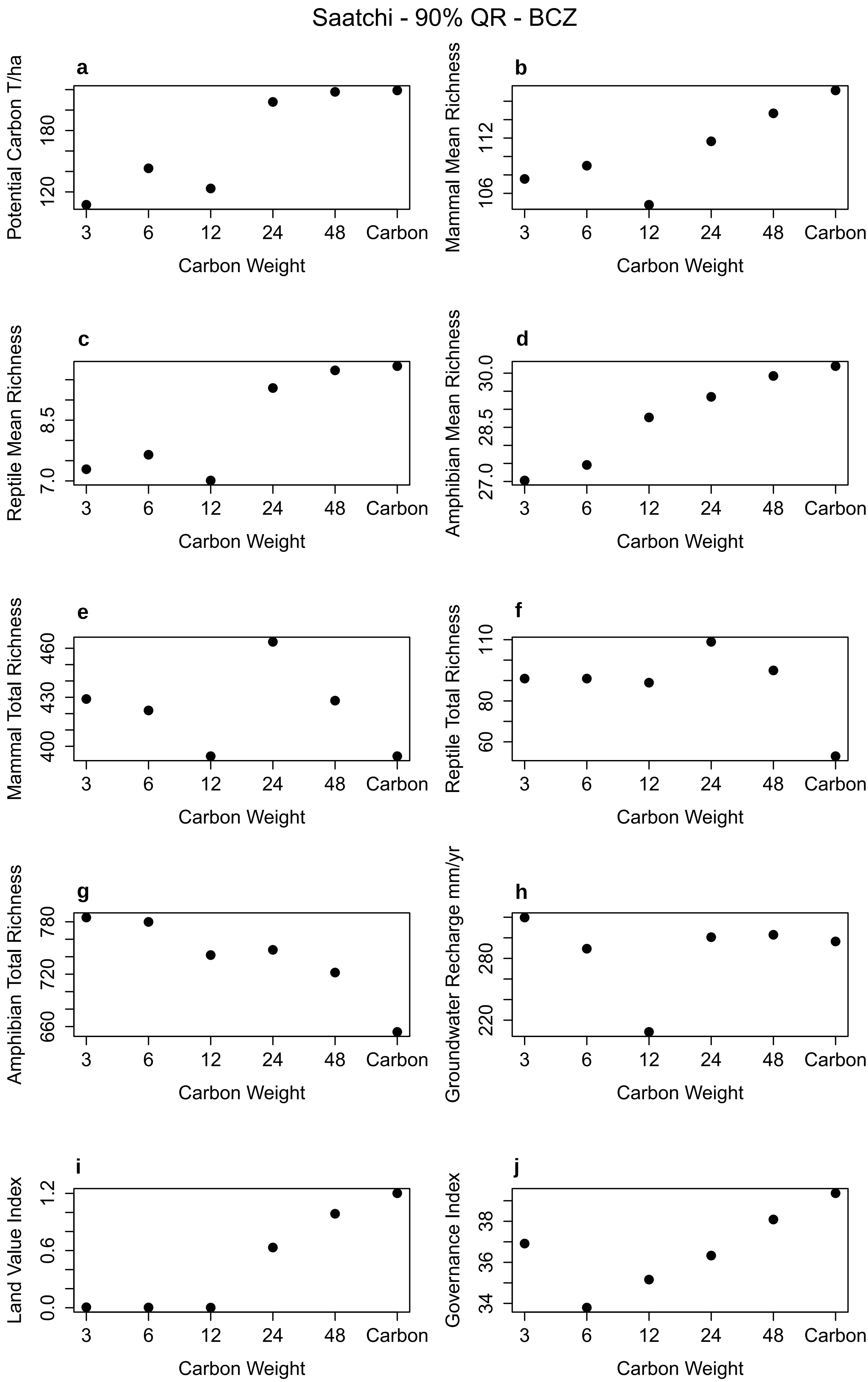


Baccini - 90% QR - ABF

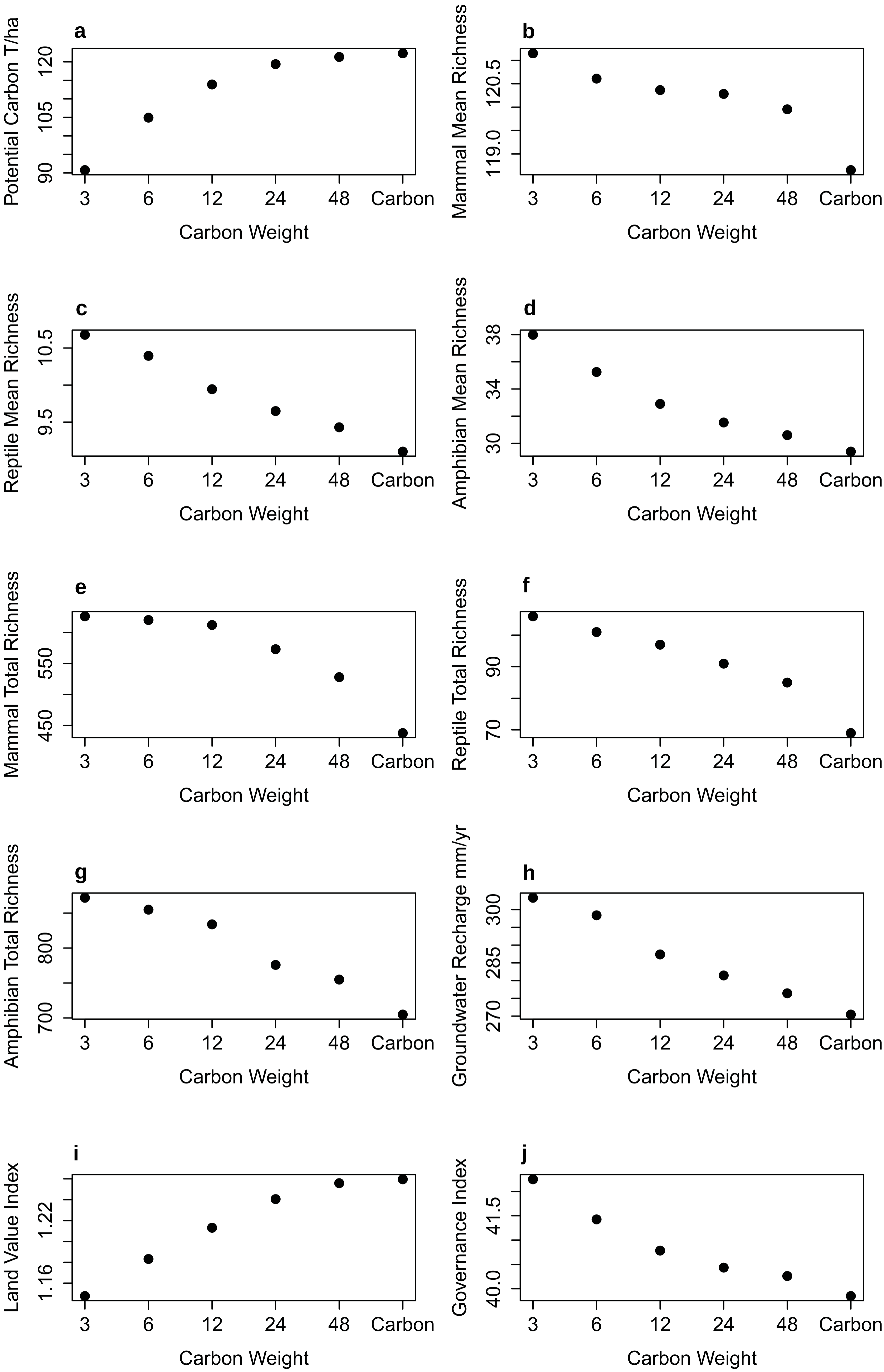


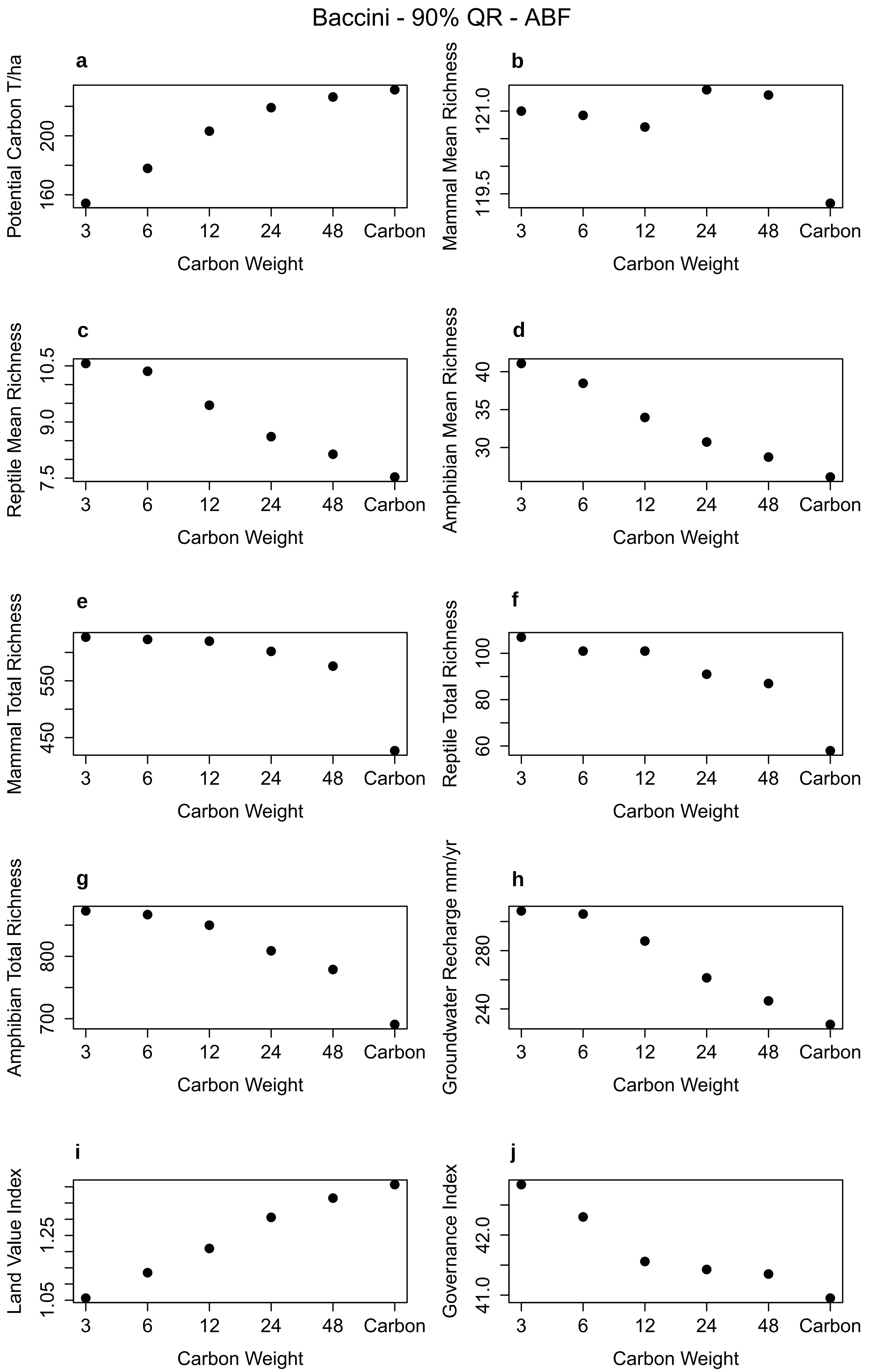
Baccini - 90% QR - BCZ

Supplementary Figure S4. Priority rank maps of tropical Africa when the weighting of C stocking potential is altered. Priority rank maps based on Zonation analyses, showing the areas that would be most suitable for carbon sequestration projects while also benefitting biodiversity, groundwater recharge, land value and governance. Maps a-e represent different analyses in which the weighting of carbon stocking potential was altered between 3 (**a**), 6 (**b**), 12 (**c**), 24 (**d**) and 48 (**e**), while the weight of all other features was kept constant. Map (**f**) represents the carbon only maps, which were generated by using C stocking potential alone, and did not consider any other benefits or costs; it is thus a ranking of sites in terms of the C stocking potential. Yellow areas indicate the 5% highest ranked planning units and are thus deemed high priority, whereas red areas indicate the lowest ranked planning units and are deemed low priority. Results are shown for different sets of analysis (Supplementary Fig. S1), which are indicated at the bottom of each page: C stocking potential maps were obtained from one of two different base maps, namely Saatchi or Baccini maps; C stocking potential was calculated using one of two different methods, namely 90% quantile regressions (90% QR) or ordinary least square regressions (OLS); and two different cell removal rules were used: the added benefit function (ABF) and the basic core area Zonation (BCZ) cell removal rule. The comparative Saatchi – 90% QR – ABF map is shown in Fig. 2.

