SPIQ-FS Dataset

Version 0

Estimation of marginal damage costs for loss of ecosystem services from land-use change or ecosystem degradation

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Summary

Marginal damage costs in international dollars (US$2020 Purchasing Power Parity) ha^{-1} yr^{-1} for ecosystems in 8 biomes (coral reefs, coastal systems, inland wetlands, lakes and rivers, tropical forest, temperate forest, woodland and shrubland, and grasslands) are estimated for 202 countries. The damage costs estimate 2020 present value of present and future economic losses from loss in 2020 of ecosystem services provided by 1 ha of the respective aquatic or terrestrial ecosystem.

The marginal damage costs for each country and each biome are provided as random variables of loss in parametric form in Table 7 on page 61. Two parameters, mu and sigma, are estimated for a lognormal distribution of probable US$2020 PPP present from loss in 2020 of ecosystem services provided by 1 ha. The samples from which the parametric forms are derived and the correlation matrix for covariance of loss across countries are available in the SPIQ-FS dataset.

Use for economic loss

The objective of the SPIQ-FS dataset is to enable estimates of economic risk due to food system activities and the economic potential of food system transformation. The intended use involves aggregation across countries and quantities, for example, in global studies of dietary change or for multinational company or value chain estimates of impact.

The marginal cost estimates should not be used for local or site-specific studies.

The estimate represents aggregated economic loss to a present or future economy (e.g. reduction in GDP or consumption as an income-equivalent welfare loss) and not transfers between individual economic actors or sectors (e.g. payments from households to the health sector for health costs).

The average present value of probable US$2020 PPP marginal economic loss from loss in 2020 of ecosystem services provided by 1 ha for each country and biome is reported in Table 6 on page 53. The average value should be used to calculate the average value of total economic losses from food system activities across multiple countries and quantities since it is additive.

To calculate risk in total economic losses from land conversion or ecosystem degradation within a country, the distribution of probable US$2020 PPP marginal economic loss from loss in 2020 of ecosystem services provided by 1 ha in Table 7 should be multiplied by the effective ha lost by land conversion or ecosystem degradation. This may overestimate the uncertainty in total economic losses for a large quantity of effective ha lost and may underestimate the uncertainty for a small quantity of effective ha lost given only the knowledge that the loss of effective ha occurs within the country[1].

[1] Over- or under-estimation may result since it is unclear whether 1 ha of ecosystem services lost due to food system activities represent independent lotteries of economic loss. When aggregating to a total economic loss for n effective ha lost, the sum of n random variables each with lognormal distribution given by Table 7 as a representation of the uncertainty in total economic loss should not be used without a sufficient argument for independence within the impact pathways of each unit of emission. For example, the total economic impact of CO_2 emissions in 2020, treating each emission as a random draw from the distribution of economic loss for 1 metric ton of CO_2 emitted and summing the random variables, will result in a gross error if economic loss is not independent between each emission due to a common component in the impact pathway (e.g. a systematic underestimate in the chemistry of radiative forcing). Uncertainty for marginal damage costs when quantities are unspecified is not fully resolved in SPIQ Version 0.

To calculate risk in total economic losses from land conversion or ecosystem degradation jointly with other impact quantities such as GHG emissions, and across multiple countries, the correlation matrices in the SPIQ dataset should be used to reconstruct a joint distribution of probable US$2020 PPP present values for the impact quantities[2]. Samples from the joint distribution of marginal damages should be multiplied by their respective quantities for each country and then added. The resulting set is a sample of total economic losses. Economic risk or economic potential is generally underestimated without using joint sampling.

It is not recommended to use the average values in Table 6 separate from the uncertainty estimate in Table 7.

Use for economic potential

The marginal damage costs in Table 7 and any totals for economic losses calculated using them **do not include the value (benefits) provided to society from the activity resulting in 1 effective ha of lost ecosystem services**. There is no comparison with a counterfactual to estimate the balance of value between avoided damages and the costs to abate effective ha of lost ecosystem services. Abatement costs include the option of 'paying the cost' of losing the production value from land-conversion.

Reducing effective ha of lost ecosystem services will not 'save the costs' to the global economy of amounts calculated using the values in Table 6 on page 53 and Table 7 on page 61. Damage costs should be paired with abatement costs and counterfactuals to determine the economic risk from food system activities and the economic potential in food system transformation.

To arrive at total economic losses, it is assumed that the total effective ha of lost ecosystem services due to the food system activity are calculated. For example, land conversion may result in ha of lost ecosystem services over many years until diminished by discounting or eventual return to natural state. For ecosystem degradation, total effective ha loss caused by a pulse such as nitrogen pollution in 2020 will involve a short time horizon due to recovery of services.

To account for land conversion in assessment of the economic potential of food system transformation, duration for the costs and benefits of land-conversion should be considered.

Methodology and caveats

Impact pathway

Land conversion changes the basic functioning of ecosystems (habitat loss, disruption of biophysical inputs, disruption of biological cycles and food chains, etc.), resulting in a loss of services provided by ecosystems as inputs to human economic activities.

[2] Covariance in economic losses due to joint emission or production of impact quantities from food system activities, for example 1 kg of NH_3 emission in country i and 1 metric ton of CO_2 emitted in country j, is estimated in the document "SPIQ-FS Version 0: double counting and estimation of correlations between impact quantities". The parametric form given in Table 7 represents what is called the marginal distribution of a joint distribution across countries and quantities of marginal damages for the impact quantities associated to food system activities. Determination of the correlations considers spatial and temporal coincidence of impact. All SPIQ-FS Version 0 damages are for impact quantities produced in 2020. A later version may consider joint distribution across countries and quantities and years of emission/production.

Conversion implies a classification scheme whereby anthropogenic activity or natural forces create sufficient change in the biophysical properties of a land area and the ecosystems it supports, that the classification of the land area changes.

Land degradation impairs the functioning of ecosystems such that the value of the ecosystem services provided by the land area and the ecosystems it supports decrease.

Conversion and degradation apply also to aquatic areas and ecosystems, and can be from direct or indirect anthropogenic activities, such as clearing forests for cropland or desertification caused by increasing mean annual temperature.

Calculation and uncertainty

Multiplying effective loss of ha of ecosystem services from conversion or degradation by the annual value of the ha of ecosystem services provides an estimate of annual economic losses from conversion or degradation.

The Ecosystem Services Valuation Database (ESVD) contains over 4800 individual estimates of value ha^{-1} yr^{-1} of ecosystem services in US$2020 PPP across 92 countries, 15 biomes, and 23 ecosystem service (Table 2) per biome. 8 of the biomes are relevant for conversion and degradation from food system activities: coral reefs, coastal systems, inland wetlands, lakes and rivers, tropical forest, temperate forest, woodland and shrubland, and grasslands and savannah (Table 1). Open oceans are included in the ESVD, but not in the SPIQ-FS dataset.

After removing outliers, ecosystem service values from ESVD in the 8 biomes considered were grouped into 4 HDI tiers (low development, medium development, high development, and very high development) and 3 aggregates of value of services (provisioning, regulating, and cultural). Uncertainty in the values comes from treating the range of values from the database grouped into each HDI tier and class of service as a random variable. The total value for ecosystem services in an HDI tier is the sum of the provisioning, regulating, and cultural ecosystem services.

The inability to resolve ecosystem services at a finer level than the aggregate classes of provisioning, regulating, and cultural, is reflected in wide uncertainty bands for value ha^{-1} yr^{-1} of ecosystem services in US$2020 PPP. For most of the estimates derived from the ESVD the interquartile range of ecosystem services is greater than an order of magnitude.

The grouping was used as the coverage of countries and ecosystem services in the ESVD, and parameters are likely to cause variation in the mean value ha^{-1} yr^{-1} of the total value of ecosystem services ha^{-1}, showed low significance and explanatory power at a country level (Section 3.3.2).

Caveats in using the ESVD include potential bias toward higher value from chosen sites in source studies (high value tourist locations, high value coastal fisheries, etc.). Even with adjustment from outliers, the value ha^{-1} of coral reefs and coastal systems are much higher than forests and grassland. It is unclear if the higher bias is explained by scarcity. There is statistical evidence from the ESVD that, generally, ecosystem services in the high level of development HDI tier have a higher value, in international dollars, than the very high level of development HDI tier.

The WWF EcoRegions dataset contains 867 distinct spatial biome classifications. The lack of data in ESVD at the level of the 23 ecosystem services mean that higher detail classification of ecosystems and characterisation of the classes of ecosystem services they provide could not be used to derive alternative weights for aggregating the value of the ecosystem service, treated as a random variable, into a total value of services ha^{-1} yr^{-1} without extremely large uncertainty.

Users should be aware of the potential of double counting of the total value per ha of changes in ecosystem services from land conversion in cost-benefit studies. Estimates of woodland and grassland service can include food provisioning (use as orchards and cropland), which should be adjusted if the study is separately counting the benefits of conversion of forest or inland wetland to agricultural land. Similarly, some studies count separately the loss of carbon sequestration services from forested land converted to cropland.

Global Perspective

For perspective, the damage costs of average annual land conversion attributable to agriculture for 202 countries are estimated in Section 3.8.2. The damage costs are calculated by pairing the marginal ecosystem values for 202 countries (Table 6 and Table 7) with global land conversion data from the HILDA+ land transitions dataset.

For each country the net ha of conversion between agricultural use and grassland or forest ecosystems was used as the quantities of effective loss of ha of grassland or forest biomes. The average annual amount of grassland and forest conversion over 2015-2019 from HILDA+ was used as an estimate of 2020 net conversion (Figure 31). Net conversion of forest globally was ~5Mha (5 million hectares). Net conversion of grassland globally was ~-0.1 Mha - more agriculture land was abandoned in grassland biomes than grassland was converted, on average, over 2015-2019.

Expected economic loss in 2020 from net conversion attributable to agriculture in 2020 was US$2020 0.5 billion yr^{-1}, with a greater than 5% chance that losses are over US$2020 3 billion yr^{-1} (Figure 32). Section 3.8.2 discusses how the annual losses of land conversions attributable to agriculture in 2020 compares to total losses from food system GHG and nitrogen emissions in 2020.

How much of the estimated economic loss from land conversion can be recovered from transforming agricultural production and food systems is unclear without global modelling studies placing food system mitigation costs within the context of least cost abatement of land use change.

Contents

3 Land-use change

3.1 Quantities associated to impact

The services provided by the natural world as inputs to human economic activities are called ecosystem services [1] [3] [4]. The major global land use for economic activity is agriculture and forestry. Agricultural use competes between providing food, fibre, and biofuel. Other services provided by ecosystems have been identified that provide inputs into economic activity, including water filtering, water retention preventing soil erosion, carbon sequestration, pollination, flood prevention, temperature regulation, genetic material, natural beauty (for tourism), etc [4].

Activities in the food system that result in cropland or pastureland replacing natural land use within an existing ecosystem (e.g., deforestation for cattle grazing) result in impact from the loss of the ecosystem services from the original land-use [3, 5]. The impact is part of a market failure if the losses of those ecosystem services are not considered in the costs of conversion and the costs end up being detrimental overall, and a negative externality if a third party to the economic transactions and benefits from the conversion bears the costs resulting from loss of ecosystem services (e.g., loss of carbon sequestration).

Hectares (ha=10^4 m^2) is the commonly used quantity to measure change in land use [3]. Ecosystem services are a flow of value from land, so they are measured in the unit of the service (e.g., visitors, yield, species, litres of water purified, etc.) ha^{-1} yr^{-1}.

Impacts can come from conversion or degradation of ecosystems. Despite the title of “land-use change”, territorial, riverine, coastal, and marine ecosystems provide ecosystems services that can be altered because of activities in the food system.

3.1.1 Conversion of ecosystem

Conversion is when change in ecosystem services comes from conversion of land from one use and type in an ecosystem classification to another, e.g., tropical forest is cleared to managed grassland (deforestation for cattle ranching). The marginal damage cost of conversion is then usually the difference between the provision of ecosystem services between the classes on the ha converted.

For conversion, it should be made overt whether food provisioning and carbon sequestration services are included in the value of the ecosystem services of the original or converted land type.

If land-use CO2 equivalents of conversion effects have already been counted within GHG emission quantities in a cost study, then double counting will occur by using a valuation of the ecosystem services with a carbon sequestration service embedded in it.

Most food system economic analysis will want to compare the benefits of land use for agriculture and other environmental effects. Knowing the food provisioning service is included in valuation of agricultural land (and hence in the difference estimate in conversion), means that an adjustment to that amount can be included if the value in that food provisioning service is being displaced to other land units (e.g., intensification or dietary change) or reduced (e.g., dietary change and drop in demand).

Costing of impact should also include the effect of conversion on the quality of ecosystem of which that land, water body, coastal or marine site, was a part.

3.1.2 Quantity of services of ecosystem

Indirect effects of conversion or other food system activity (e.g., nitrogen emissions) can also degrade the provision of ecosystem services without reaching a threshold of conversion of the ecosystem from one 'type' (e.g., tropical forest) to another (grassland) [5]. By comparing the total service provision, e.g., 100ha of tropical forest after the effect is only providing the services equivalent to 80ha of tropical forest before the effect, reduction in the quality of services can be framed as an 'effective loss' of ha, e.g. 20 ha in the example. Reduction in a category of service provision (e.g., water retention, or litres water filtration per ha) can be measured individually in effective loss of ha yr (where yr reflect the timespan of the degradation) but this need not be the same amongst all services being provided.

EFfective ha^{-1} yr^{-1} Loss of ecosystem Services (EFhaLS) converts a change of quality in ecosystem services into a quantity of impact from conversion (to a null system of no service provision) so that marginal damage costs per ha yr can be applied to both quantity changes of ha and services.

EFhaLS was used in the estimation of impact of reactive nitrogen in surface run-off in Annex A – Nitrogen Emissions.

For non-conversion land-use change effects, double counting with food and carbon sequestration services is less of an issue.

3.1.3 Inclusion of food provisioning and carbon sequestration services

A statistical analysis of the Ecosystem Services Valuation Database (ESVD) – December 2020 version is used to assign values for 202 countries to the main 8 biome classes within ESVD that have sufficient data (Table 1). EVSD includes food provisioning and carbon sequestration in the total valuation amounts (Table 2).

3.2 Database of value of ecosystem services

ESVD represent a dataset of over 4800 individual estimates of value across 92 countries from the provision of ecosystem services and losses if the ecosystem is damaged and services degraded. The valuation unit is US$2020 PPP ha^{-1} yr^{-1} across the biomes described in Table 1 and services described in Table 2. The range of valuations across the biomes provides the opportunity to understand the relationship between the marginal value accounting for factors such as location, context of the ecosystem, and socio-economic context of the services being received.

Table 1: Biomes and ecosystems used in marginal damages costs from the Ecosystem Services Valuation Database (ESVD). The variable k used in the text refers to biomes in ESVD.

Biome ID (k)	Ecosystem Name	ESVD Sub-Id
2	Coral reefs	
2	Barrier reefs	2.1
2	Atolls	2.2
2	Fringing reefs	2.3
2	Patch reefs	2.4
2	Other (coral reefs)	2.5
3	Coastal systems (incl. wetlands)	
3	Sand dunes, beaches, rocky shores	3.1
3	Tidal marshes	3.2
3	Salt marshes	3.3

3	Mangroves	3.4
3	Lagoons	3.5
3	Estuaries	3.6
3	Unvegetated sediment	3.7
3	Shellfish reefs	3.8
3	Seagrass beds	3.9
3	Kelp forests	3.11
3	Other (coastal systems)	3.12
4	Inland wetlands	
4	Swamps, marshes	4.1
4	Peatland, Non-forested	4.2
4	Peatland, Forested	4.3
4	Peatland, Tropical	4.4
4	Peatland, Boreal	4.5
4	Wetlands, Forested (on alluvial soils)	4.6
4	Wetlands, Groundwater-dependent	4.7
4	Floodplains	4.8
4	Other (inland wetlands)	4.9
5	Rivers and lakes	
5	Rivers	5.1
5	Lakes, freshwater	5.2
5	Lakes, saltwater	5.3
5	Human made water bodies	5.4
5	Other (rivers and lakes)	5.5
6	Tropical forests	
6	Tropical rain forest	6.1
6	Tropical dry forest	6.2
6	Tropical cloud forests	6.3
6	Other (tropical forests)	6.4
7	Temperate forests	
7	Temperate rain or evergreen forest	7.1
7	Temperate deciduous forest	7.2
7	Boreal/coniferous forest (‘Taiga’)	7.3
7	Other (temperate forests)	7.4
8	Woodland & Shrubland	
8	Tropical woodland & shrubland	8.1
8	Mediterranean woodland & shrubland	8.2
8	Temperate woodland & shrubland	8.3
8	Heathland	8.4
8	Other (woodland & shrubland)	8.5
9	Grass-/Rangeland	
9	Savanna	9.1
9	Tropical grasslands	9.2
9	Temperate grasslands	9.3
9	Steppe (dry, cold grassland)	9.4
9	Other (grassland)	9.5

Annex A

The ESVD bases the classification of ecosystem services described by studies using the TEEB Classification [6] and CICES (v5.1) classification systems [7].

Table 2: TEEB classification of ecosystem services in ESVD. Used to aggregate valuations in ESVD to totals per biome per ecosystem by adding the value of services observed in studies. The variable m used in the text refers to biomes in ESVD.

TEEB ID (*m*)	Ecosystem Service	ES Code	Ecosystem Sub-Service
Provisioning			
1	Food	11	Fish
		12	Meat
		13	Plants / vegetable food
		14	Non-Timber Forest Products (NTFPs) [food only]
		15	Food [unspecified]
		16	Other
2	Water	21	Drinking water
		22	Industrial water
		23	Water Other
		24	Irrigation water [unnatural]
		25	Water [unspecified]
3	Raw materials	31	Fibres
		32	Timber
		33	Fuel wood and charcoal
		34	Fodder
		35	Fertiliser
		36	Other Raw
		37	Raw materials [unspecified]
		38	Sand, rock, gravel
		39	Biomass fuels
4	Genetic resources	41	Plant genetic resources
		42	Animal genetic resources
		43	Genetic resources [unspecified]
5	Medicinal resources	51	Biochemicals
		52	Models
		53	Test-organisms
		54	Bioprospecting
6	Ornamental resources	61	Decorative Plants
		62	Fashion
		63	Decorations / Handicrafts
		64	Pets and captive animals
Regulating			
7	Air quality regulation	71	Capturing fine dust
		72	Air quality regulation [unspecified]
		73	UVb-protection
8	Climate regulation	81	C-sequestration
		82	MDS-production
		83	Climate regulation [unspecified]
		84	Microclimate regulation
		85	Gas regulation

9	Moderation of extreme events	91	Storm protection
		92	Flood prevention
		93	Fire Prevention
		94	Prevention of extreme events [unspecified]
10	Regulation of water flows	101	Drainage
		102	River discharge
		103	Natural irrigation
		104	Water regulation [unspecified]
11	Waste treatment	111	Water purification
		112	Soil detoxification
		113	Abatement of noise
		114	Waste treatment [unspecified]
12	Erosion prevention	121	Erosion prevention
13	Maintenance of soil fertility	131	Maintenance of soil structure
		132	Deposition of nutrients
		133	Soil formation
		134	Nutrient cycling
14	Pollination	141	Pollination of crops
		142	Pollination of wild plants
		143	Pollination [unspecified]
15	Biological control	151	Seed dispersal
		152	Pest control
		153	Disease control
		154	Biological Control [unspecified]
16	Maintenance of life cycles	161	Nursery service
		162	Refugia for migratory and resident species
17	Maintenance of genetic diversity	171	Biodiversity protection
Cultural			
18	Aesthetic information	181	Attractive landscapes
19	Opportunities for recreation and tourism	191	Recreation
		192	Tourism
		193	Ecotourism
		194	Hunting / fishing
20	Inspiration for culture, art and design	201	Artistic inspiration
		202	Cultural use
		203	Inspiration [unspecified]
21	Spiritual experience	21	Spiritual / Religious use
22	Information for cognitive development	221	Science / Research
		222	Education
		223	Cognitive [unspecified]
23	Existence, bequest values	231	Existence value
		232	Bequest value

3.2.1 Data processing and ambiguities

We processed the 4808 individual valuations in the ESVD extracted from 787 studies across 92 countries to determine the total valuation per country per biome and the total within provisioning, regulating and cultural ecosystem services as presented in Table 2. Marginal value of ecosystem services in the ESVD are given in US$2020 PPP and studies already involving Value Transfer (VT) and OTher methods (OT) were excluded. 3116 valuations per country per biome per ecosystem per ecosystem service were used before outlier analysis.

The ESVD studies cover a range of valuation methods, from willingness to pay, to trade-off in preferences, to change in market proxies and examination of total production functions [8]. The social cost of carbon (but not the same value for the social cost of carbon) is used for most of the valuations of carbon sequestration. Broadly the valuation amounts are considered a cost to society. This may overestimate as many studies identify private costs and the cost bearers but may underestimate as defensive expenditure (abatement) is used in some studies.

Not all study sites listed in ESVD considered multiple services of a specific biome under The Economics of Ecosystems and Biodiversity (TEEB) classification, Table 2, and some studies concentrated on particularly services. Therefore, aggregating just using the ESVD entries per country per biome is likely to be an under-valuation. It is not clear that all ecosystems of the same type provide the same level of ecosystem services per ha. Therefore, obtaining a total for a biome by adding up the average value in the ESVD for each type across 23 services, as done in the "Summary values" tab of the ESVD xls file (*https://www.es-partnership.org/esvd/esvd-download/esvd-version-december-2020/*), can lead to an over-valuation.

Outliers in service categories can skew the total value of services for country level analysis. Studies of low area but popular tourist areas can skew the per ha per yr representation of the value of services for the much larger but less studied area of the same ecosystem in the same country. One study had a value of approximately US$ 2020 PPP 46 million ha^{-1} yr^{-1} of beach from a specific site – applying that to all ha of beaches in a country with many beaches but few representative studies of other beaches is highly distorting. Allowing single high values as a representation of an ecosystem service value introduces false certainty, since few other studies have been conducted. Section 3.3.1 describes the outlier analysis. After outlier analysis 2908 valuations remained.

We aggregate total values per country per biome using the given ESVD valuations per ecosystem per ecosystem service. We treat the estimates per biome per ecosystem per ecosystem service in a country as a discrete random variable and add them up (as random variables) across the services to obtain a total. This provides uncertainty in total marginal value per ha per yr per biome per country. Some of the uncertainty therefore reflects differences in the studies, some of the uncertainty is from the scale of modelling – epistemological uncertainty in quantities at a national resolution in what ecosystems within biomes are being affected, and what ecosystem services.

3.3 Statistical analysis for value transfer of ecosystem services

We examined the regression model of the ESVD dataset proposed in [9]. Weak to moderate relationships of ecosystem values per country per biome with some of the variables proposed in [9] were found. Once residuals are considered though, error and uncertainty can result in many orders of magnitude difference for marginal values of ecosystem services. Generally, there is only a weak positive dependence on Gross National Income (GNI). Showing that, if ESVD is a consistent dataset on which to base marginal values per ha of ecosystem services, the ecosystem services are valued proportionately higher compared to GNI per capita in low development countries compared to high development countries. Another general result from the signs of the regression coefficients observed in the meta-analysis in [9] is the link between ecosystem valuation and connection of the ecosystem service to the economy: protection status and reduced agriculture in countries generally decreases values.

Overall, transfer of ecosystem service marginal values using national level statistics, despite using the most extensive selection of studies across countries available (ESVD), results in high uncertainty in extrapolating values to ecosystem services in other countries. Using the suggested regression and residuals to interpolate values across countries in the ESVD database was observed to have poor fit with validation values.

The degeneracy of country data makes the dataset suitable to hierarchal modelling, though many countries have single points of data, and it is not clear regional grouping is the best choice. After studying regression models based on [9] in Section 3.3.2, we generate a simpler model of clustering values into United Nations Development Programme (UNDP) HDI brackets and service classes in Section 3.4. Assisted by the regression analysis, we examine relationships between the distribution of values within and across HDI brackets and service classes. We use the results of the grouping analysis of ESVD valuations to assign total value in US$2020 PPP ha^{-1} yr^{-1} to biome types per country using HDI tiers.

Overall, a mechanistic model with higher resolution on the ecological and socio-economic context of the system such as offered by Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) would be preferred in the future over further statistical analysis of the study set [10-12].

3.3.1 Outliers in ecosystem services per biome

We examined outliers in valuation of ecosystem services per biomes with sufficient data (represented as k=2 up to k=9 in Figure 2 to Figure 9).

Singular high estimates were examined manually in the dataset, if there were many samples in the data then a standard outlier removal process (based on mean absolute deviation away from the average value) was used to examine outliers.

With outliers removed, totals per country and per biome were examined (Section 3.3.2). The distribution totals for all values per biome (treating each ecosystem service as a random variable and adding the random variables) are shown in Figure 1. These distributions are for illustration, we are interested in examining trends in the value across countries and income groups further below.

The amounts listed in the ESVD dataset as ‘summary values’ for each biome are shown as grey dashed lines in Figure 1. The reason the mean value, and in most cases the medians, but not the modes (the most likely value) of our values are higher than the means of the ESVD dataset is due to the different procedure with outliers. Where the shape of the distribution of values in Figure 2 to Figure 9 was visible, we did not truncate by using a ‘window’ procedure. Our process of removing outliers examined density of values in the distribution and removed percentiles, not a count of low and high values. For skew distributions (some of the distributions are clearly symmetric on a log-transformed x-axis) using windows can bias the mean by removal of higher values. The procedure we used retains uncertainty about high values while still removing outliers and the mean is not biased downward.

Annex A

A few high value sites and services (e.g., tourism and existence values) are skewing the high mean value per ha per yr for k=2 (Coral Reefs), k=3 (Coastal systems), k=4 (Inland Wetlands) and k=5 (Rivers and Lakes). Biome k=8 (woodland and shrubland) has too few values to smooth out the valuation through summation.

We totalled using valuations of services as random variables, where each valuation from a study site was given equal weight – hence the large spread of values for k=2-5 biomes, because there was a greater number of data points and more services were summed up. An improvement on this process when undertaking value transfer is to build the distributions by weighting the study sites in ESVD by the probability that they match a transfer site (for example the proportion of such study sites – like ha of high value tourist beaches in proximity to agricultural activity compared to other beaches in a country).

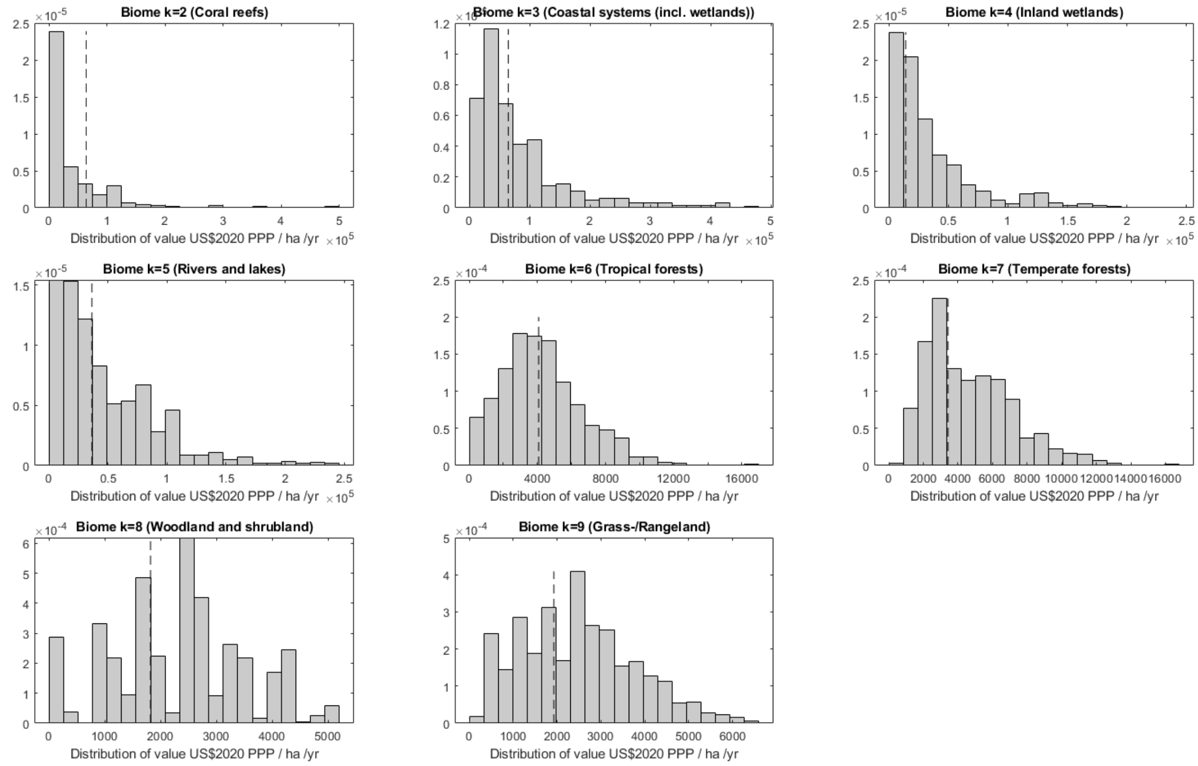

Figure 1 Uncertainty in summing across valuations of ecosystem services in the ESVD database to obtain estimates of the value in US$2020 PPP ha^{-1} yr^{-1} of ecosystems in the biomes. The distributions represent all values for all ecosystems of a biome in the ESVD. Comments on positive skew due to over representative high value study sites and potential corrections in the text. The black dotted vertical lines are the "Summary Values" for each biome in the EVSD.

Our use of the marginal value of ecosystem services for k=2-5 is in Annex – Nitrogen. We use the marginal values for biomes k=6 to k=9 for deforestation and reclamation of abandoned farmland. Therefore, we do not correct the distributions in Figure 1. We suggest, with a mechanistic model with higher resolution on the ecological and socio-economic context of the system such as in the InVEST modelling suite, weightings could be generated by spatial information on the context and the ESVD dataset could then be used for (a) validation, and (b) an uncertainty estimate by examining the weighted residuals around a modelled value.

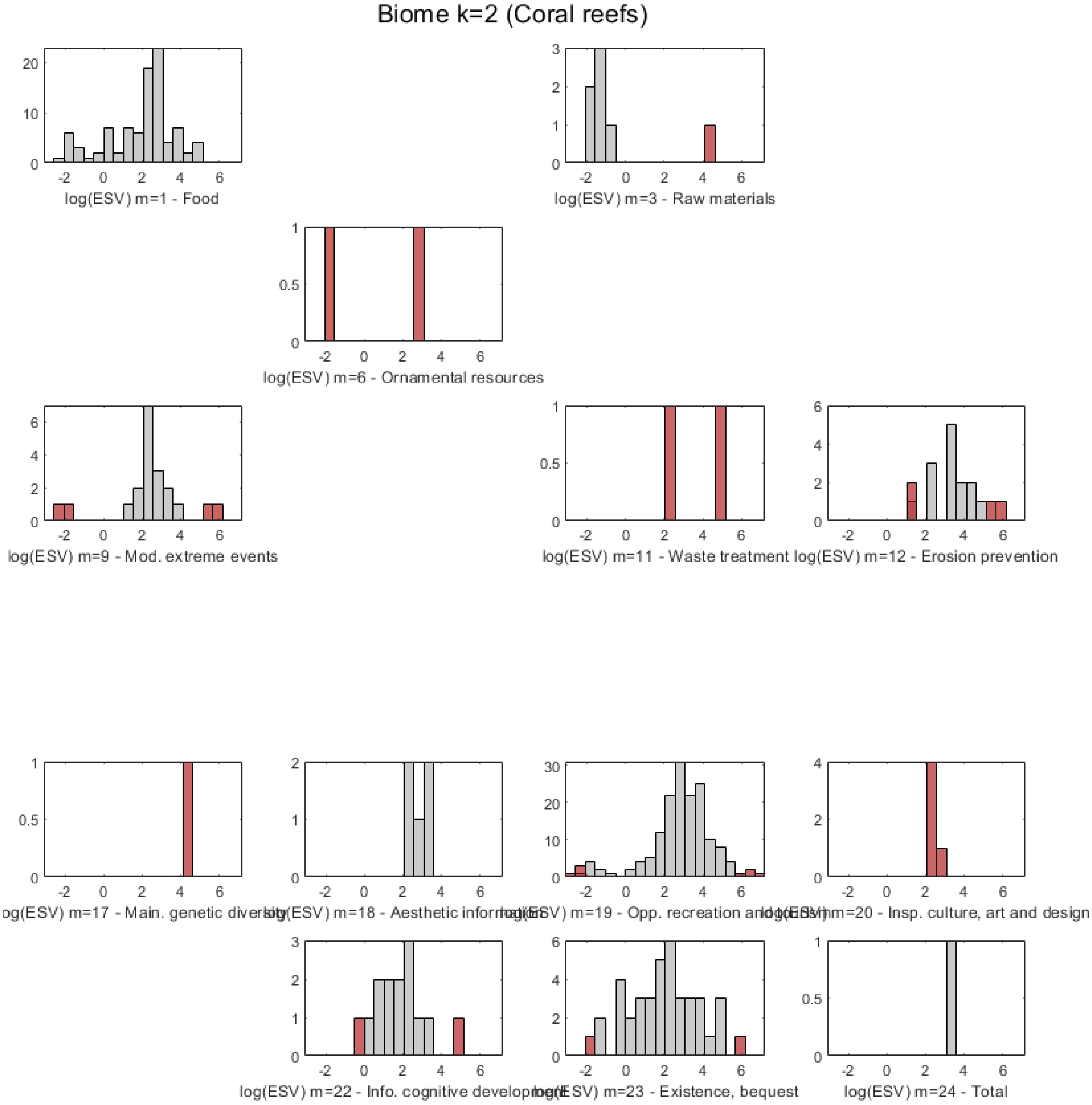

Figure 2: Frequency histograms of per ha per yr values for ecosystem services in coral reef biome. Count of values in the y-axis and order of magnitude (log10) of the ecosystem value in the x-axis. From lack of representativeness values for services under m=6, m=11, m=17, and m=20 were removed (red bars). For m=3, m=22 outliers with value >10^4 were removed (and the same percentage of lowest values), for m=9,12,23 outliers with value >10^5 were removed (and the same percentage of lowest values, red bars), and for m=19 outliers with value >10^6 were removed (and the same percentage of lowest values, red bars).

Annex A

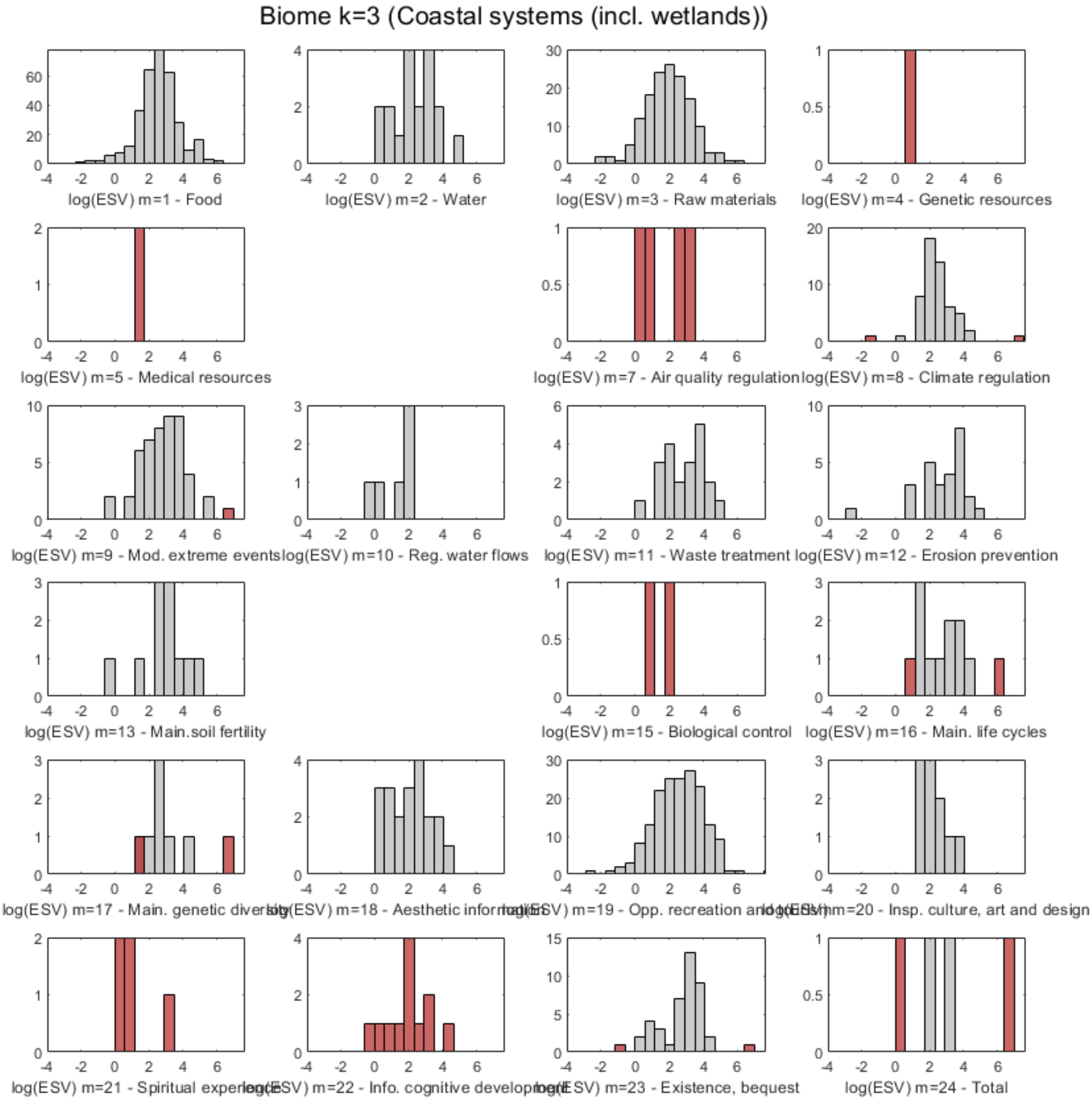

Figure 3: Frequency histograms of per ha per yr values for ecosystem services in coastal systems biome. Count of values in the y-axis and order of magnitude (log10) of the ecosystem value in the x-axis. From lack of representativeness services under m=4, m=5, m=7, m=15, m=21, m=22 were removed (red bars). For m=8,9,17,23 outliers with value 10^6 were removed (and the same percentage of lowest values, red bars), and for m=16 outliers with value >10^5 were removed (and the same percentage of lowest values, red bars).