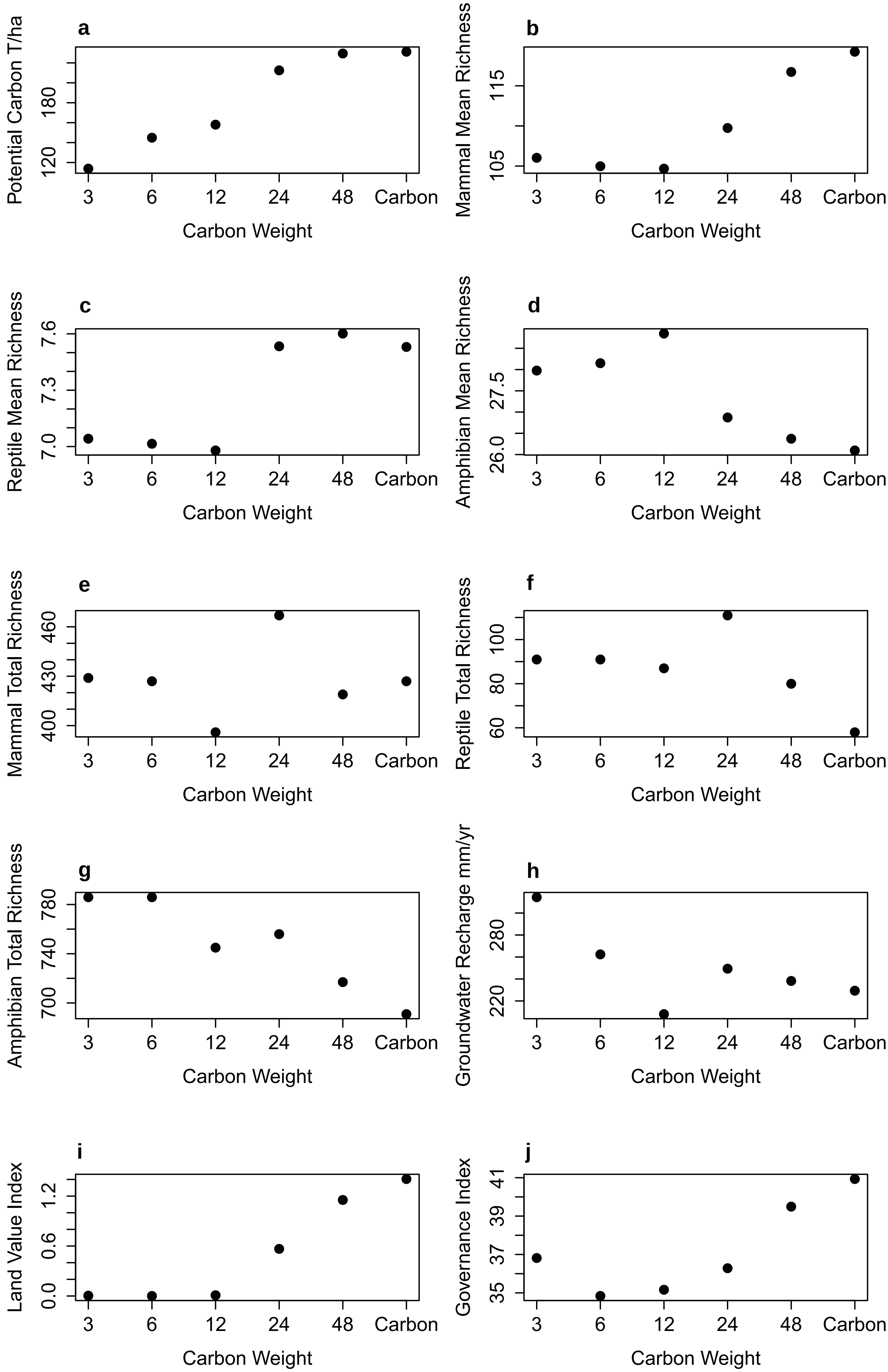

Saatchi - 90% QR - BCZ
a
Potential Carbon T/ha
120
180
b
Mammal Mean Richness
106
112
c
Reptile Mean Richness
7.0
8.5
d
Amphibian Mean Richness
27.0
28.5
30.0
e
Mammal Total Richness
400
430
460
f
Reptile Total Richness
60
80
110
g
Amphibian Total Richness
660
720
780
h
Groundwater Recharge mm/yr
220
280
i
Land Value Index
0.0
0.6
1.2
j
Governance Index
34
36
38
3
6
12
24
48
Carbon
Carbon Weight