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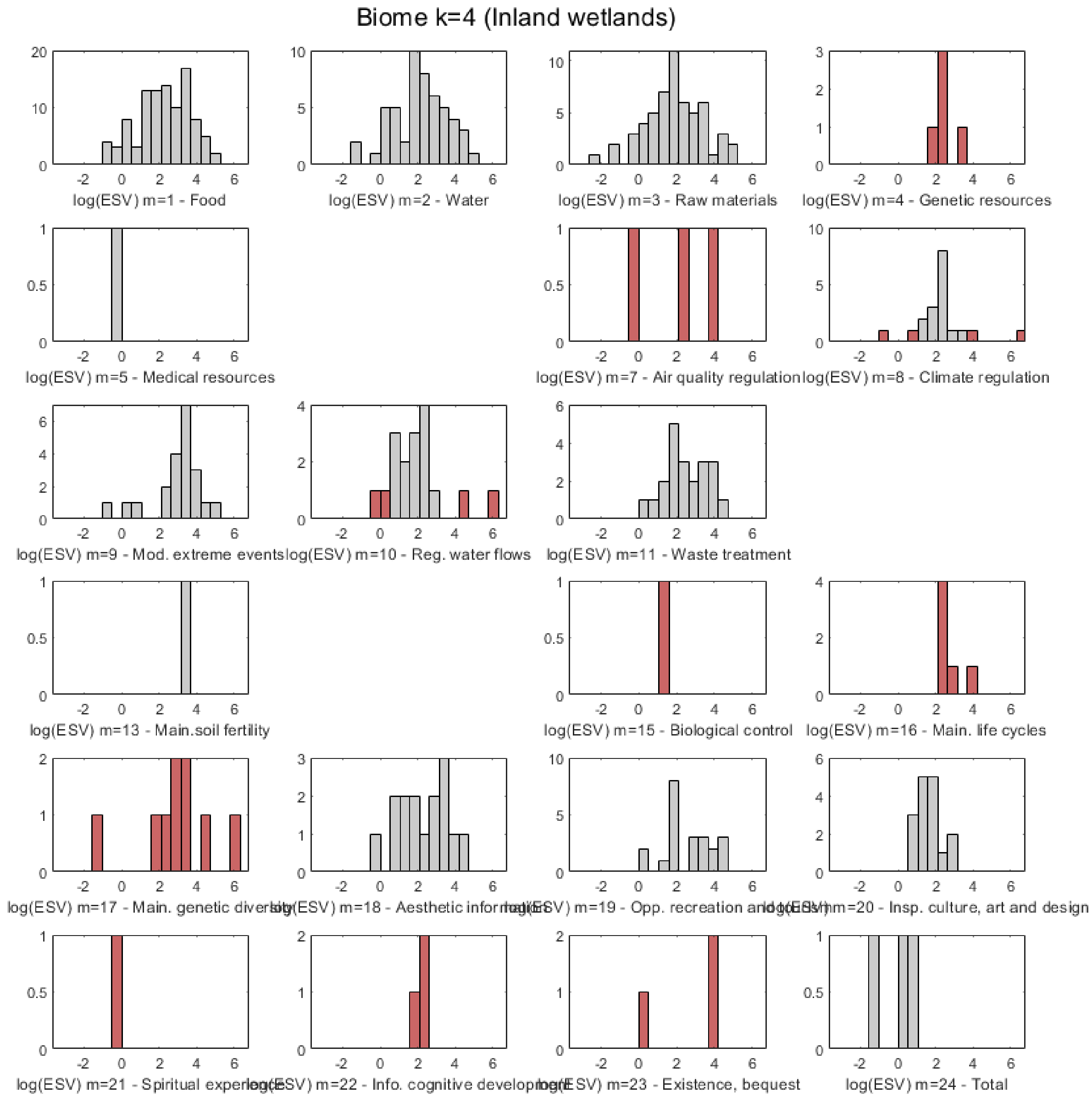

Figure 4: Frequency histograms of per ha per yr values for ecosystem services in inland wetlands biome. Count of values in the y-axis and order of magnitude (log10) of the ecosystem value in the x-axis. From lack of representativeness services under m=4, m=7, m=15, m=16, m=17, m=21, m=22 and m=23 were removed (red bars). For m=8 and m=10 outliers with value >10^4 were removed (and the same percentage of lowest values, red bars).

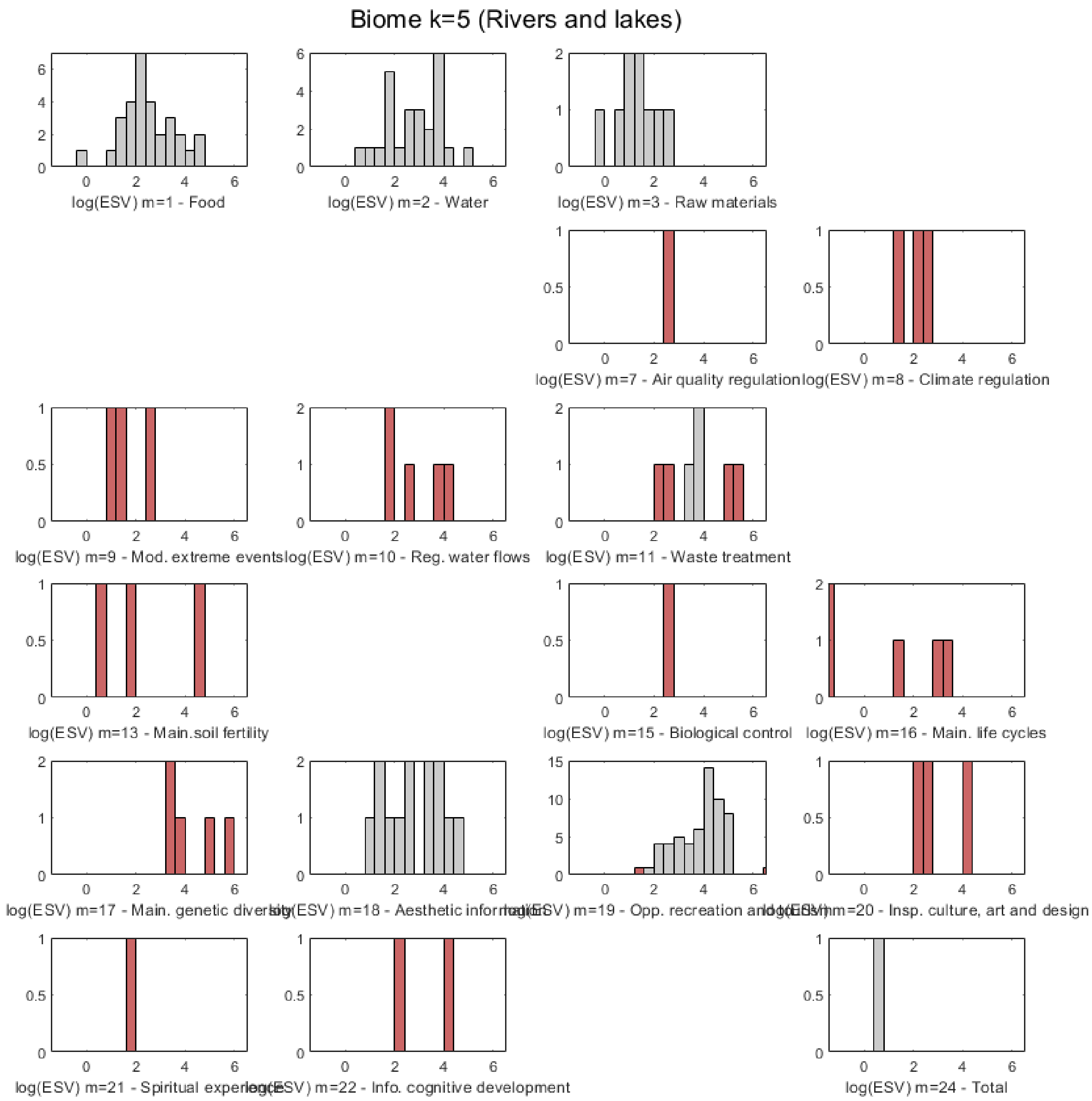

Figure 5: Frequency histograms of per ha per yr values for ecosystem services in rivers and lakes biome. Count of values in the y-axis and order of magnitude (log10) of the ecosystem value in the x-axis. From lack of representativeness services under m=7, m=8, m=9, m=10, m=13, m=15, m=16, m=17, m=20, m=21 and m=22 were removed (red bars). For m=19 recreation and tourism the outlier with value >10^6 was removed (and the same percentage of lowest values, red bars). For m=11 the outlier with value >10^4 was removed (and the same percentage of lowest values, red bars).

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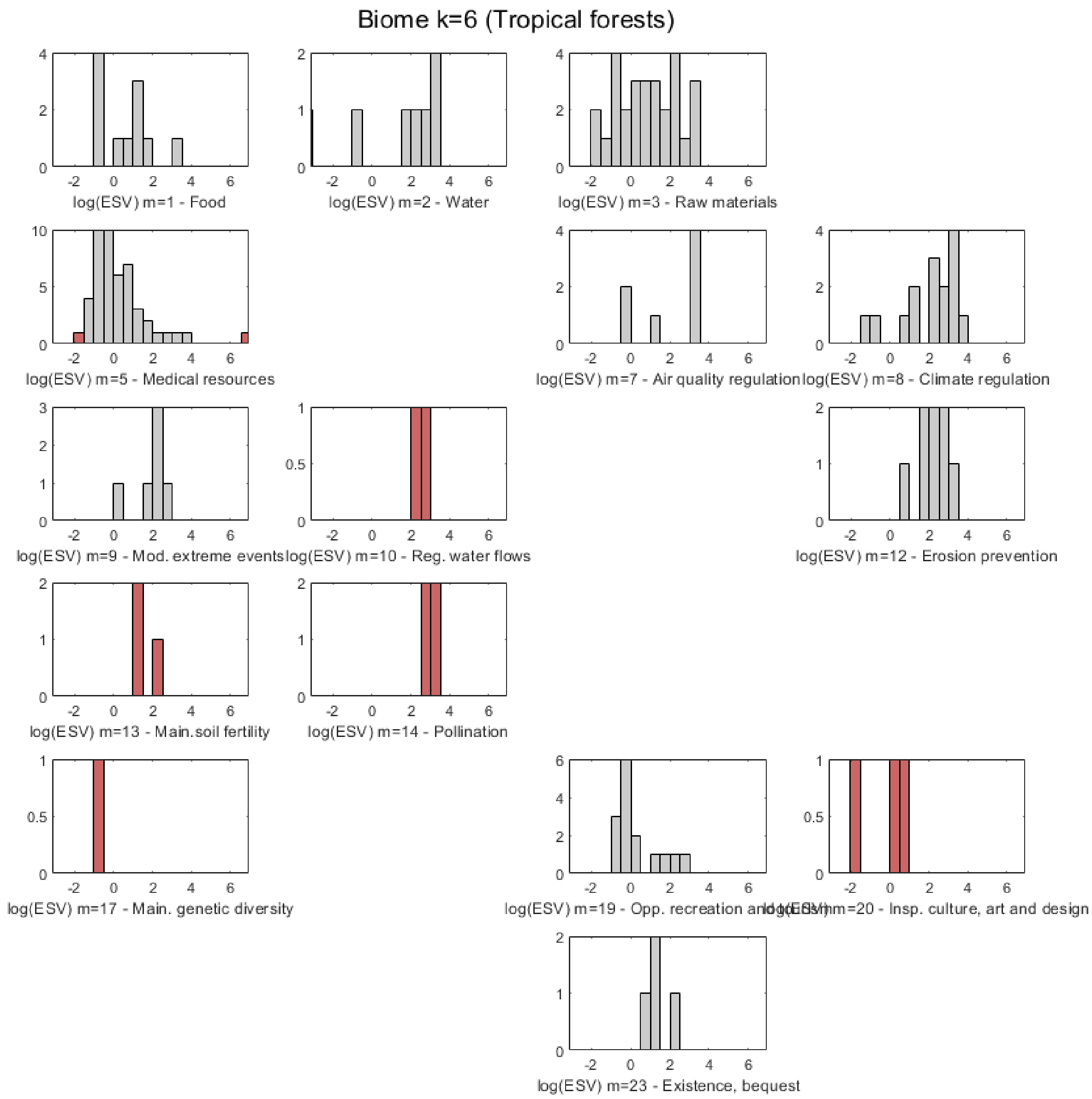

Figure 6: Frequency histograms of per ha per yr values for ecosystem services in tropical forests biome. Count of values in the y-axis and order of magnitude (log10) of the ecosystem value in the x-axis. From lack of representativeness services under m=10, m=13, m=14, m=17 and m=20 were removed (red bars). For m=5 medical resources the outlier with value >10^6 was removed (and the same percentage of lowest values, red bars).

Annex A

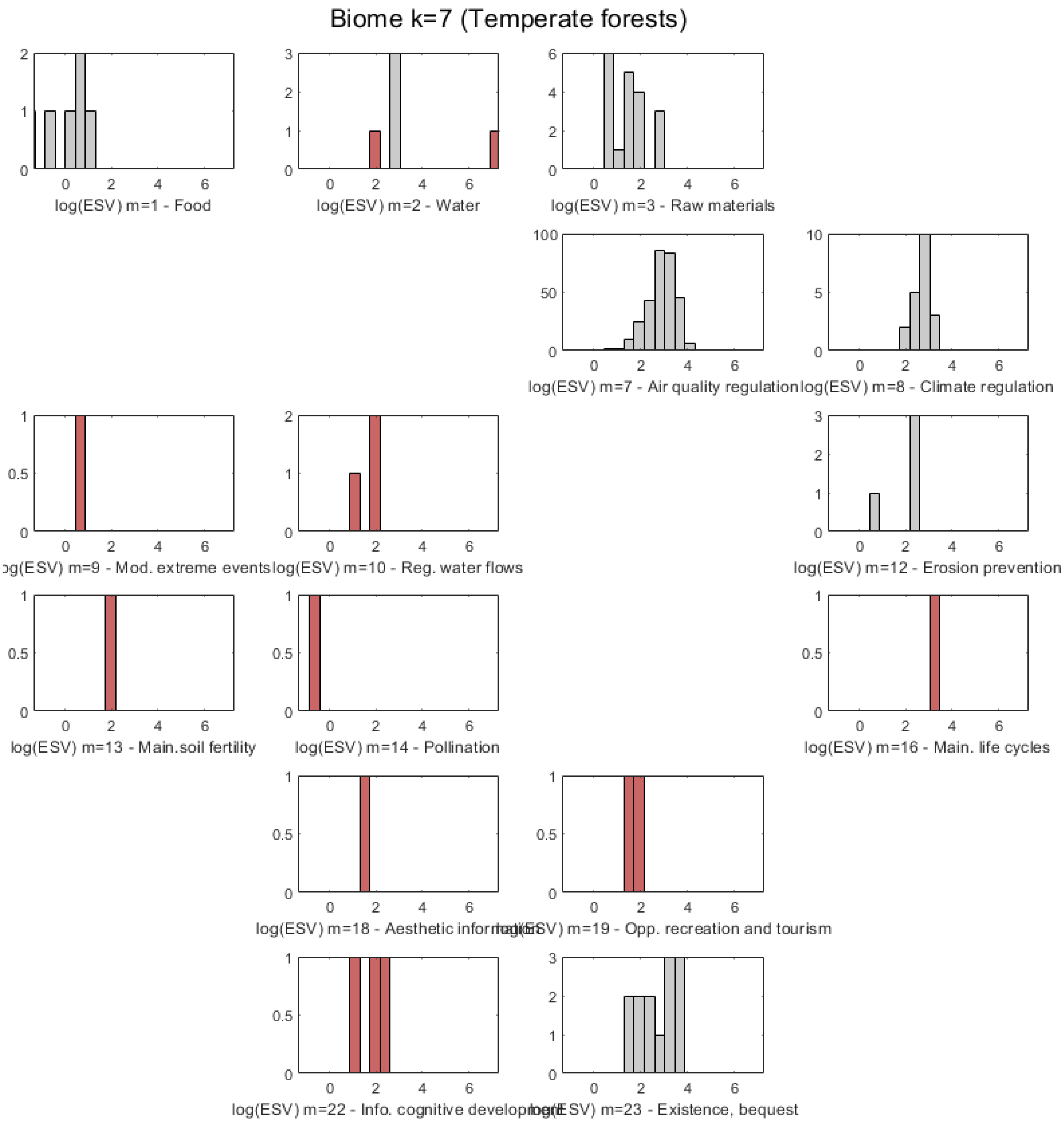

Figure 7: Frequency histograms of per ha per yr values for ecosystem services in temperate forests biome. Count of values in the y-axis and order of magnitude (log10) of the ecosystem value in the x-axis. From lack of representativeness values for services m=9, m=10, m=13, m=14, m=16, m=18, m=19, m=22 were removed (red bars). For m=2 water the outlier with value >10^6 was removed (and the same percentage of lowest values, red bars).