Saatchi - OLS - ABF



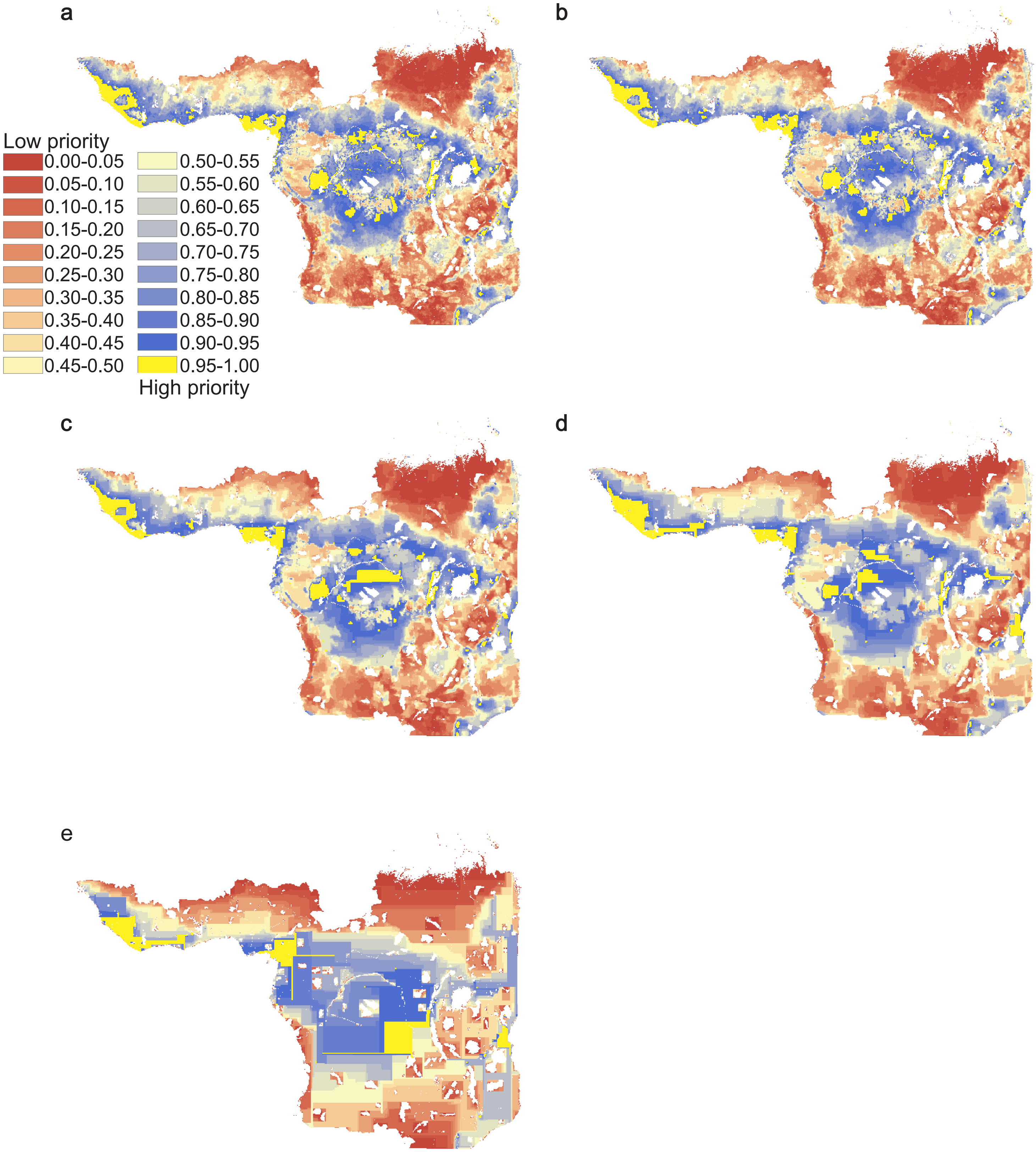

Baccini - 90% QR - ABF
a
Potential Carbon T/ha
160
200
b
Mammal Mean Richness
119.5
121.0
c
Reptile Mean Richness
7.5
9.0
10.5
d
Amphibian Mean Richness
30
35
40
e
Mammal Total Richness
450
550
f
Reptile Total Richness
60
80
100
g
Amphibian Total Richness
700
800
h
Groundwater Recharge mm/yr
240
280
i
Land Value Index
1.05
1.25
j
Governance Index
41.0
42.0
3
6
12
24
48
Carbon
Carbon Weight

Baccini - 90% QR - BCZ



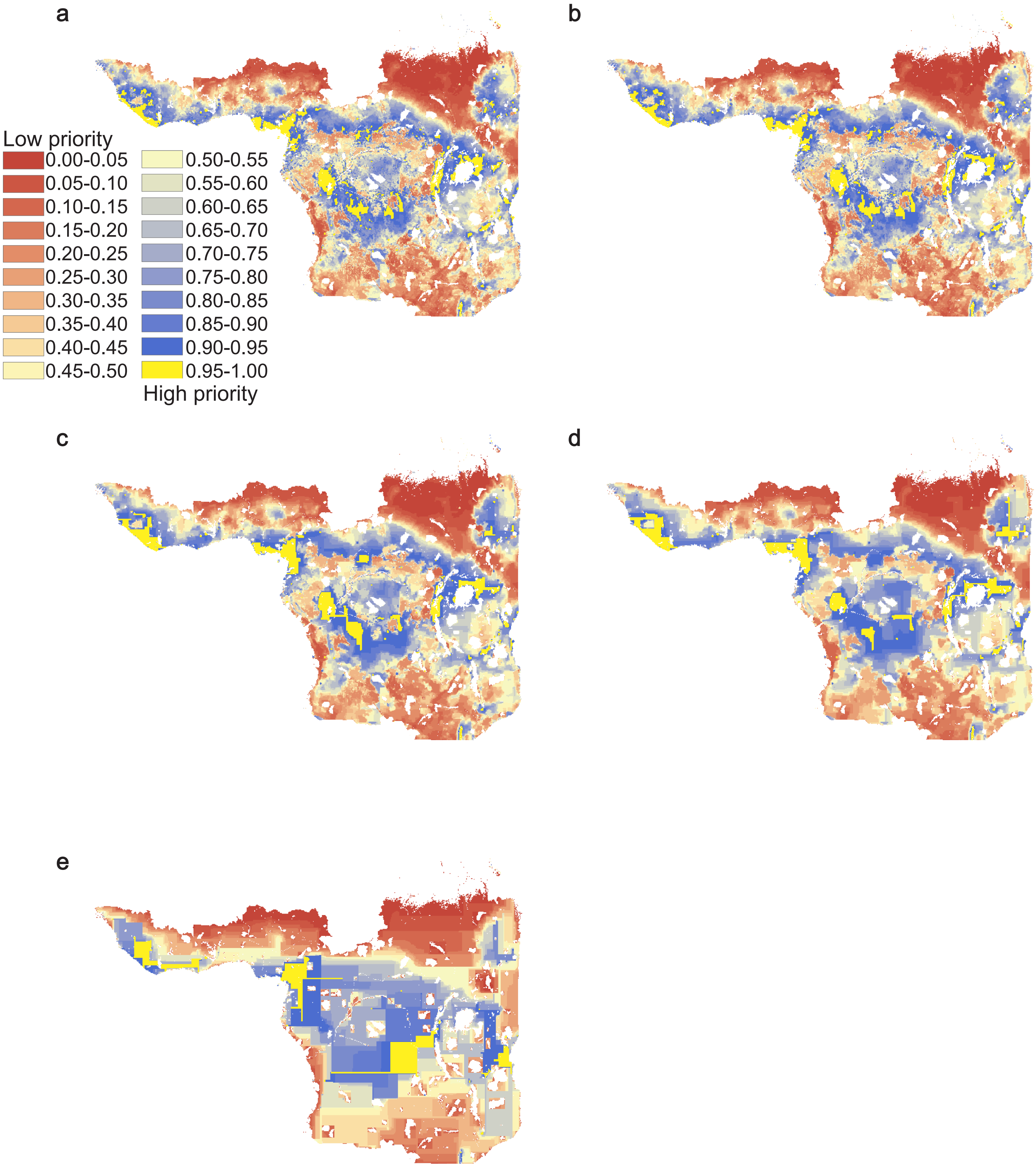
Supplementary Figure S5. Performance plots of features at different C stocking potential weightings. The performance of the 5% top-ranked planning units (yellow areas in Fig. 2) when C stocking potential was differently weighted (3, 6, 12, 24, 48, Carbon only; x-axis) in Zonation analyses is shown. Results are shown for different sets of analysis (Supplementary Fig. S1), which are indicated at the top of each page: C stocking potential maps were obtained from one of two different base maps, namely Saatchi or Baccini maps; C stocking potential was calculated using one of two different methods, namely 90% quantile regressions (90% QR) or ordinary least square regressions (OLS); and two different cell removal rules were used: the added benefit function (ABF) and the basic core area Zonation (BCZ) cell removal rule. The comparative Saatchi – 90% QR – ABF map is shown in Fig. 3. (**a**) 'Potential Carbon' – the total additional C biomass that could be stored in all 5% top-ranked planning units. (**b-d**) Biodiversity 'Mean Richness' – the mean richness per 5% top-ranked planning unit. (**e-g**) Biodiversity 'Total Richness' – the taxon richness summed across all 5% top-ranked planning units. (**h**) Groundwater recharge, (**i**) land use value and (**j**) governance were averaged across all 5% top-ranked planning units in the landscape.

Saatchi

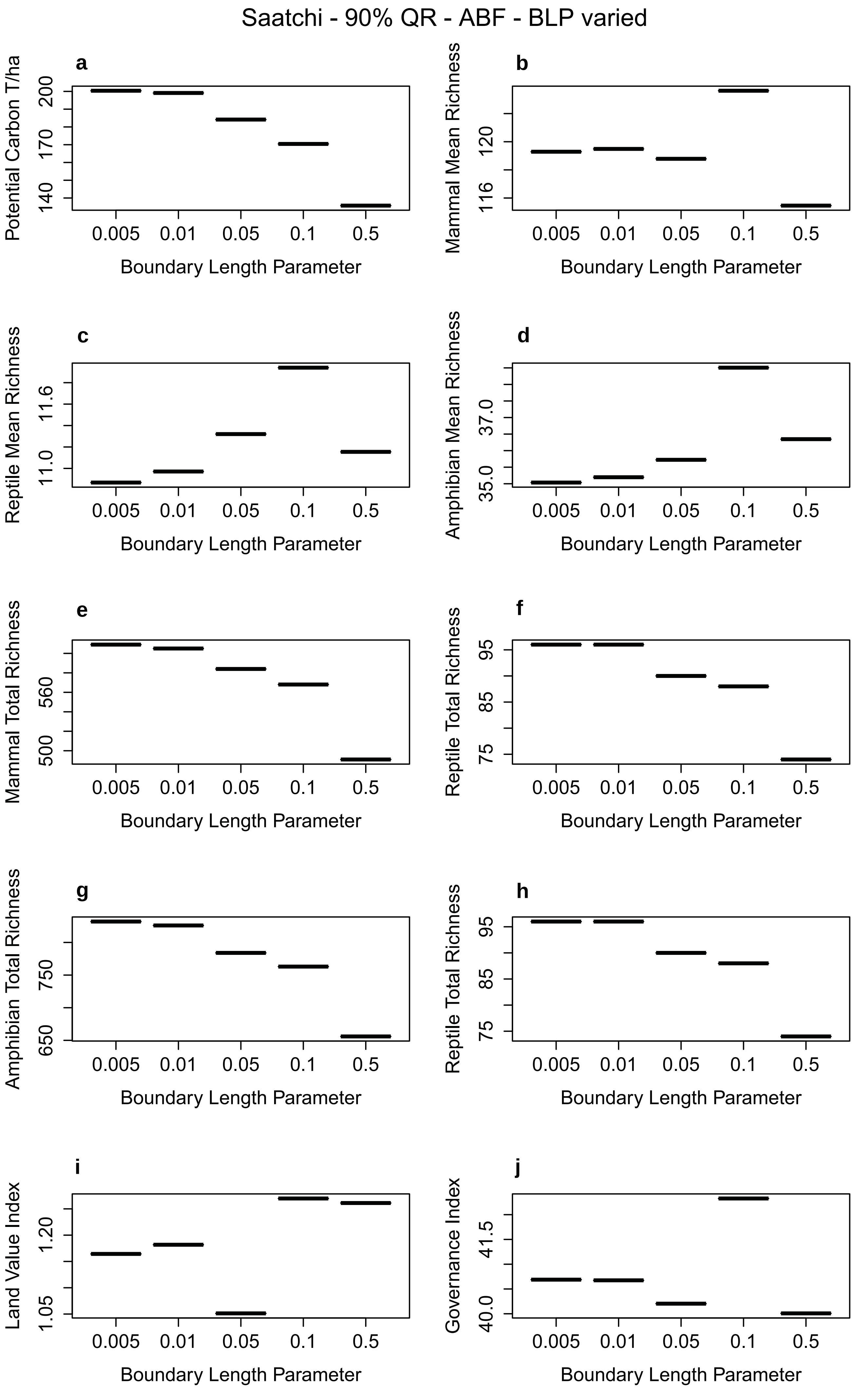


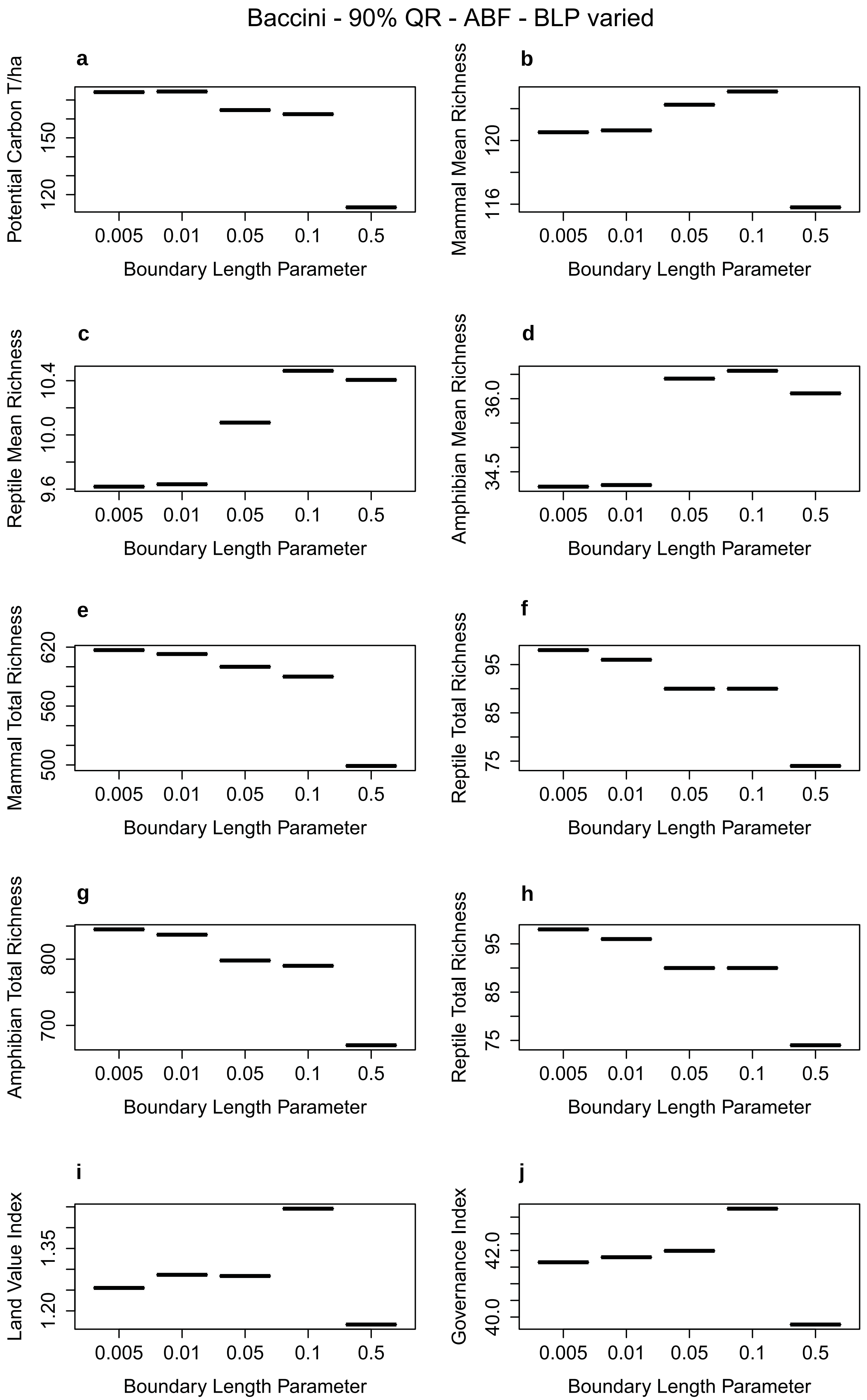
a
b
Low priority
0.00-0.05
0.05-0.10
0.10-0.15
0.15-0.20
0.20-0.25
0.25-0.30
0.30-0.35
0.35-0.40
0.40-0.45
0.45-0.50
0.50-0.55
0.55-0.60
0.60-0.65
0.65-0.70
0.70-0.75
0.75-0.80
0.80-0.85
0.85-0.90
0.90-0.95
0.95-1.00
High priority
c
d
e