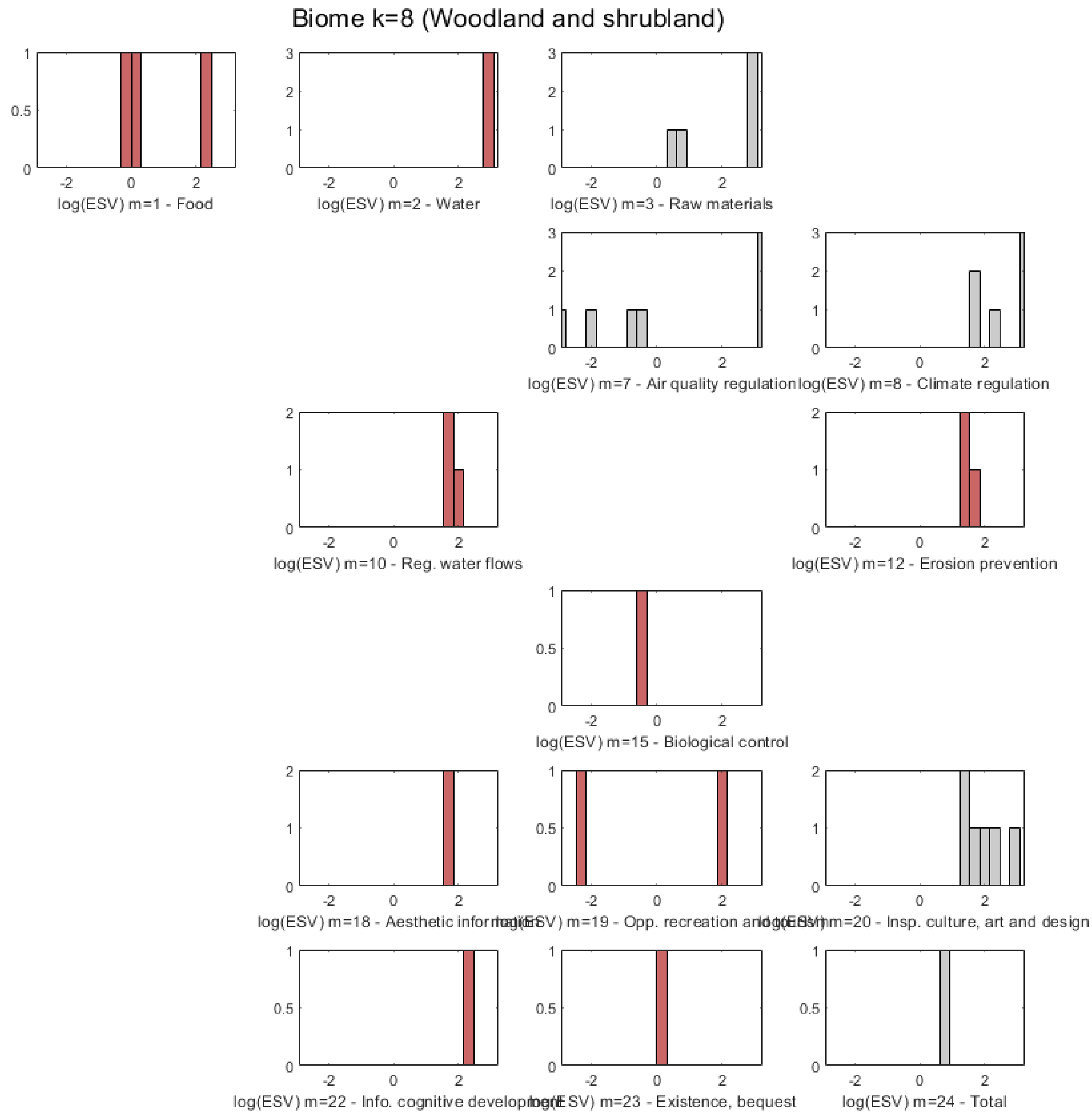

Figure 8: Frequency histograms of per ha per yr values for ecosystem services in Woodland biome. Count of values in the y-axis and order of magnitude (log10) of the ecosystem value in the x-axis. From lack of representativeness only m=3 (raw materials), m=7 (air regulation), m=8 (climate regulation), and m=20 (inspiration for culture) were kept (grey bars).

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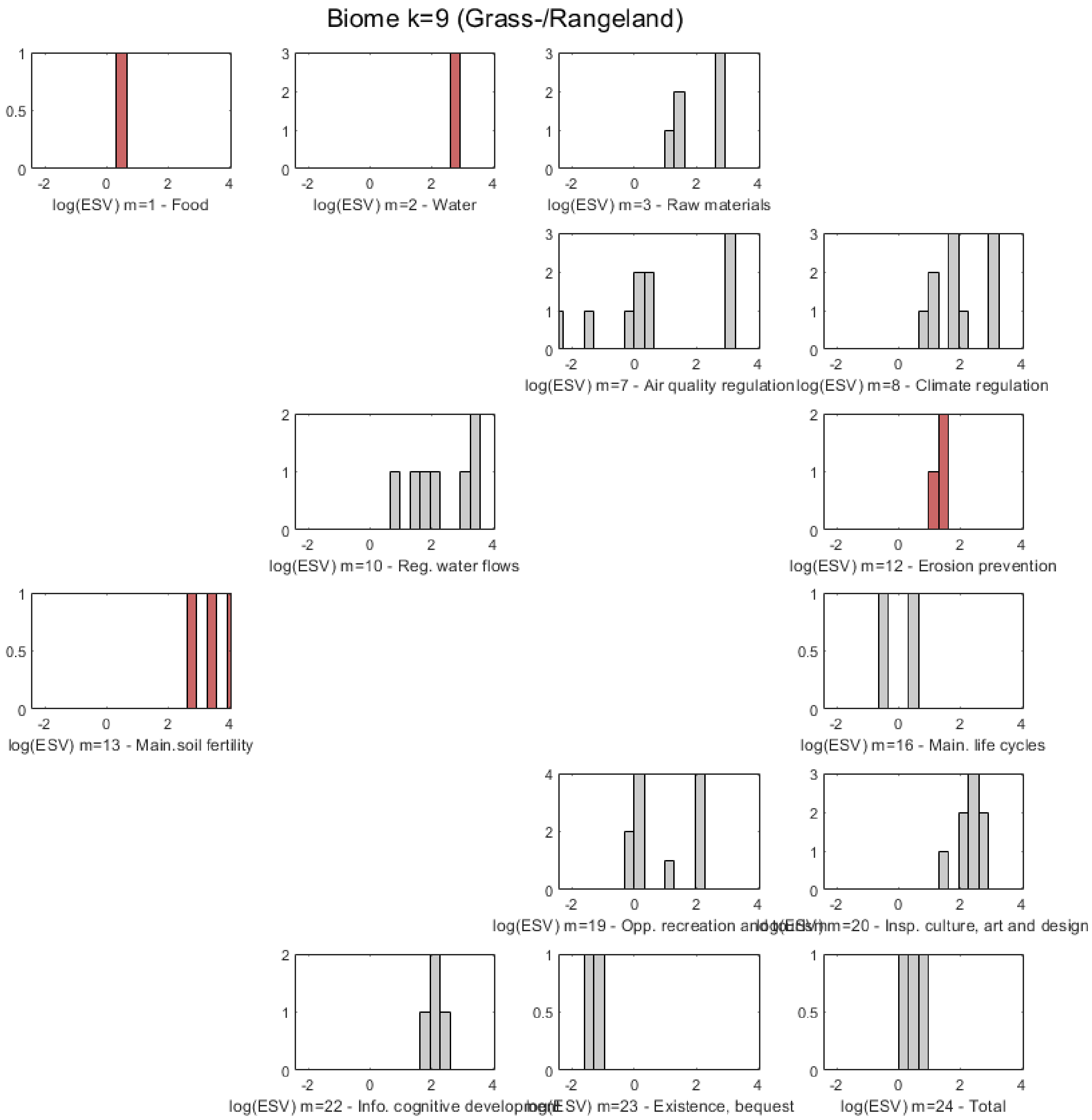

Figure 9: Frequency histograms of per ha per yr values for ecosystem services in Grassland biome. Count of values in the y-axis and order of magnitude (log10) of the ecosystem value in the x-axis. From lack of representativeness of data, m=1 food, m=2 water, m=13 maintenance of soil fertility, and m=12 erosion prevention were removed (red bars). Even though the count of other services are low, they are small values and clustered.

3.3.2 Examination of regression model for value transfer of ecosystem services

[9] argued that transfer of the value of ecosystem services based on linear regression on national data has lower transfer error than using global values. We repeat a method similar to [9] to analyse regression of totals for biomes. We are less interested in the division of ecosystem services and more interested in the total per biome (so we swap some dummy variables used in [9]), and we seek to examine and described the uncertainty, which was not available from [9].

[9] used GNI, population density PDen, and some contextual factors relating to land-use and conservation such as percentage of agricultural activity in the county (APer), percentage of forest cover (FPer) as well as the total proportion of protected land (LProt) and marine area (MProt). Vulnerability in ESVD is provided through an ordinal description of protection status (Not Protected (NProt) < Partially Protected (PProt) < Fully Protected (FProt)), though there is no explanation for the loads and stressors on the ecosystem and the condition of the ecosystem as an ordinal variable now included in ESVD would be a better variable, but records are incomplete. [9] examined the sensitivity of the ecosystems values to this range of parameters, and to reduce parameters, we use the reduced specifications in [9] which eliminated variables with little explanatory power. In place of a continent dummy variable used in [9], we use HDI, and we use LProt and MProt (amount of land and marine protection) data from the World Bank. Adapting [9], so we can examine the residuals for the valuation per biome CF_k within the biome categories (k refers to a given biome):

$$\log(CF_k) = \beta_{0,k} + \beta_{1,k} \cdot \log(PDen) + \beta_{2,k} \cdot \log(GNI) + \beta_{3,k} \cdot HDI + \beta_{4,k} \cdot APer + \\ + \beta_{5,k} \cdot FPer + \beta_{6,k} \cdot MProt + \beta_{7,k} \cdot LProt$$

The model from [9] is underspecified as it lacks contextual ecosystem variables. Unsurprisingly r^2 values are low since all non-dummy variables are country based and there are multiple times more data points than countries for each sample. To obtain a clearer trend using national statistics, we examined the distribution of values within the biome for each country.

We formed the distribution of values for each biome, for each country as done before on a global scale (Figure 1). This was done to derive a mean value and a standard deviation for each distribution of any country and biome combination. As described last section, in analogy to the global study, the total CF_k is the mean of valuations per biome in a country, which in the ESVD corresponds to $k = 2, \ldots, 9$ as shown in Table 1, summed across ecosystem services per biome (Table 2). The resulting ESVD mean and standard deviation values per biome per country are treated as a dependent variables for a linear regression using the country level variables (PDen, GNI, HDI, APer, FPer, MProt, LProt). In forming the country level distributions per biome the ESVD is filtered as described above and similar to [9].

We separately fitted the mean and standard deviation (there are the same number of data points as countries for each biome) to examine heteroscedacity.

Total distributions from the EVSD database for Biome k=2, coral reefs, involved 33 countries (Figure 10). Taking the mean Y_k of the total distributions for each of the 33 countries, provided 33 data points for a regression model with $r^2 = 0.345$. Only one variable was significant (PDen, $p < 0.05$) reflecting potential scarcity of the ecosystem services and small island countries with coral reefs associated to tourism: $r^2 = 0.217, \beta_{0,2} = 0.55, \beta_{1,2} = 1.33$ provides a reduced model

$$\log(Y_2) = \beta_{0,2} + \beta_{1,2} \cdot \log(PDen)$$

Regression on the standard deviation for countries with >1 value revealed no significant variables and $r^2 = 0.101$. The residuals of the intercountry and intracountry values against the mean trend for the full model are in Figure 11. A normal fit to the residuals estimates a greater than 20% chance that the full model overestimates value by 1 order of magnitude or more.

Total distributions from the EVSD database for Biome k=3, coastal systems, involved 51 countries (Figure 12). Taking the mean value Y_k for each of the 51 countries, provided 51 data points for a regression model without any significant relationship $r^2 = 0.0923$ and no significant variables. The lowest p-value involves HDI at 0.38. Regression on the standard deviation for countries with >1 value revealed no significant variables and $r^2 = 0$. We applied the same error term when extrapolating coastal ecosystem values across all countries. The residuals of the intercountry and intracountry values against the mean are in Figure 13. A normal fit to the residuals estimates a greater than 19% chance that the full model overestimates value by 1 order of magnitude or more.

Total distributions from the EVSD database for Biome k=4, inland wetlands, involved 38 countries (Figure 14). Taking the mean value Y_k for each of the 38 countries, provided 38 data points for a regression model with moderate explanation of variance $r^2 = 0.478$. Three variables were significant (APer, FPer, LProt at p < 0.01) with a reduced model: $r^2 = 0.324$, $\beta_{0,4} = -4.14, \beta_{4,4} = 4.8455, \beta_{5,4} = 4.9814, \beta_{7,4} = -6.05$)

$$\log(Y_5) = \beta_{0,4} + \beta_{4,4} \cdot APer + \beta_{5,4} \cdot FPer + \beta_{7,k} \cdot LProt$$

Regression on the standard deviation for countries with >1 value revealed no trend $r^2 = 0$. The residuals of the intercountry and intracountry values against the mean are in Figure 15. A normal fit to the residuals estimates a greater than 14% chance that the full model overestimates value by 1 order of magnitude or more.

Total distributions from the EVSD database for Biome k=5, lakes and rivers, involved 25 countries (Figure 16). Taking the mean value Y_k for each of the 25 countries, provided 25 data points for the regression model with a weak relationship $r^2 = 0.19$. No variables were significant. Regression on the standard deviation for countries with >1 value revealed heteroscedasticity $r^2 = 0.16$ with HDI a significant variable (p<0.05). The residuals of the intercountry and intracountry values against the mean are in Figure 17. A normal fit to the residuals estimates a greater than 21% chance that the full model overestimates value by 1 order of magnitude or more.

Total distributions from the EVSD database for Biome k=6, tropical forests, involved 14 countries (Figure 18). Taking the mean value Y_k for each of the 14 countries, provided a limited 14 data points for a regression model with moderate explanation of variance $r^2 = 0.701$. GNI was the only significant variable for a reduced model: $r^2 = 0.51, \beta_{0,6} = -5.89, \beta_{2,6} = 2.14$

$$\log(Y_6) = \beta_{0,6} + \beta_{2,6} \cdot \log(GNI)$$

Only the reduced model is significant as the degrees of freedom in the full model are too low. There are only 8 countries with >1 value in the dataset and no relationship with standard deviation was significant for the reduced model. The residuals of the intercountry and intracountry values against the mean trend are in Figure 19. Except for 1 outlier residual, the residuals have an average error within real values being 200% higher than the full model. We estimate <5% chance that the full model overestimates value by 1 order of magnitude or more.

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From lack of data we aggregated valuation in the temperate forest (k=7) and woodland, shrubland and grasslands (k=8,9) biomes. Total distributions from the EVSD database for Biomes k=7,8,9 involved 8 unique countries (Figure 20). There are no degrees of freedom for an 8 parameter model, so there is no meaning in a full regression. There was no significant trend with GNI or HDI in a reduced model for the mean or standard deviation. The residuals of the intercountry and intracountry values against the mean value (there is no trend) are in Figure 21.

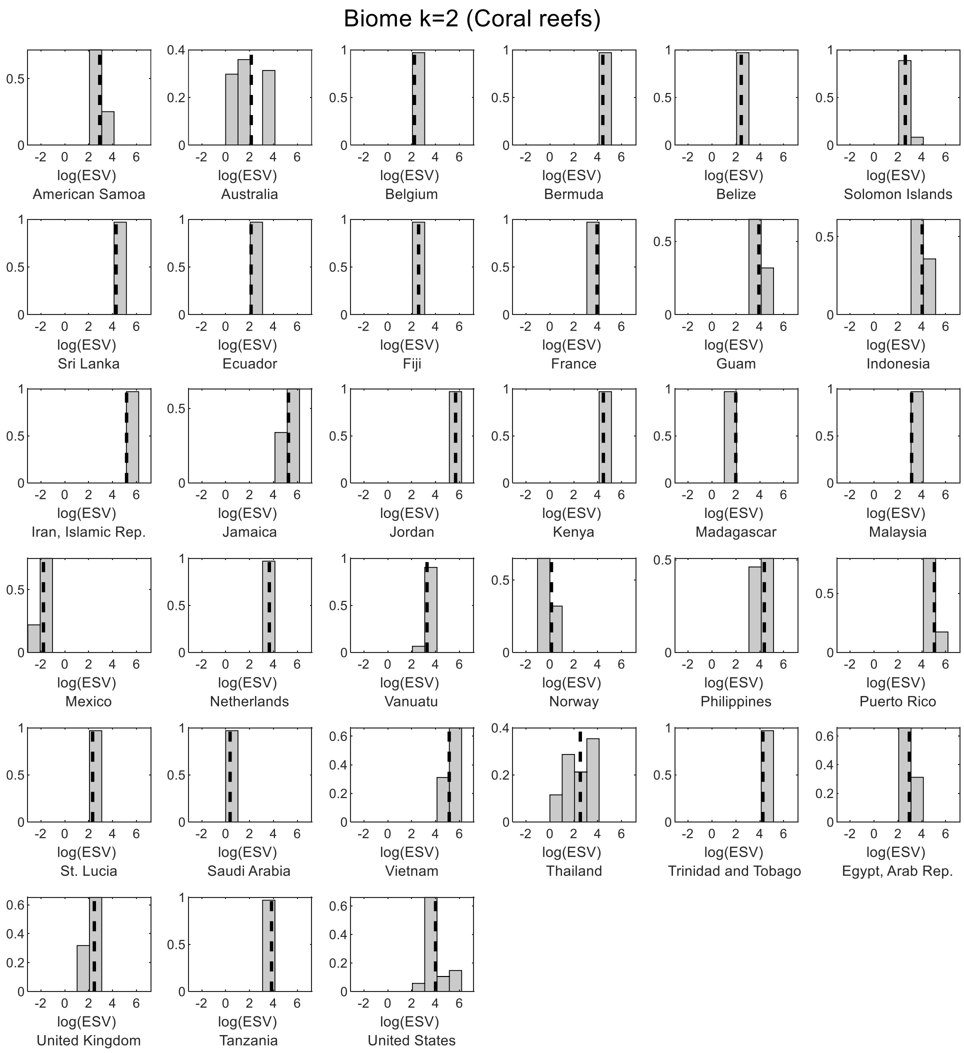

Figure 10: Variance in county estimates of ecosystem values US\$2020 PPP ha^{-1} of coral reefs from the ESVD database. Scale is log10: bottom axes display orders of magnitude. The mean value is presented as the black dotted line.

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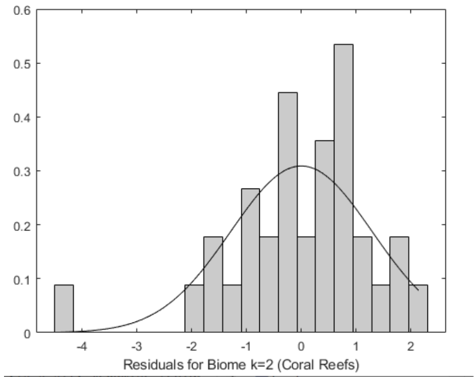

Figure 11: Residuals in the linear regression of ecosystem values US$2020 PPP ha⁻¹ of coral reefs against country level parameters. Bottom axes display orders of magnitude.

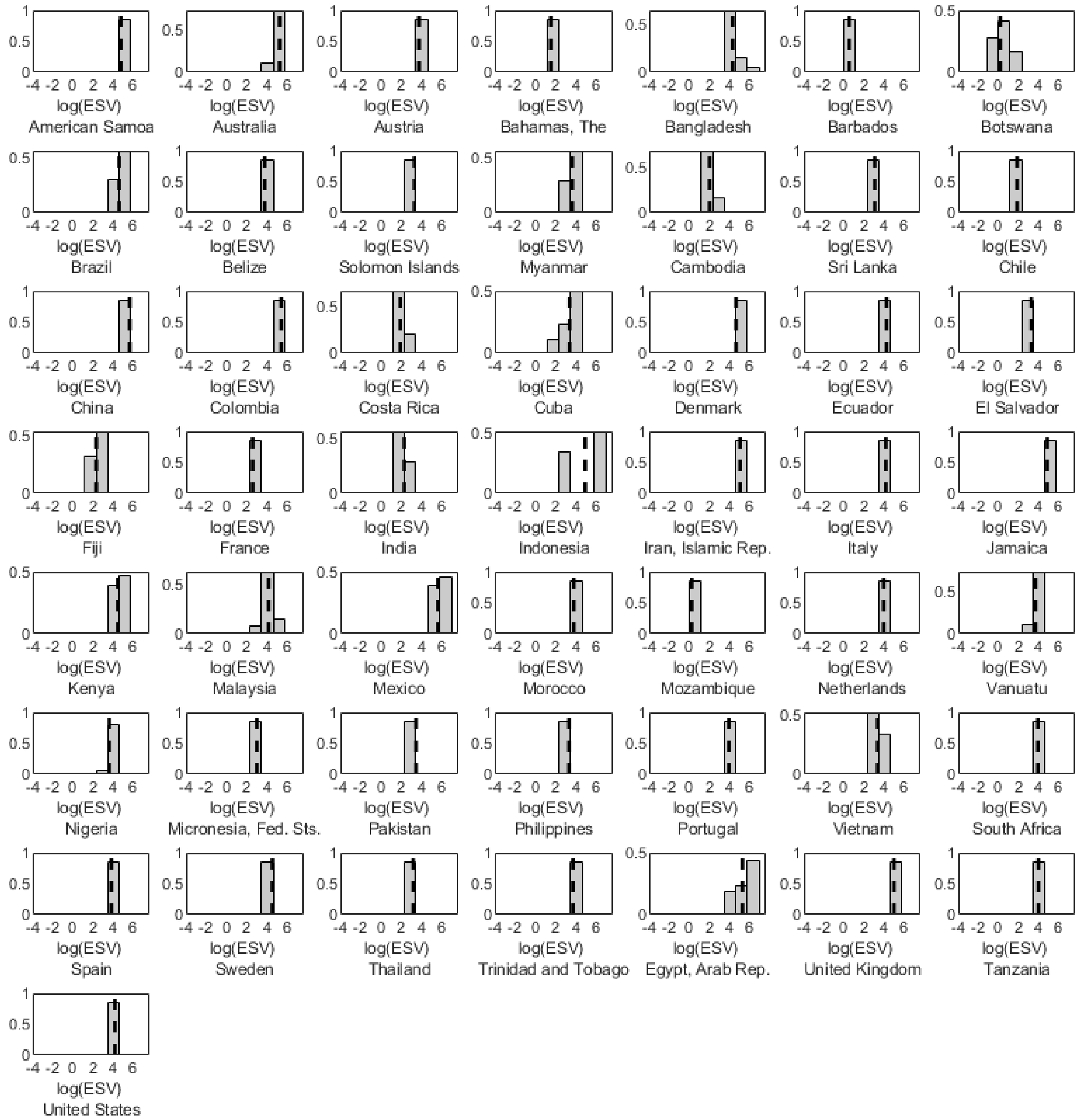

Figure 12: Variance in county estimates of ecosystem values US$2020 PPP ha⁻¹ of coastal systems from the ESVD database. Scale is log10: bottom axes display orders of magnitude.

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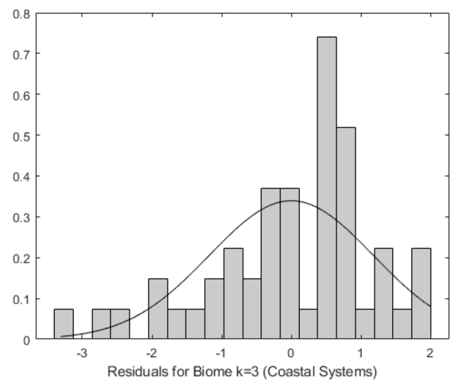

Figure 13: Residuals in the linear fit of ecosystem values US$2020 PPP ha^{-1} of coastal systems to country level parameters. Fitting a normal distribution represents uncertainty in value in the fitted trend. Bottom axes display orders of magnitude.

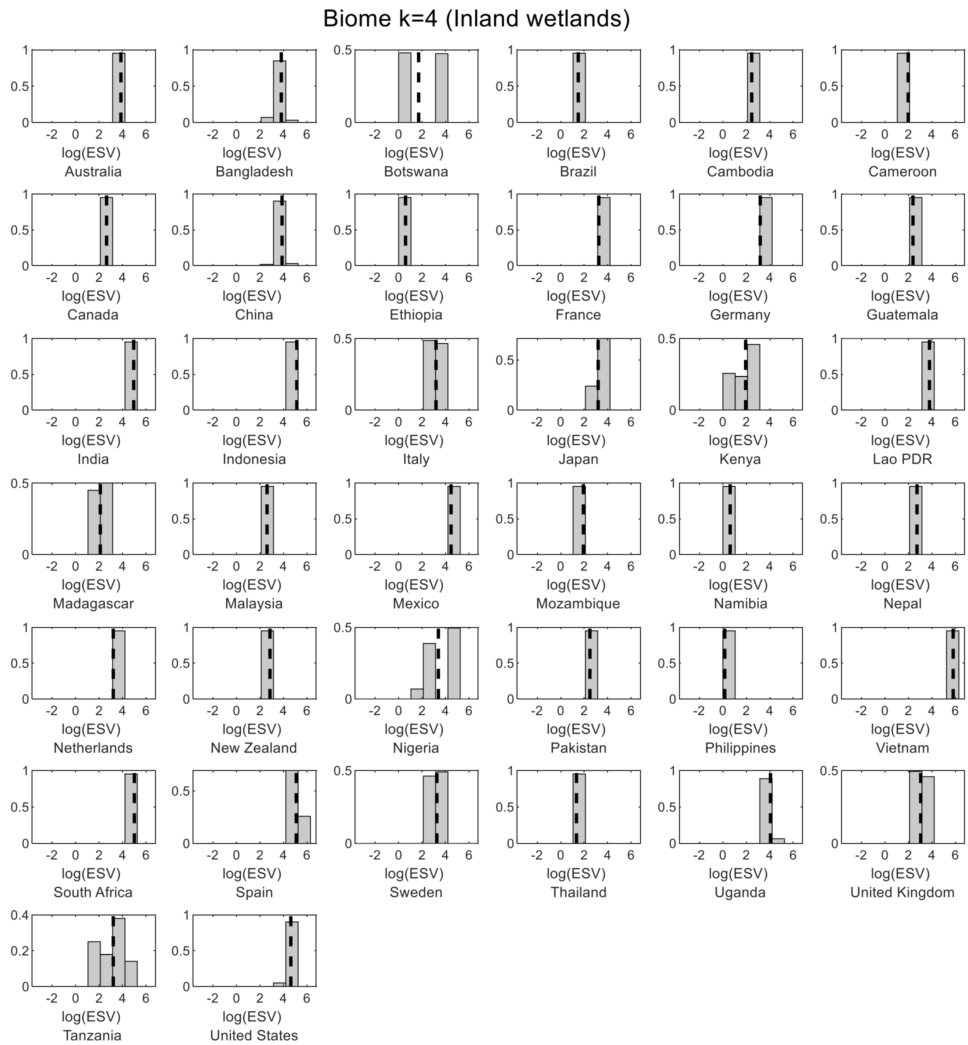

Figure 14: Variance in county estimates of ecosystem values US$2020 PPP ha^{-1} of inland wetlands from the ESVD database. Scale is log10: bottom axes display orders of magnitude.

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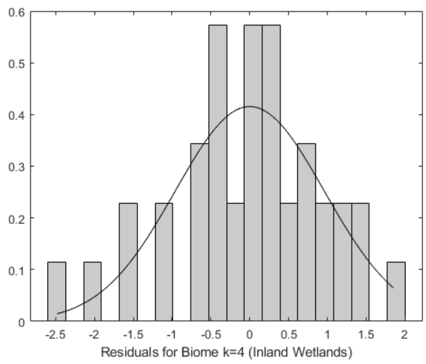


Figure 15: Residuals in the linear fit of ecosystem values US$2020 PPP ha^{-1} of inland wetlands to country level parameters. Fitting a normal distribution represents uncertainty in value in the fitted trend. Bottom axes display orders of magnitude.

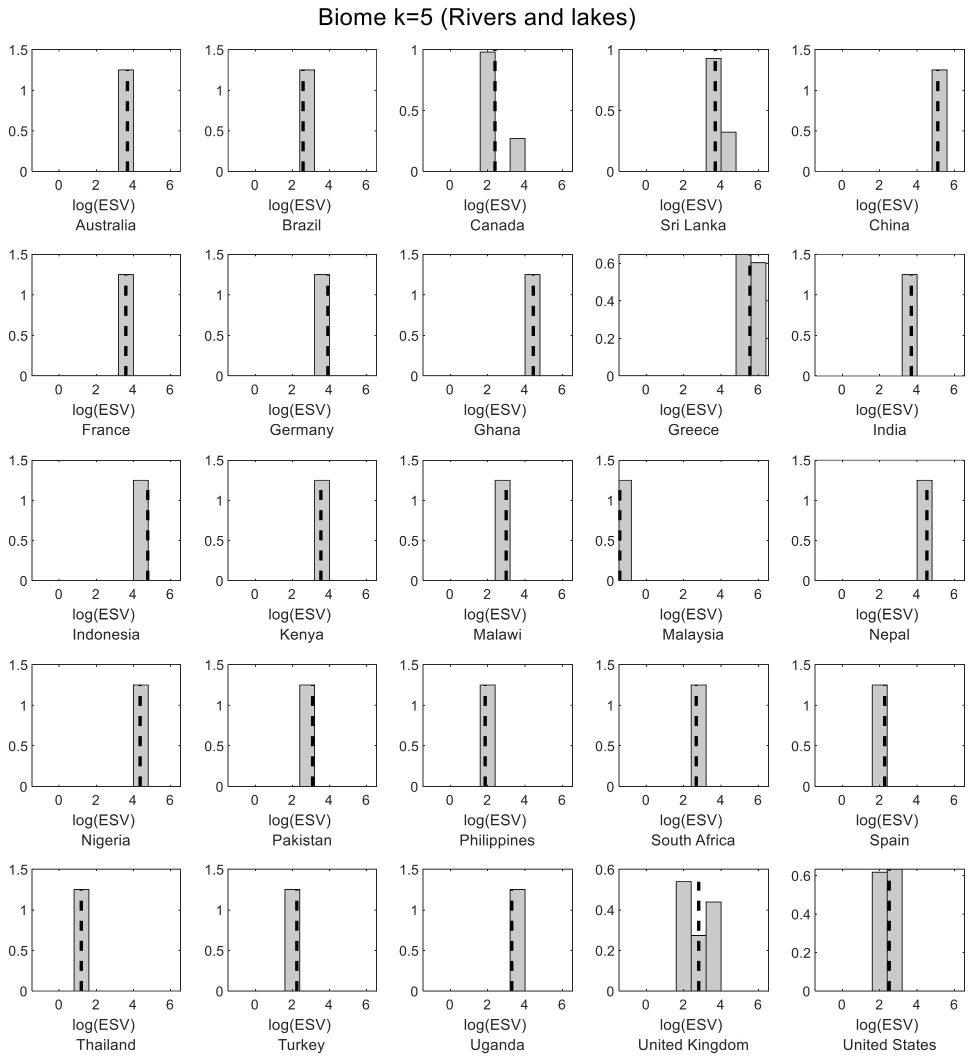


Figure 16: Variance in county estimates of ecosystem values US$2020 PPP ha^{-1} of lakes and rivers from the ESVD database. Scale is log10: bottom axes display orders of magnitude.

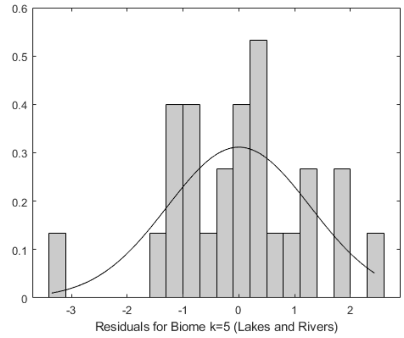


Figure 17: Residuals in the linear fit of ecosystem values US$2020 PPP ha^{-1} of lakes and rivers to country level parameters. Regression on the mean in each country introduced an upward bias. Fitting a normal distribution represents uncertainty in value in the fitted trend. Bottom axes display orders of magnitude.

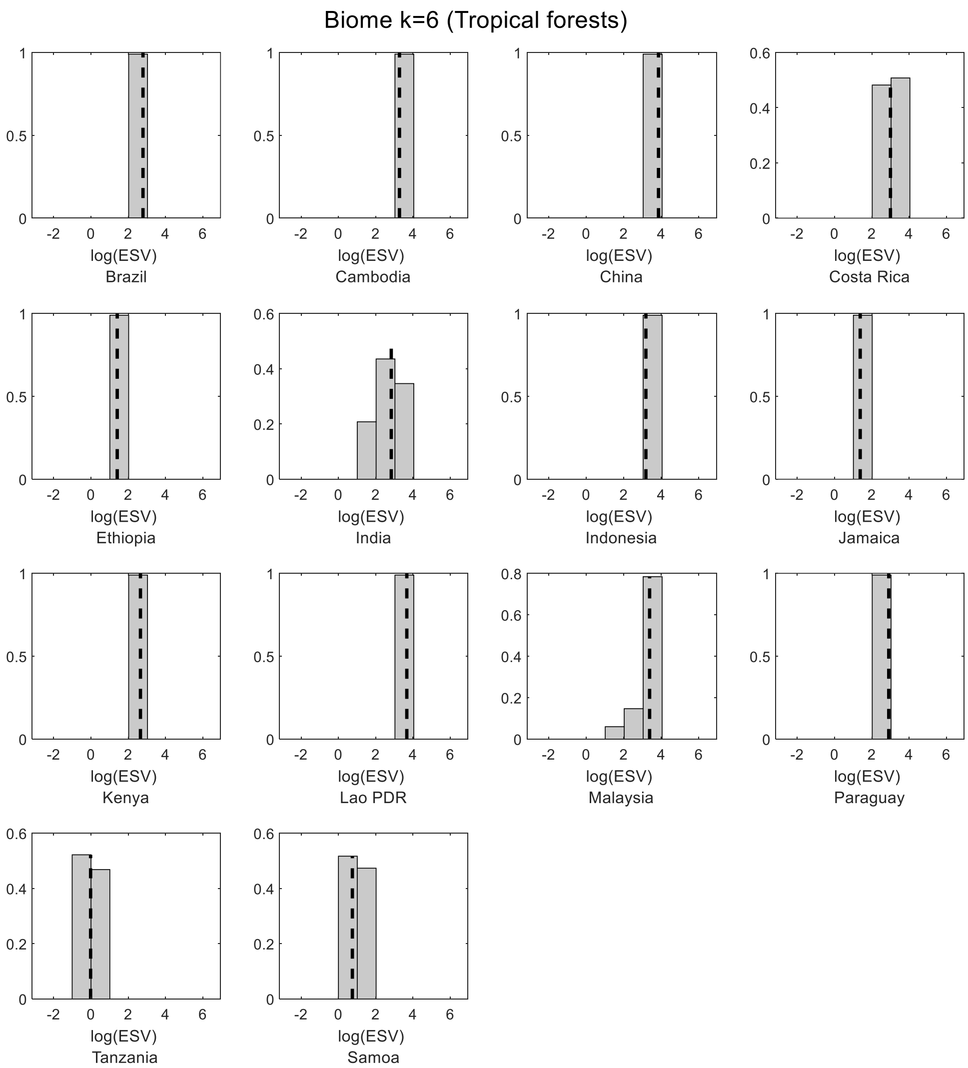


Figure 18: Variance in county estimates of ecosystem values US$2020 PPP ha^{-1} of tropical forests from the ESVD database. Scale is log10: bottom axes display orders of magnitude.

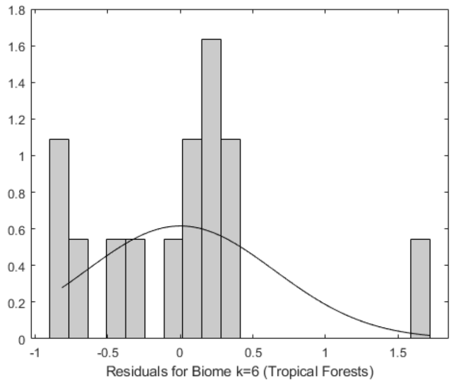


Figure 19: Residuals in the linear fit of ecosystem values US$2020 PPP ha^{-1} of tropical forests to country level parameters. Fitting a normal distribution represents uncertainty in value in the fitted trend. Bottom axes display orders of magnitude

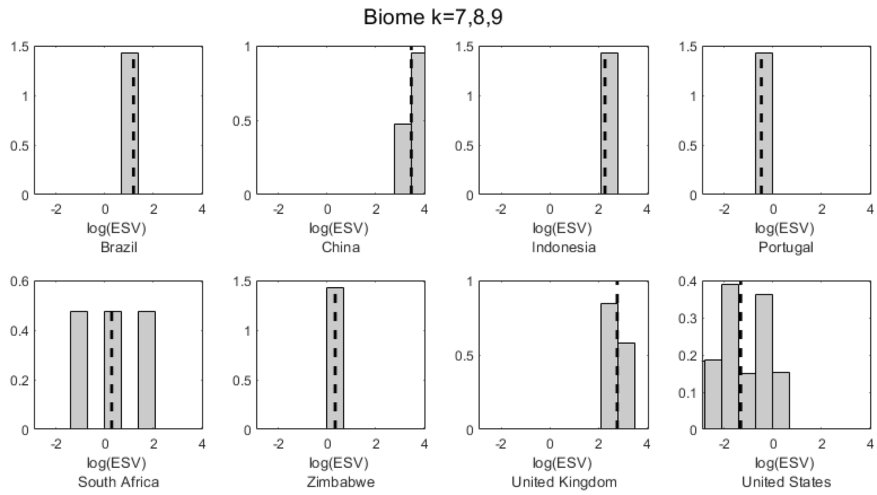


Figure 20: Variance in country estimates of ecosystem values US$2020 PPP ha^{-1} of temperate forests, shrublands and grasslands from the ESVD database. Scale is log10: bottom axes display orders of magnitude.

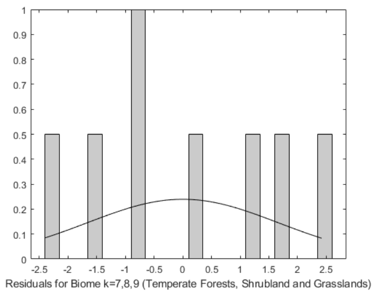


Figure 21: Residuals in the linear fit of ecosystem values US$2020 PPP ha^{-1} of temperate forests, shrublands and grasslands to country level parameters. Bottom axes display orders of magnitude.

Overall, transfer of ecosystem service marginal values using national level statistics, despite using the most extensive selection of studies across countries available (ESVD), results in high uncertainty in extrapolating values to ecosystem services in other countries. There is little confidence, given the studies within ESVD, that linear regression involving country level statistics can provide reasonable value transfer amounts without high levels of uncertainty. There are not enough studies across countries at the ecosystem or ecosystem services level of detail to understand further the relationships and potential errors introduced by totalling across ecosystem services, nor to warrant non-linear regression analysis.

3.4 Examination of distributional grouping

Without clear trends across countries, due to lack of trends or lack of sample size within ESVD, we analyse variation by grouping country data into totals in United Nations Development Programme (UNDP) HDI tiers (*http://hdr.undp.org/en/content/human-development-index-hdi*) and the classes of provisioning, regulating and cultural services (Table 2). The coarser grouping analysis increases the statistical power of the valuation data available from the ESVD but results in a lower mean valuation.