Baccini

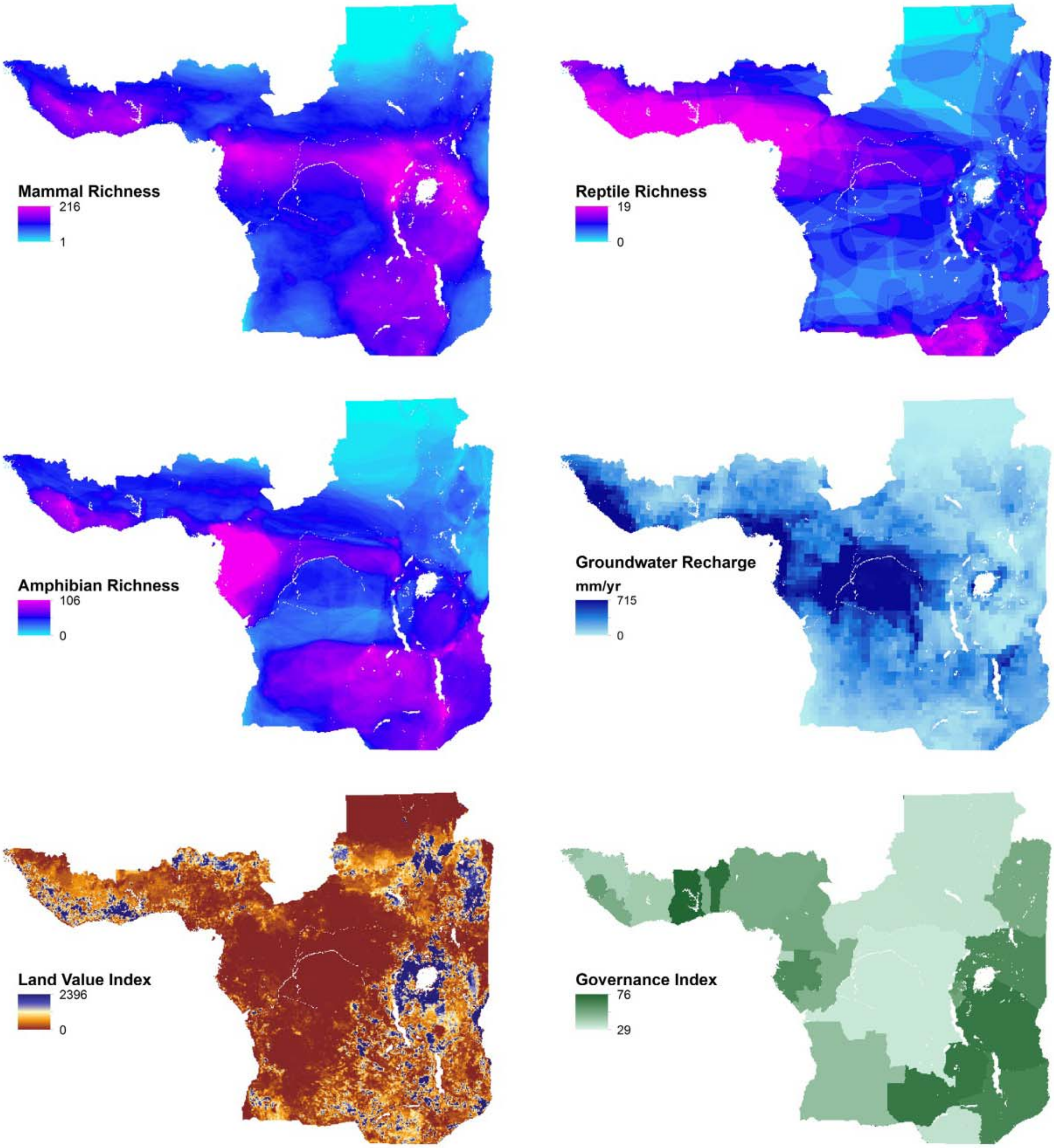


Supplementary Figure S6. Priority rank maps of tropical Africa when the boundary length parameter is altered. The boundary length parameter, which promotes connectivity, was altered between 0.005 (**a**), 0.01 (**b**), 0.05 (**c**), 0.1 (**d**) and 0.5 (**e**). Priority rank maps show the areas that would be most suitable for carbon sequestration projects while also benefitting biodiversity, groundwater recharge, land value and governance with increasing connectivity selected for. The weighting of all features was kept constant between analyses (12 for C stocking potential; three for all other features). Yellow areas indicate the 5% highest ranked planning units and are thus deemed high priority, whereas red areas indicate the lowest ranked planning units and are deemed low priority. Results are shown for analyses conducted on C stocking potential maps derived using 90% QR on both the Saatchi and Baccini maps (indicated at the top of each page). The ABF cell removal rule was used during Zonation analyses.


Saatchi - 90% QR - ABF - BLP varied
a
Potential Carbon T/ha
140
170
200
b
Mammal Mean Richness
116
120
c
Reptile Mean Richness
11.0
11.6
d
Amphibian Mean Richness
35.0
37.0
e
Mammal Total Richness
500
560
f
Reptile Total Richness
75
85
95
g
Amphibian Total Richness
650
750
h
Reptile Total Richness
75
85
95
i
Land Value Index
1.05
1.20
j
Governance Index
40.0
41.5
0.005
0.01
0.05
0.1
0.5
Boundary Length Parameter


Baccini - 90% QR - ABF - BLP varied
a
Potential Carbon T/ha
120
150
b
Mammal Mean Richness
116
120
c
Reptile Mean Richness
9.6
10.0
10.4
d
Amphibian Mean Richness
34.5
36.0
e
Mammal Total Richness
500
560
620
f
Reptile Total Richness
75
85
95
g
Amphibian Total Richness
700
800
h
Reptile Total Richness
75
85
95
i
Land Value Index
1.20
1.35
j
Governance Index
40.0
42.0
0.005
0.01
0.05
0.1
0.5
Boundary Length Parameter

Supplementary Figure S7. Performance plots with different boundary length parameters. The performance of the 5% top-ranked planning units (yellow areas in Fig. 2) when the boundary length parameter was increased in Zonation analyses. The weighting of all features was kept constant (12 for C stocking potential; three for all other features) for all analyses. Analyses were run on C stocking potential data obtained from Saatchi and Baccini datasets (indicated at the top of each page) using 90% QR, and the ABF cell removal rule was used during Zonation analyses. (**a**) 'Potential Carbon' – the total additional C biomass that could be stored in all 5% top-ranked planning units. (**b-d**) Biodiversity 'Mean Richness' – the mean richness per 5% top-ranked planning unit. (**e-g**) Biodiversity 'Total Richness' – the taxon richness summed across all 5% top-ranked planning units. (**h**) Groundwater recharge, (**i**) land use value and (**j**) governance were averaged across all 5% top-ranked planning units in the landscape.