Figure 22 to Figure 29 show the disaggregation of valuations for biomes k=2 to 9 (Table 1). The 12 distributions in the top left panel of each figure represents, for each biome, and each of 4 HDI tier (HDI1 = very low development, HDI2 = low development, HDI3 = high development, HDI4=very high development), the relative frequency histograms of valuations in the ESVD disaggregated by the service being provisioning, regulating, or cultural.

Except for a few clear cases, where is no statistical power to use 2-way ANOVA for the distributions of disaggregation by HDI tier and service class. Generally, there is low confidence in distinct distributions.

The 4 distributions in the top right panel of Figure 22 to Figure 29 represent a histogram for the total valuation for the given biome for a country within the given HDI tier. The total is formed as before, except that here the 3 service classes are sampled randomly, and the samples are added. For the number of samples, we use the sum of the number valuations across the provisioning, regulating and cultural services classes, in forming totals under random choice in the service classes by HDI tier. Higher resampling in the 12 HDI-by-service class distributions (which show the relative frequency histograms of the actual number of valuations in the EVSD) to understand the total distribution by HDI tier, would introduce an artificial certainty to statistical tests.

Inspection of total values by HDI tier shows the potential for using 1-way ANOVA to distinguish distributions of value by HDI tier for k=2 to 6. Total values by HDI tier possess better fit statistics for normal distribution under log transform than global values, revealing the potential for mixing in the full distribution of values, and making available the use of lognormal fits to estimate marginal values. Samples, mean of the log10 transformed total values for the biome by HDI tier, and the p-value for the standard Anderson-Darling test for normality, are shown for each biome and each HDI tier in Table 3 and described below.

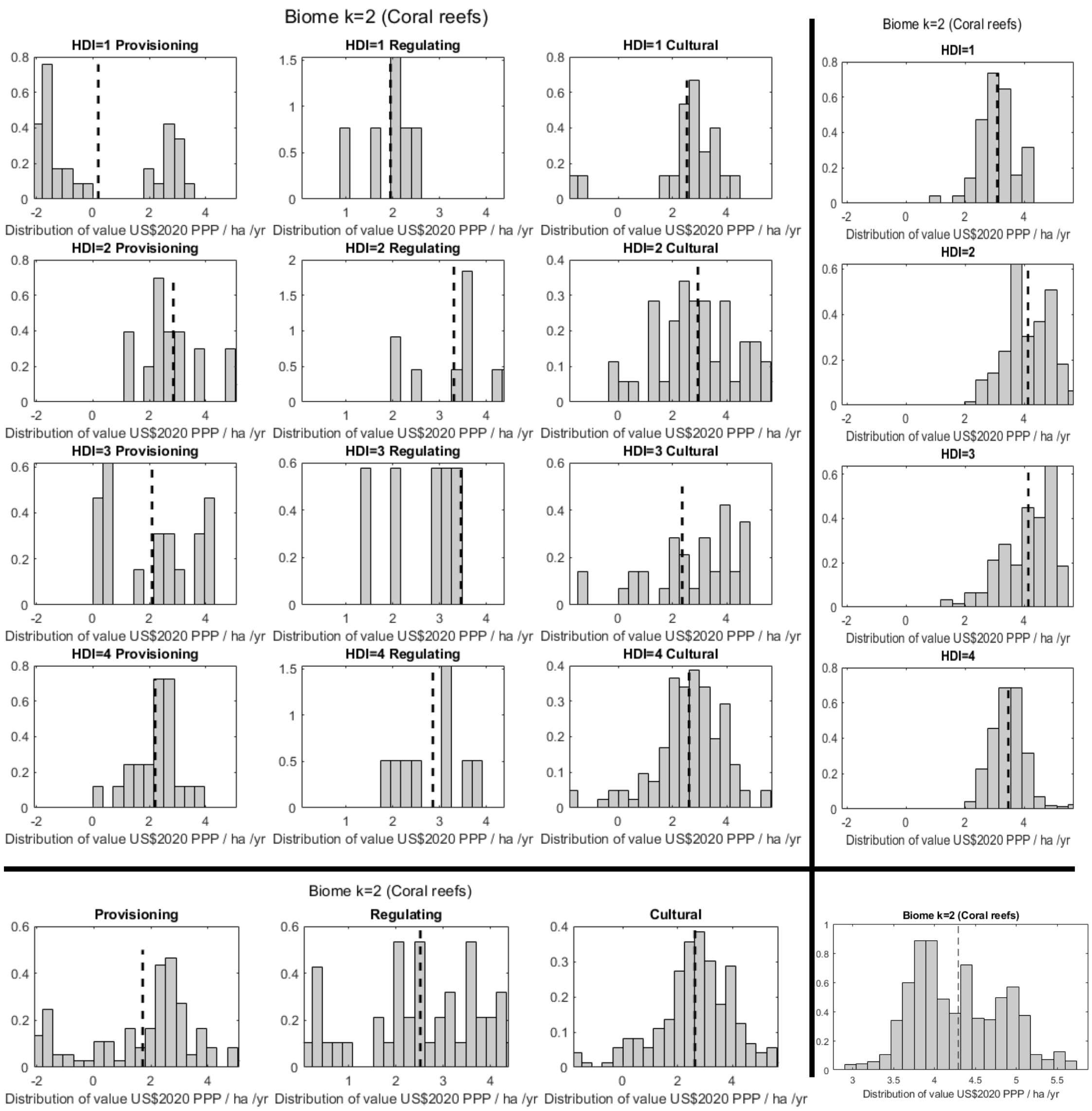
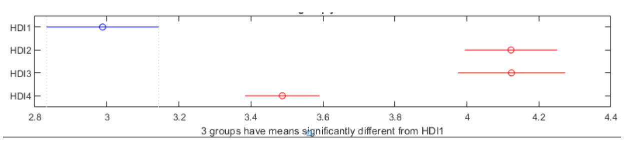


Figure 22: Ecosystem service valuations in ESVD and US$2020 PPP for Biome k=2 (coral reefs), disaggregated by UNDP HDI tier (1=low development, 2=medium development, 3=high development, 4=very high development) and class of service according to the TEEB classification (provisioning, regulating, or cultural). Panels on the right show totals by HDI tier, panels on the bottom show TEEB class of service without disaggregation by HDI tier. Bottom right is the distribution of values without disaggregation. All axes in log10, showing orders of magnitude.

For k=2, total value by HDI tiers 1-4 (the right panel in in Figure 22) cannot be rejected as normally distributed by the Anderson-Darling test and 1-way ANOVA (p=0.05) rejects that they are the same distribution. Totals by tier HDI=2 and HDI=3 cannot be rejected as the same distribution and have mean and standard deviation within tolerance. HDI 4 and HDI 1 are distinct distributions from HDI=2 and HDI=3. Therefore, given the sufficient sample in the ESVD we use lognormal distributions to represent ecosystem value across HDI classes with the (log10) means and standard deviation given by the samples of summing totals from the service classes. HDI2 and HDI 3 are given the same distribution as there is little confidence that they are different.



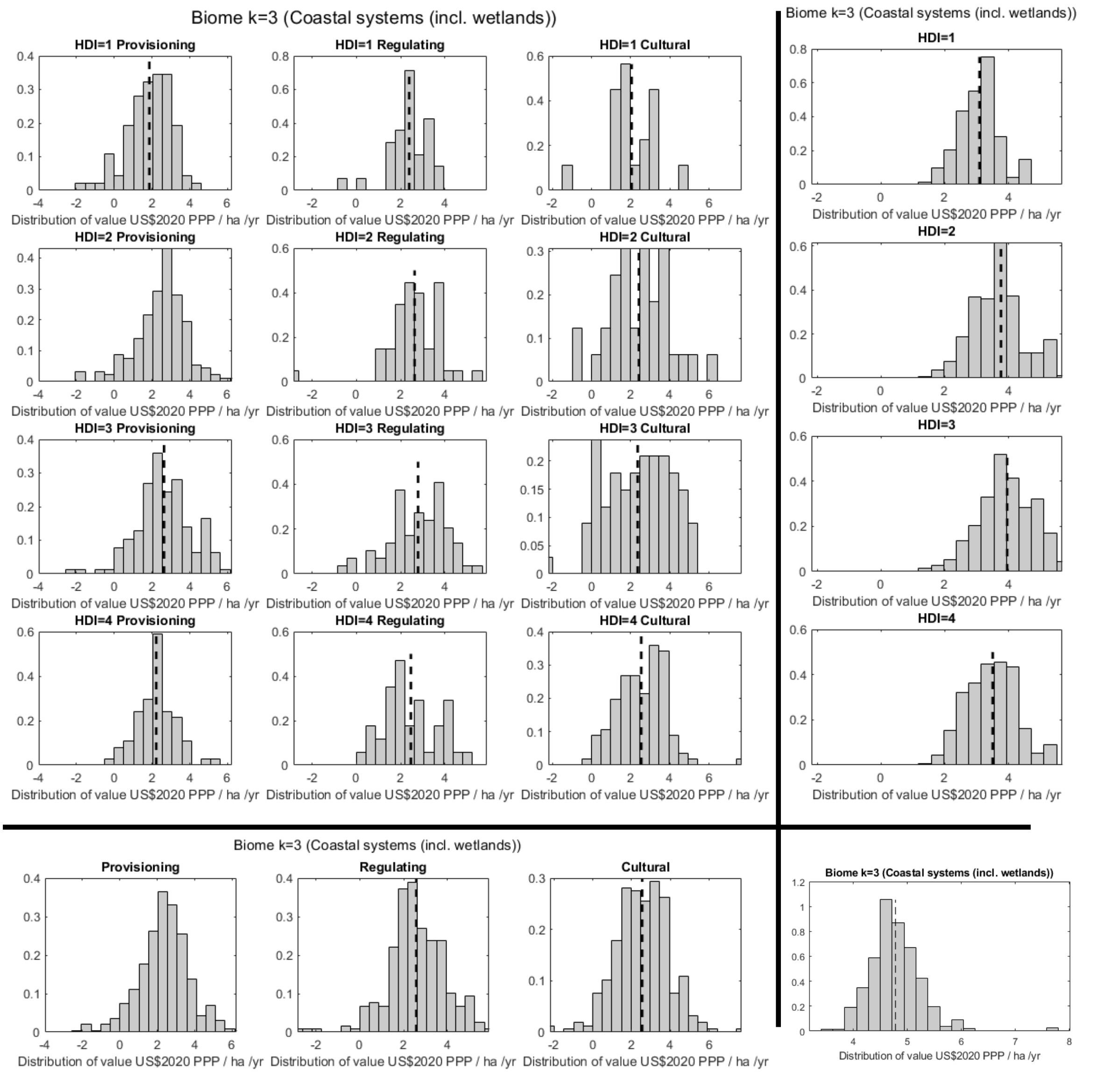
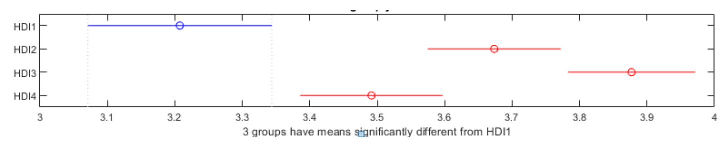


Figure 23: Ecosystem service valuations in ESVD and US$2020 PPP for Biome k=3 (coastal systems), disaggregated by UNDP HDI tier (1=low development, 2=medium development, 3=high development, 4=very high development) and class of service according to the TEEB classification (provisioning, regulating, or cultural). Panels on the right show totals by HDI tier, panels on the bottom show TEEB class of service without disaggregation by HDI tier. Bottom right is the distribution of values without disaggregation. All axes in log10, showing orders of magnitude.

For k=3, total value by HDI tiers 1-3 (the right panel in in Figure 23) cannot be rejected as normally distributed by the Anderson-Darling test. Mixture in cultural services in HDI4 gives the HDI total distribution a p-value of 0.12, so HDI4 (the sample size is 225) would be better represented as a mixture model. A 1-way ANOVA (p=0.05) rejects the distributions are the same distribution. Noting the caveat on the shape of HDI4, we use lognormal distributions to represent ecosystem value across HDI classes with the (log10) means and standard deviation given by the samples of summing totals from the service classes.



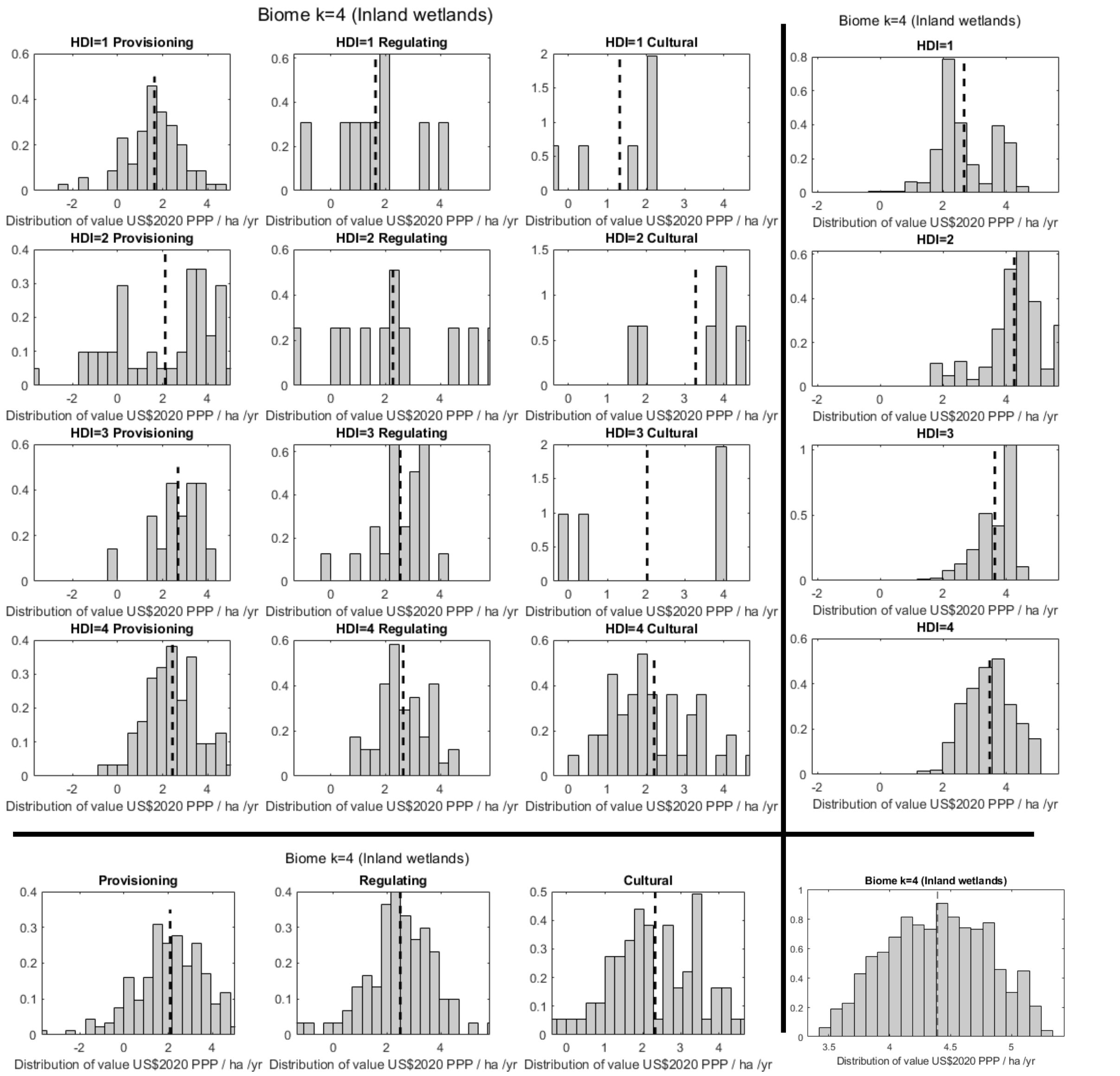
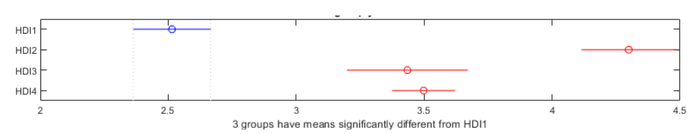


Figure 24: Ecosystem service valuations in ESVD and US$2020 PPP for Biome k=4 (inland wetlands), disaggregated by UNDP HDI tier (1=low development, 2=medium development, 3=high development, 4=very high development) and class of service according to the TEEB classification (provisioning, regulating, or cultural). Panels on the right show totals by HDI tier, panels on the bottom show TEEB class of service without disaggregation by HDI tier. Bottom right is the distribution of values without disaggregation. All axes in log10, showing orders of magnitude.

For k=4, total value by HDI tiers 1-3 (the right panel in Figure 24) cannot be rejected as normally distributed by the Anderson-Darling test. Potential mixture in cultural services in HDI4 gives the HDI total distribution a p-value of 0.08, so HDI 4 (the sample size is 225) would be potentially better represented as a mixture model. A 1-way ANOVA (p=0.05) cannot reject that HDI 3 and HDI 4 are the same distribution. Noting the caveat on the shape of HDI4, we use lognormal distributions to represent ecosystem value across HDI classes with the (log10) means and standard deviation given by the samples of summing totals from the service classes. HDI 3 and HDI 4 are given the same mean, but use the standard deviation given by the empirical samples.