Supplementary Figure S8. Features used in spatial prioritization. The features other than carbon sequestration potential (which is shown in Fig. 1 and Supplementary Fig. S1) used in Zonation analyses to optimize planning unit selection for carbon sequestration while taking other ecosystem services and socioeconomic factors into consideration.

Supplementary Methods

Carbon maps. Potential carbon storage was calculated based on two available carbon stocking maps, both created at 1 km^2 resolution. Baccini et al.[17] published their map of above-ground carbon storage for tropical Africa in 2008, and Saatchi et al.[16] published a similar map for the global tropics in 2011. We restricted the extent of our analyses to the extent of the former, to make the maps comparable. Both maps are based on the relationship between remote sensing data and ground data of carbon biomass where these are available, and extrapolating this relationship across the landscape; though different remote sensing data, ground data and correlative methods were used to create the two maps[16,17]. The map produced by Baccini et al.[17] has the advantage of being calibrated on African, rather than global data, while the Saatchi et al.[16] map has the advantage of being the more recent of the two.

Calculating C stocking potential. Instead of looking for trends in means, as regression techniques usually do, quantile regressions (QR) can be used to test for trends in any part of the distribution[1]. We used 90th-quantile regression (90% QR) to model the potential carbon that could be stored in an area by modeling the upper trend of carbon storage against environment factors[2]. In effect, these analyses therefore modeled the higher carbon values found for a suite of environmental conditions. Analyses were based on the assumption that aboveground carbon storage is influenced by environmental factors, and that areas with lower amounts of carbon for a suite of environmental conditions have been modified by anthropogenic and/or natural disturbance factors, such as harvesting or fires. Indeed, it has been shown that woody cover in savannas is strongly influenced by disturbance regimes, decreasing in response to fires, herbivory, vegetation clearing and logging[61-63].

To model the relationship between the upper limits of biomass and the environment, QR with $\tau = 0.9$ (representing the 90% quantile) were run. The response variable was above-ground carbon biomass, and the predictors environmental variables, namely climate[51] (mean annual temperature, temperature seasonality, mean annual precipitation and precipitation of the driest quarter) and soil variables[53] (topsoil soil bulk density, which is the mass of a group of particles divided by their volume and therefore describes the water-carrying capacity of soil, and soil pH, which is linked to soil fertility). All QR models with all different possible combinations of the environmental predictors and with and without all combinations of their quadratic terms were built and run. Akaike weights were used to select the best model amongst these[64]. The best model contained all combinations of the predictors and their quadratic term (Supplementary Table S2). The coefficients obtained from this best QR model were then used to construct a map of maximum carbon storage across Africa using regression analyses. The value of grid cells for which negative biomass was predicted was changed to zero. It was from these maps of maximum C storage that the actual amount of carbon storage was subtracted to obtain maps of C stocking potential (see Methods).

Due to inaccuracies that may be present in C storage maps, and because there is expected to be variation in the data around the quantile regression line obtained by QR, we used a conservative $\tau = 0.9$ to conduct QR. However, for comparative purposes we also repeated constructed a map of maximum C biomass using QR with $\tau = 0.98$, using the same response and predictor variables as for the 90% QR. The actual amount of C storage was again subtracted from the 98% QR map of maximum C stocks to obtain a measure of C stocking potential. The 98% QR analyses were run only for the Saatchi-based map (Supplementary Table S1). The 90%- and 98%- generated maps of C stocking potential were compared using Spearman rank correlations.

We conducted a second set of analyses where we used a combination of the afore-mentioned environmental variables and human influence to predict maximum C biomass by ordinary least square (OLS) regression. Human influence is an index that was compiled from human population density; landscape transformation such as agriculture; accessibility by roads, rivers and ocean; and power infrastructure, as measured by night light visibility from space[18]. Therefore, OLS were run with biomass as response variable and the four above-mentioned climatic variables and two soil variables used in QRs, as well as human influence as predictor variables (Table S2). Akaike weights were again used to select the best model from all combinations of predictor variables and their quadratic terms, with the exception of the quadratic term of annual precipitation, which, when included in models, resulted in a decreasing trend in the residuals at high precipitation levels. Using the coefficients from this model, but with the values for human influence set to zero, a map of maximum C storage was created (i.e. a map of C stocking biomass in the absence of human influences). In all cases, the values of grid cells for which negative biomass was predicted was changed to zero. Again, actual C biomass was subtracted from this map to create the C stocking potential map calculated by OLS.

To ensure that the assumptions of OLS were met[65], biomass, annual precipitation and soil pH were square-root transformed, mean annual temperature was squared, and temperature seasonality and precipitation of the driest quarter were log-transformed. The predictors (but not biomass) for the QR were similarly transformed.

Confidence of 90% QR model estimates for the calculation of maximum C biomass was assessed by repeating 2000 analyses based on 127766 (80% of the entire dataset) randomly sampled (without replacement) PUs and conducting 90% QR on each of these subsetted data. The estimates obtained from each of the 90% QR analyses were recorded, and the mean and standard deviation of the estimates obtained from these. These confidence analyses were only conducted for the 90% QR-generated maximum C biomass maps, as we mainly based our results on these (see Results). For the Saatchi 90% QR-generated maximum C biomass map uncertainty was also mapped: the coefficients of the first 1000 90% QR models produced on the above-mentioned subsetted data were used to re-run regression analyses to calculate maximum C biomass per PU. The standard deviation of the predicted maximum C biomass for every PU was calculated for these 1000 models and mapped. Due to these analyses being very time-intensive, these analyses were run using only the first 1000 set of coefficients, and only for the Saatchi-generated map.

The maximum C biomass calculated using the three above-mentioned methods (90% QR, 98% QR and OLS), and the two datasets (Saatchi et al.[16] and Baccini et al.[17]) were regressed with C biomass recorded in intact forest patches across tropical Africa taken from the Afritron dataset[66] to assess the accuracy of our measures of C stocking potential. The “raw start C biomass”[66] values from 78 sites (site CAP-10 was excluded as it fell outside the study area) were compared to corresponding predicted maximum C biomass using least-square regressions.