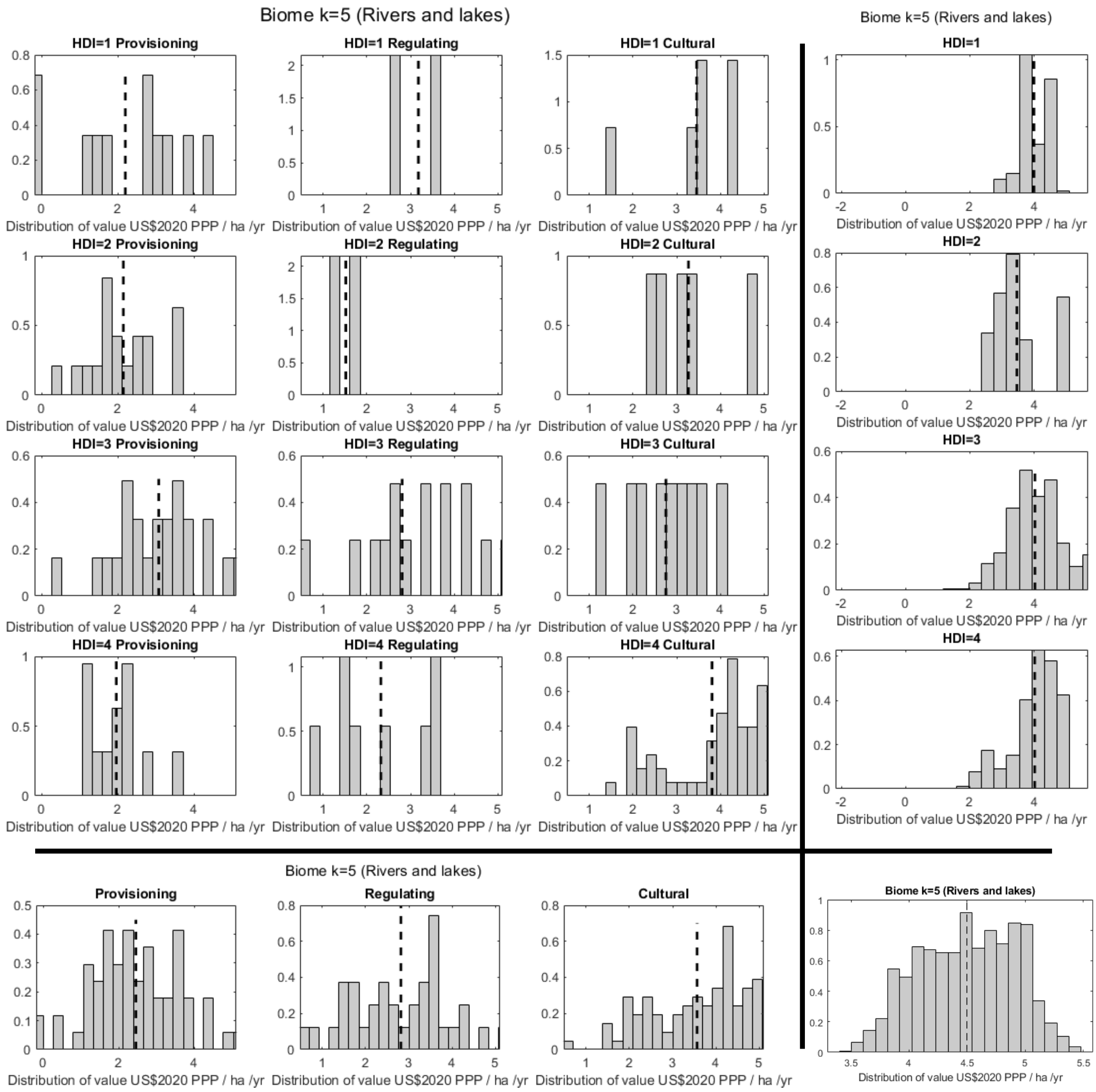


Figure 25: Ecosystem service valuations in ESVD and US$2020 PPP for Biome k=5 (lakes and rivers), disaggregated by UNDP HDI tier (1=low development, 2=medium development, 3=high development, 4=very high development) and class of service according to the TEEB classification (provisioning, regulating, or cultural). Panels on the right show totals by HDI tier, panels on the bottom show TEEB class of service without disaggregation by HDI tier. Bottom right is the distribution of values without disaggregation. All axes in log10, showing orders of magnitude.

For k=5, total value by HDI tiers 1-4 (the right panel in in Figure 25) cannot be rejected as normally distributed by the Anderson-Darling test. HDI1 has low samples size (19 samples) and large variation within service classes, and the p-value in the test is not robust to sampling. Based on a 1-way ANOVA (p=0.05) and shape, HDI2 can be distinguished from HDI3 or HDI4, but not significantly from HDI1. HDI1 can cannot be distinguished significantly from HDI3 or HDI4. We represent them by lognormal distributions, with HDI3 and HDI4 the same, HDI2 distinct, and HDI1 a weighted mean and standard deviation between HDI2 and HDI3-4 (the weights used are the chance that the mean of the HDI1 distribution could be the mean of the HDI2 distribution, the HDI3 distribution or the HDI4 distribution respectively).

Annex A

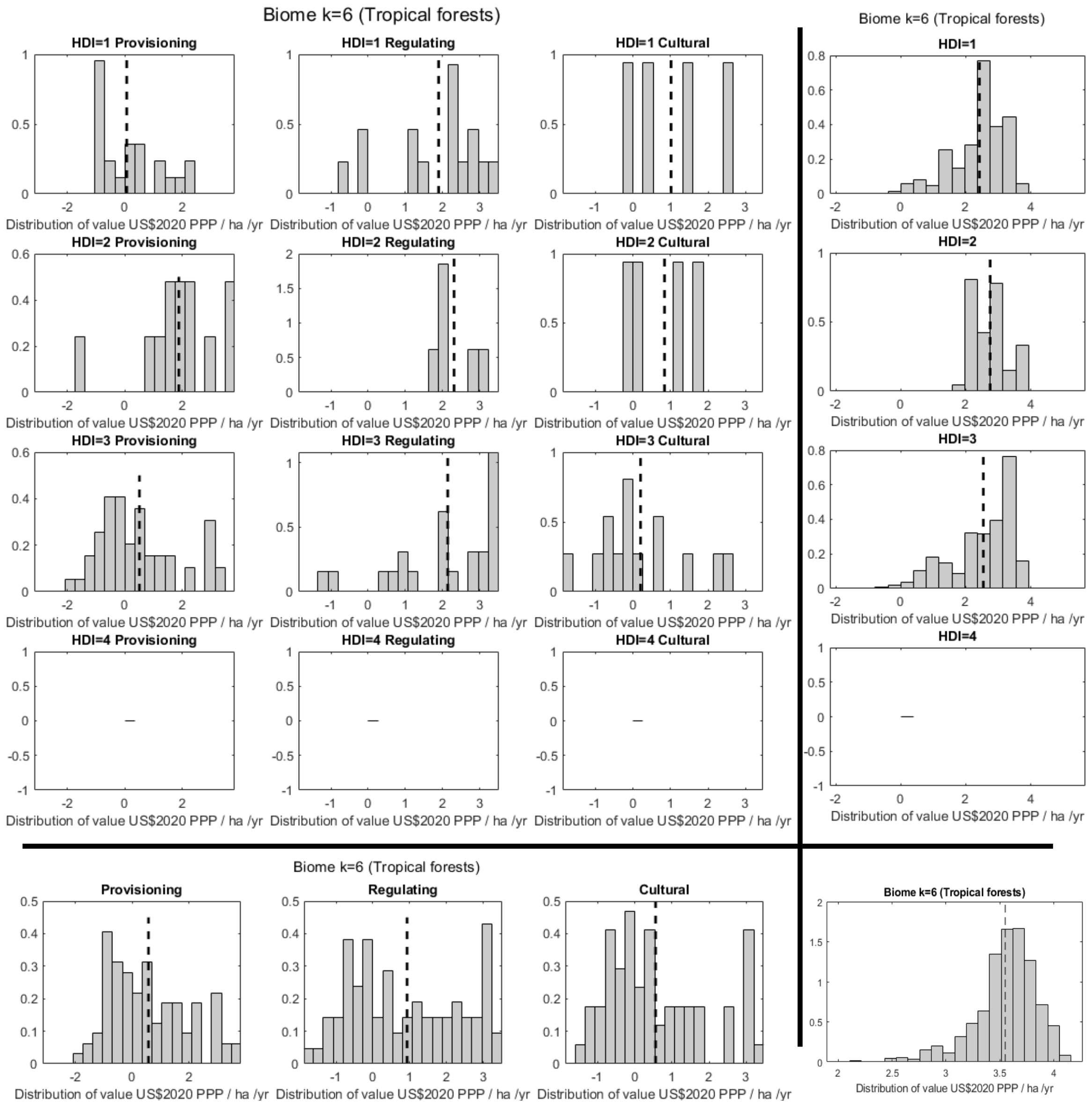
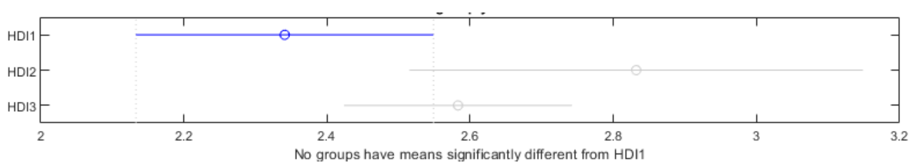


Figure 26: Ecosystem service valuations in ESVD and US$2020 PPP for Biome k=6 (tropical forests), disaggregated by UNDP HDI tier (1=low development, 2=medium development, 3=high development, 4=very high development) and class of service according to the TEEB classification (provisioning, regulating, or cultural). Panels on the right show totals by HDI tier, panels on the bottom show TEEB class of service without disaggregation by HDI tier. Bottom right is the distribution of values without disaggregation. All axes in log10, showing orders of magnitude.

For k=6, total value by HDI tiers 1-3 (the right panel in in Figure 26) cannot be rejected as normally distributed by the Anderson-Darling test. There were no samples for HDI=4. HDI2 has low samples size (22 samples) and large variation within service classes, and the p-value in the test is not robust to sampling. Based on a 1-way ANOVA (p=0.05) and shape, HDI1-HDI3 cannot be distinguished. We represent them by lognormal distributions with pooled mean and pooled standard deviation and impute the same distribution for HDI4.



Annex A

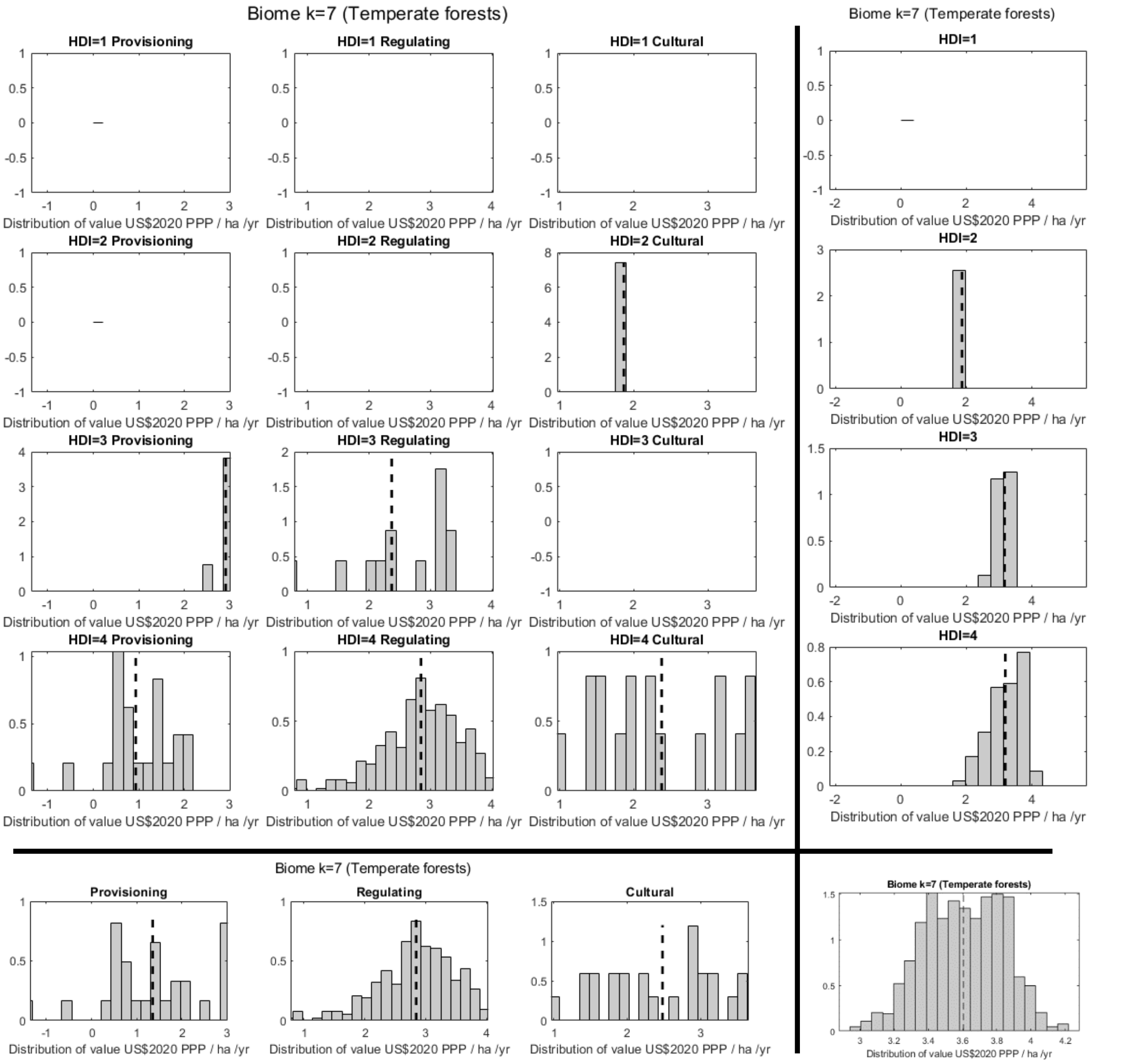
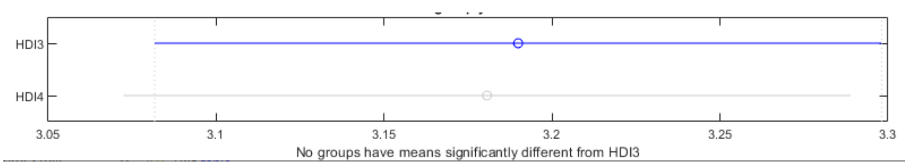


Figure 27: Ecosystem service valuations in ESVD and US$2020 PPP for Biome k=7 (temperate forests), disaggregated by UNDP HDI tier (1=low development, 2=medium development, 3=high development, 4=very high development) and class of service according to the TEEB classification (provisioning, regulating, or cultural). Panels on the right show totals by HDI tier, panels on the bottom show TEEB class of service without disaggregation by HDI tier. Bottom right is the distribution of values without disaggregation. All axes in log10, showing orders of magnitude.

For k=7,8,9 there was little data outside of HDI=3 and HDI=4 tiers. For k=7, distributions of total value for HDI=3 and HDI=4 cannot be rejected as normally distributed by the Anderson-Darling test. HDI3 has low samples size (20 samples) and the p-value in the test is not robust to sampling. Based on a 1-way ANOVA (p=0.05) and shape, HDI3 and HDI4 cannot be distinguished. We represent them by lognormal distributions with pooled mean and pooled standard deviation and impute the same distribution for HDI1 and HDI2.



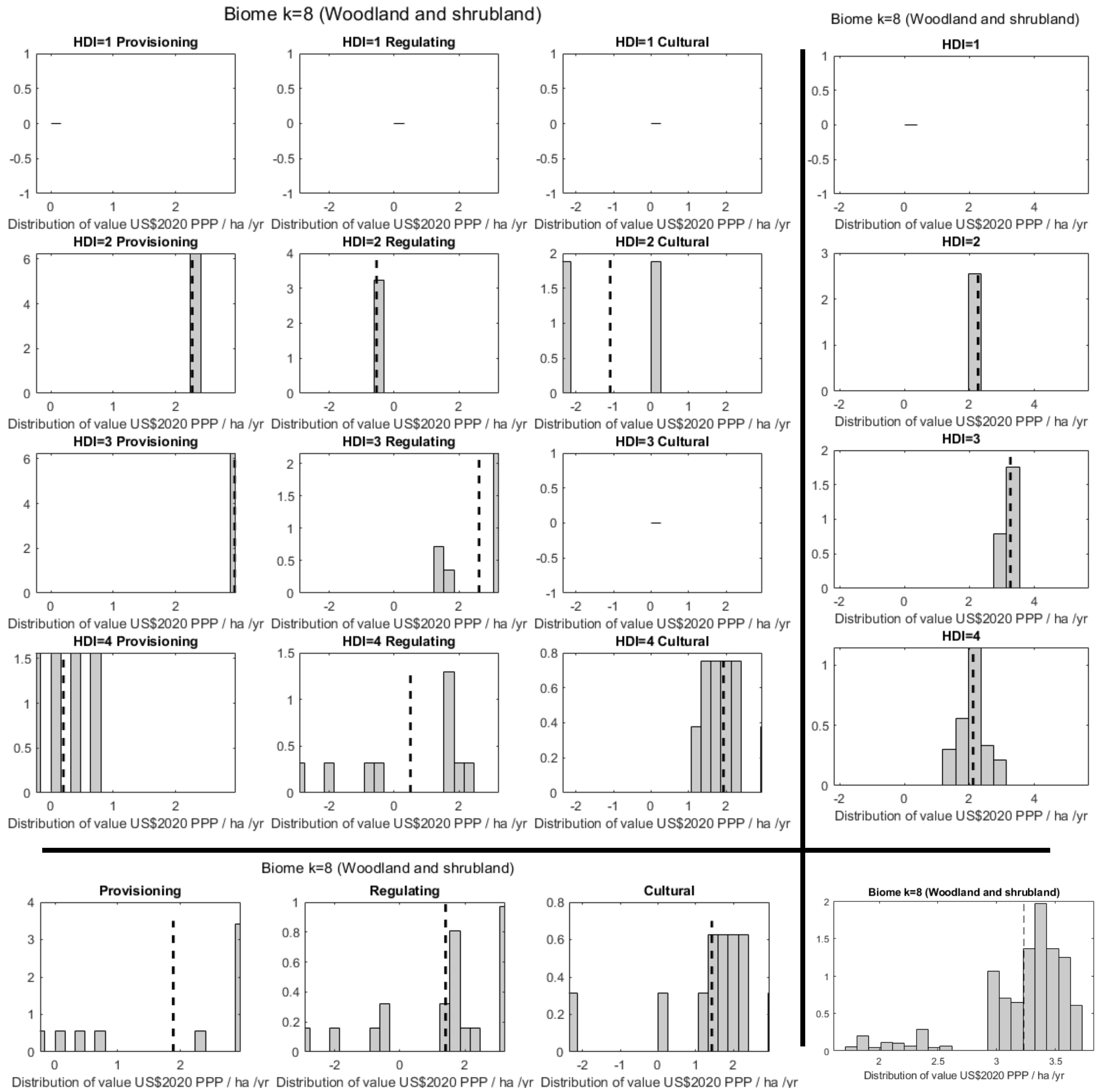
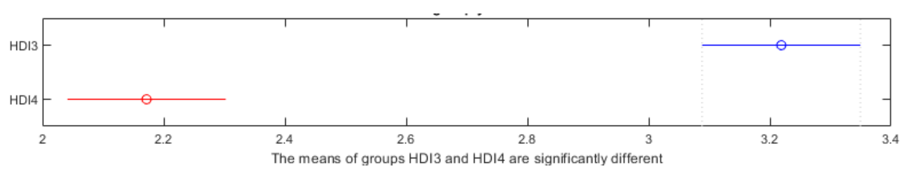


Figure 28: Ecosystem service valuations in ESVD and US$2020 PPP for Biome k=8 (woodlands and shrublands), disaggregated by UNDP HDI tier (1=low development, 2=medium development, 3=high development, 4=very high development) and class of service according to the TEEB classification (provisioning, regulating, or cultural). Panels on the right show totals by HDI tier, panels on the bottom show TEEB class of service without disaggregation by HDI tier. Bottom right is the distribution of values without disaggregation. All axes in log10, showing orders of magnitude.

For k=8, distributions of total value for HDI=3 and HDI=4 have low sample sizes. The p-value in the Anderson-Darling test the test is not robust to sampling and there is not enough data to determine normality of shape. Based on a 1-way ANOVA (p=0.05) the means of HDI3 and HDI4 can be distinguished. However, HDI 3 is biased by low samples. Given the low sample size for both HDI3 and HDI4 we impute the HDI4 distribution for HDI1, HDI2 and HDI3.