All data were resampled to 5’ resolution. QR and OLS were run in R v. 2.8.1 and 2.15.0[9] using the packages quantreg[67], qpcR[68] and leaps[69].

Data layers in Zonation analyses. All data maps were projected to an equal area resolution (Lambert Azimuthal) and resampled to 10-km resolution, which is similar in extent to the 5-minute resolution at which the QR and OLS were run. This ensured that all planning units (PUs) in the analyses were of equal area. Shapefiles of distribution maps for all species of mammals, reptiles and amphibians were resampled to a small resolution (1 × 1 km). All larger (10 × 10 km) cells that contained a 1 × 1-km presence for a species were subsequently classified as presences for the species. These maps are the best available at the large spatial scale at which these analysis are being conducted; they are, however, interpolated and for some organisms there is some uncertainty in ranges[31].

Zonation Settings. The added benefit function (ABF) was used as cell removal technique in Zonation analyses. This technique removes cells based on the loss in representation over the landscape, summed for all species in a PU[54]. If the removal of a PU results in a small reduction in the representation of species, it will be removed prior to a PU the removal of which would result in a large loss of representation of species. For comparative reasons, analyses were also repeated using the basic core area Zonation (BCZ) cell removal technique. By considering the most valuable occurrence in each PU, this technique attempts to retain important locations for all features. In BCZ cell removal, if only a small portion of a species' distribution remains in the landscape after preceding cell removal, the PUs in which the species still occurs are retained[54], thereby minimizing biological loss during cell selection. However, as this technique seemed less successful at trading off different benefits (Supplementary Fig. S5), we based our presentations on runs conducted using ABF and only present some of the BCZ analyses for comparison. Because more than 1500 species distribution maps were used in the runs, the process was time intensive. Therefore a warp factor of 20 was used (20 cells were removed at a time). Removal was only allowed from edge cells to decrease computation time; however, an additional 1,000 edge points (random points in the landscape from which removal may occur), were added to the landscape from which removal could occur[55].

Elephants (*Loxodonta africana*) were excluded from the mammal biodiversity features, as they may significantly reduce woody biomass[62] and would thus typically not be appropriate in C stocking projects.

Removal of unsuitable landscapes in spatial prioritization analyses. Existing protected areas and unsuitable land cover types were removed from all Zonation analyses. Protected areas often make important contributions to C storage, and would likely receive greater benefits from reduced deforestation than from reforestation incentives[70]. Protected areas were identified from the World Database on Protected Areas[71], and areas classified as IUCN categories I-V were excluded from analyses by classifying them as unsuitable using the "analysis area mask"[55]. Land cover types that were considered inappropriate for reforestation projects were sandy desert and dunes, stony desert, bare rock, salt hardpans, cities and waterbodies[72]. Areas with these land cover types were removed prior to analysis.

Performance trade-offs of using different weightings of C stocking potential. To assess how rankings changed between differently weighted analyses two sets of analyses were run. First, the True Skills Statistic TSS of the top 5% of sites was calculated. The TSS assesses the correspondence of presence-absence data between two datasets[73]. Unlike other similar measures, it is not affected by prevalence[73], which is important here. Calculation of the TSS relies on a confusion matrix of the number of localities where both datasets record absences, both datasets record presences, where the first datasets records a presence and the second an absence, and finally where the first datasets records an absence and the second a presence. In this case absences were PUs which were not in the top 5% of rankings, and presences were PUs that did fall into the top 5% of rankings. The TSS was calculated between all pairs of analyses with different weighting that were run in Zonation, for analyses based on C stocking potential maps generated from 90%

QR Saatchi and Baccini maps, and run using the ABF cell removal rule (Supplementary Table S1). The TSS varies between 0 and 1, and high values indicate high correspondence between two datasets.

Second, to not only consider the presence/absence of the top 5% ranked cells (which comprises a binary variable), we also calculated the magnitude of the changes in PU rankings between analyses with different C stocking potential weightings. For each PU the absolute difference between the rankings obtained from Zonation analyses where C stocking potential was weighted 12, and all analyses with other weightings of C stocking potential, was calculated. The mean and standard deviation of the absolute values of these differences were subsequently calculated and expressed as a percentage, which represent the mean (and standard deviation) of the change in ranking that occurred when different weightings were applied.

Comparisons of prioritization runs. We compared prioritizations generated by a) the two different methods of generating maps (QR and OLS); b) the two different cell removal techniques used (ABF and BCZ), and c) maps based on the Saatchi and the Baccini dataset (Supplementary Table S1). These Spearman rank correlations were run for analyses where carbon was weighted 12 and all other features three, as our interpretations mainly rested on this combination of weightings (see Results). Because interpretations of the prioritization analyses were largely based on the top 5% PUs selected during prioritization analyses, we again calculated TSS[73] between different sets of Zonation runs based on these PUs. The top 5% PUs were classified as 'presences' and all other sites as 'absences'.

Connectivity Analyses. To increase connectivity of PUs, analyses were repeated using different boundary length parameters (BLPs)[55]. Increasing the BLP increases the cost of the boundary length of the selected sites during the removal of cells, ensuring fewer larger, rather than many small isolated highly ranked sites . To assess the effect of the BLP on the sensitivity on the results[55], analyses were run with different levels of the BLP: 0.005, 0.01, 0.05, 0.1 and 0.5. For these analyses, a warp factor of one was used[55]. Because these analyses are extremely time-intensive, they were only run for the analyses where carbon was weighted twelve, and all other features three (Supplementary Table S1). (These are the same weightings as the map that we based our final interpretation on.) These analyses were only run on the potential C storage maps generated from the Saatchi and Baccini datasets using the 90% QR method. The ABF cell removal rule was used. (Supplementary Fig. S1)

The BLP is one of the most simple connectivity parameters in site selection, as it does not consider species-specific effects of fragmentation[55]. We therefore also attempted running Zonation analyses where connectivity was influenced by individual species' dispersal abilities using distribution smoothing[55]. As dispersal abilities were not available for most of the species in our analyses, we used several literature sources[74-76] to estimate maximum dispersal rates. For reptiles and amphibians we set one maximum dispersal distance based on the sources. For mammals we calculated the maximum dispersal distance based on body size (data obtained from Søren Faurby, pers. comm.) using a relationship between body size and range size presented in Sutherland et al.[74]. However, this relationship seemed to overestimate the range sizes of large mammals in our study (some of the computed range sizes were larger than the extent of the study area). This could be due to the fact that the function in Sutherland et al.[74] is based on a relatively small number (n=68) of (mostly non-African) species, and because dispersal distance is usually also influenced by a number of other unavailable factors, such as home range[74,77]. Due to the impossibility of obtaining home range data, and the apparent problems of calculating dispersal distance based on body size, we did not further pursue connectivity analyses using distribution smoothing.

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