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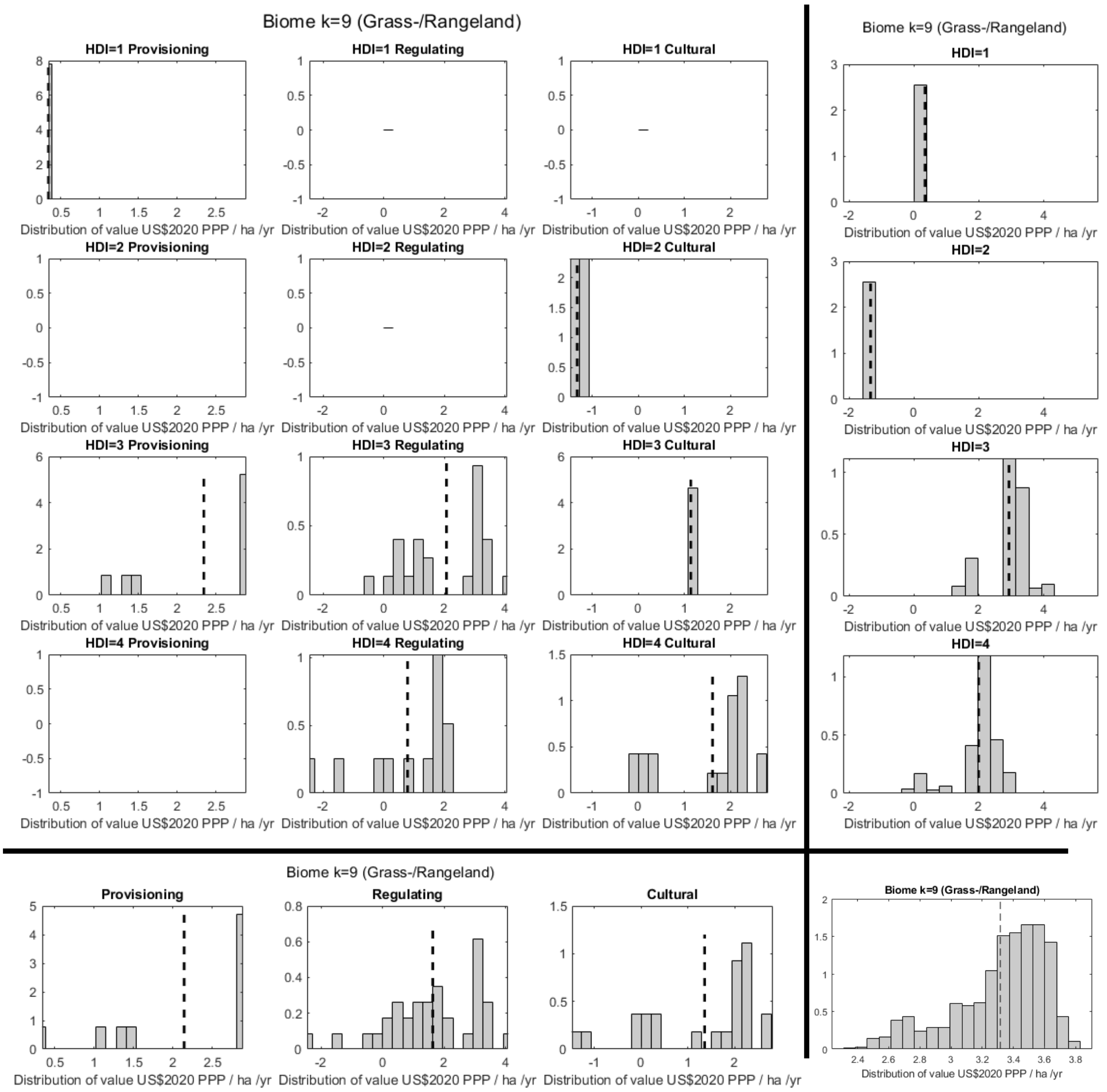
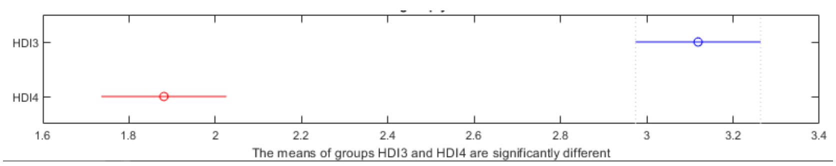


Figure 29: Ecosystem service valuations in ESVD and US$2020 PPP for Biome k=9 (grasslands and rangelands), disaggregated by UNDP HDI tier (1=low development, 2=medium development, 3=high development, 4=very high development) and class of service according to the TEEB classification (provisioning, regulating, or cultural). Panels on the right show totals by HDI tier, panels on the bottom show TEEB class of service without disaggregation by HDI tier. Bottom right is the distribution of values without disaggregation. All axes in log10, showing orders of magnitude.

For k=9, distributions of total value for HDI=3 and HDI=4 cannot be rejected as normally distributed by the Anderson-Darling test. Based on a 1-way ANOVA (p=0.05) the means of HDI3 and HDI4 can be distinguished. However, HDI4 is biased by missing provisioning valuations. To be conservative, we impute the HDI4 distribution for HDI1, HDI2 and HDI3.



3.4.1 Results of the group analysis

To summarise the grouping analysis of the totals of valuations across service classes (provisioning, regulating, cultural) in the ESVD by HDI tier are presented below. Recall a total distribution is determined by randomly choosing a valuation from the provisioning, regulating and cultural class and the summing the total. A normal shape would be expected in totals where there are many valuations in each class, since summing random variables tends toward a normal shape without large variance in standard deviation in the summands. Table 3 indicates the p-value for the Anderson-Darling test for normality, the sample size as the sum of the valuations in each of the provisioning, regulating and cultural class, and the means of the samples used in the ANOVA analysis

Table 3: results of statistical testing of the totals of valuations across service classes (provisioning, regulating, cultural) in the ESVD by HDI tier. AD refers to the Anderson-Darling test of normality

Biome (k)	HDI Tier	Valuation Sample Size	Mean (log10)	AD test p value
2	1	59	2.988	0.0046
2	2	85	4.122	0.0005
2	3	64	4.123	0.0005
2	4	142	3.487	0.0188
3	1	141	3.207	0.0005
3	2	260	3.673	0.0005
3	3	288	3.877	0.0174
3	4	225	3.491	0.1209 *
4	1	95	2.514	0.0005
4	2	64	4.299	0.0041
4	3	42	3.434	0.0005
4	4	164	3.498	0.0802 *
5	1	19	3.945	0.0218
5	2	25	3.475	0.0027
5	3	50	4.166	0.0141
5	4	75	4.089	0.0005
6	1	44	2.340	0.0173
6	2	22	2.832	0.0348
6	3	94	2.583	0.0005
7	3	20	3.190	0.0028
7	4	359	3.181	0.0005
8	3	15	3.253	0.0005
8	4	24	1.882	0.2126 *
9	3	33	3.119	0.0005
9	4	34	1.881	0.00050

From the ANOVA analysis and the normality test, Table 4 indicates the mean and standard deviation used to represent the US$2020 PPP ha-1 yr-1 value for each biome and each HDI tier. The mean and standard deviation are transferred from log10 (which was used so far to display order of magnitude) to natural logarithm in Table 6, to avoid error in using Table 4 for parameters of a lognormal distribution.

Table 4: Distributions representing totals of valuations for biomes across service classes (provisioning, regulating, cultural) in the ESVD by HDI tier. In log10 axes and parameterised by mean mu and standard deviation sigma. Hence a ha of biome k for a country in HDI tier I provides an estimated US$2020 PPP 10^N(mu,sigma) (where N represents the normal distribution) in ecosystems services per ha per year.

Biome(k)	HDI Tier(i)	mu	sigma
2	1	3.083	0.609
2	2	4.134	0.832
2	3	4.134	0.832
2	4	3.462	0.582
3	1	3.087	0.656
3	2	3.759	0.92
3	3	3.952	0.876
3	4	3.501	0.865
4	1	2.659	0.871
4	2	4.253	0.967
4	3	3.554	0.599
4	4	3.554	0.758
5	1	3.906	0.709
5	2	3.462	0.761
5	3	4.021	0.778
5	4	4.021	0.778
6	1	2.569	0.803
6	2	2.569	0.803
6	3	2.569	0.803
6	4	2.569	0.803
7	1	3.175	0.406
7	2	3.175	0.406
7	3	3.175	0.406
7	4	3.175	0.406
8	1	2.11	0.659
8	2	2.11	0.659
8	3	2.11	0.659
8	4	2.11	0.659
9	1	1.992	0.803
9	2	1.992	0.803
9	3	1.992	0.803
9	4	1.992	0.803

It is important to note that the distributions in in Table 4 represent lower mean values for biomes than seen in Figure 1. A comparison is seen in Figure 30. The lower values originate from the assumption of the number of ecosystem services provided by an ecosystem. The results of this section have assumed only that an ecosystem provides provisioning, regulating, and cultural services, sampled from the ESVD studies on what the value might be for each service. There are only three summands in the total. This is an underestimate given lack of data in ESVD across all ecosystem services. The summation in Figure 1 is across all ecosystem services that are not removed as outliers, so there are more summands. Including more summands, especially for services with low numbers of valuations which are not weighted to account for their statistical certainty, adds artificial certainty in the summand of random numbers. There are mutual exclusions between the ecosystem services (e.g., food and fibre) and variation between ecosystems within biomes that need to be taken into account in order to justify additional summands.

The means in Figure 1 (and the summary values in the ESVD) are within the uncertainty bands for the estimates of Table 4. Largely, the uncertainty range of the distributions in Table 4 captures the uncertainty with more summands in ecosystem services. Lower values are more probable, reflecting the valuation given available evidence.

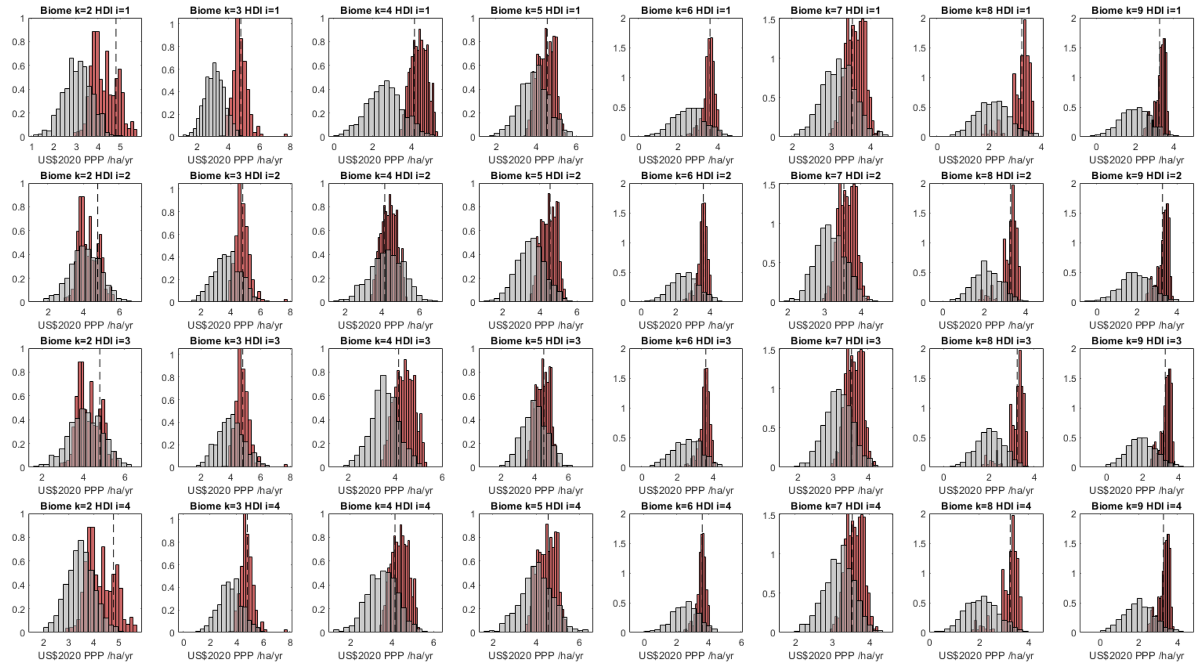


Figure 30: Distributions (grey) representing totals of valuations for biomes across service classes (provisioning, regulating, cultural) in the ESVD by HDI tier. In log10 axes using the parameterisation in Table 4. Comparison with biome valuation from summing valuations in ESVD across all ecosystem services after outlier removal (red) (Figure 1). Mean values are less, but certainty, which is artificial in the all-summands approach, is less using the service class and HDI grouping analysis. In some cases, tail risk from the grouping analysis exceeds the distributions in Figure 1.

Assignment of ecosystem service value to countries is done by HDI tier. Landlocked countries without territories and without coral reef or coastal systems are still given an ESV for those habitats. In a valuation the quantity of change in ha or effective ha lost of ecosystems that a country or its territories does not possess can only be zero. Hence there will be no change in value despite being assigned an ecosystem service value if the country or its territories were to possess ha of the given ecosystem.

3.4.2 Discounting and substitution of natural capital

We have not discussed discounting and temporal effects of habitat conversion or degradation. Some estimates in the ESVD include discounting factors. Where possible the ESVD includes the discount rate and time, and the original amount. However, only a few studies consider discounting, and it is not systematic across the valuations recorded in the ESVD.

Several considerations are involved in understanding the total loss over time from habitat conversion or degradation. They are too complex to factor into a generic set of marginal ecosystem service values.

First is the modelling of the conversion or degradation itself. Ecosystems may revert, or may recover once stressors are removed, so the trajectory of causes of the degradation or conversion needs to be defined by the assumptions and projections of the quantity modelling.

Second is the substitutability of natural capital with other forms of capital [13], as this determines the form and rate of discounting to apply over the temporal trajectory of ecosystem change and degradation.

Third is the temporal change in the value of ecosystem service per ha per year. A marginal cost for conversion or degradation at a later time requires scenario modelling to understand the critical socio-economic and environmental drivers that may alter the value of ecosystem services at a future date [14], e.g. increased scarcity and/or new uses.

In the absence of the capacity to determine temporal changes in the value of ecosystem service per ha per year and a formulation of substitutability of natural capital, a study should determine a timescale for conversion, use the assumption of constant Ecosystem Service Value (ESV) for the present time, and apply a discount rate consistent with other marginal damage costs.

3.5 Quantification of correlations

The local nature of ecosystem services means that we do not consider correlation in the ecosystem valuations. For very large changes in habitat, then failure of provisioning, regulation and cultural services on a wide scale creates mutual scarcity and higher values for ecosystem services. Complicated modelling of joint dependence in ecosystem services is left for individual studies. An advantage of examining and framing ecosystem service valuations using normal distributions on log axes is that Pearson correlation matrices log-transformed can be used to reconstruct joint distributions.

Correlation of conversion of habitat or degradation with effective loss of services (a loss of value) with marginal costs from other quantities of impact, and sensitivity analysis, is described in Annex B. Here the interactions of the impacts of ecosystem service losses are discussed to estimate block correlation coefficients (Table 5) for Table 3 in Annex B. For the sensitivity analysis described in Annex B, weak, moderate, and strong interactions between marginal costs are described by set correlation coefficients indicating proportion of covariance (Pearson):

Correlation	**P**	
Strong negative	-0.8	
Moderate negative	-0.5	
Weak negative	-0.2	
None	0	
Weak positive	0.2	

Moderate positive	0.5	
Strong positive	0.8	

To use block correlation between country level costs, we make broad assumptions and must factor in the different responses of ecosystems within biomes. Low correlation does not indicate independence and no interactions, it may indicate positive correlations of some ecosystems in biomes and negative effects of others and an estimate of the balance between the two.

Interactions at the level of marginal damages, that is, in the impact pathway given a joint change in a unit of GHG emissions and an effective ha of ecosystem services lost, are described in the correlation coefficients here. Interactions between quantity change (the number of units) and joint distributions on vectors of quantities must be factored by modelling of quantities, not marginal damages.

Table 5: Block Pearson correlation coefficients between uncertain marginal damage costs

Marginal cost of…	GHG emission	Water use	Land use	Nr Emissions	Poverty	NCDs	Chronic & Hidden Hunger
Conversion or degradation of ha of biome resulting in a loss of ecosystem services	+0.5	+0.2		+0.5	-0.2	0	-0.2

Marginal damage costs from climate change and loss of ecosystem value per ha per year
Underestimated temperature effects, or shifts in precipitation, from a marginal increase in GHG concentrations will result in higher marginal damage costs of climate change. Processes of conversion such as desertification are a component of temperature damages, which would be increased by higher values for the ecosystem services (in biomes k=2 to 9) against the value of deserts and drier landscapes [15].

Degradation of coral reefs and coastal systems sensitive to climate change can increase scarcity and higher value for remaining services. Assuming increased losses with higher temperature, then the loss of services coincides with increasing value of services. Ecosystems adapt to temperature change, but the rate of change is generally faster than the adaptation rate for ecosystems [16]. One study estimate 20-30% of global total ecosystem service value will be involved in climate transition under scenario RCP 2.6 and 37-50% under RCP 8.5 [17].

Some regulatory services related to climate change, such as storage of methane in tundra, are not usually valued. The higher the cost of climate damages, the higher the value of carbon or methane sequestration services by terrestrial, aquatic, and marine ecosystems generally. Climate regulation services mitigate higher temperatures and temperature extremes.

Many ecosystem services depend on an underlying diversity of species which is expected to reduce under temperature increase [18]. Overall, climate change is expected to increase defaunification [19, 20]. Tropical forests and wetlands are expected to be more stressed under higher temperature, with an increase in temperate biomes [21]. The overall loss of services between decreasing and degrading biomes from temperature change and increasing biomes is unclear because of the economic trade-offs inherent in the services between human use (e.g., agriculture) and dependence on natural inputs (e.g., regulation).

Though climate and land-use are highly coupled, the major shared driver is anthropogenic forcing [20]. It is not entirely clear that human intervention to adapt to higher temperatures and extreme weather will also reduce the cost of a lost ecosystem service. Flood protection might protect against loss from the coincidence of reduced water retention and extreme precipitation events, but it may also degrade services in downstream ecosystems. The interactions between land and climate are complex, and they operate on different timescales in terms of conversion. Will a broadly higher than expected cost for loss of ecosystem services now interact with temperature changes over the longer term? Under scenarios of continued conversion and effective loss of ha, a converted or effective ha lost is likely to persist in the timeframe to 2050 which overlaps with climate impacts from methane and a proportion of temperature costs before they are discounted out by longer timeframes. The full interaction between climate impacts of a GHG emissions now (or at a future date), particularly CO2 and loss of ecosystem services now (or at the same future date) is unclear.

Temporal factors and the complexity of the interaction between climate and land means that we assign a moderate positive correlation.

Marginal damage costs from blue water withdrawal and loss of ecosystem value per ha per year
Water quality is not directly addressed in this cost factor except through an effective deprivation of useable blue water due to reduced water quality. Nitrogen load as a water quality factor is a component of the impact pathway for the marginal damage costs of nitrogen emissions below.

Global spatially explicit studies show a large coincidence between effects on human populations of potential water deprivation from a unit of water withdrawal in the present and agricultural and biodiversity stressors for rivers and lakes [22]. A greater than expected amount of deprivation from the same unit of withdrawal, which would increase per unit damage of water withdrawal, will have adverse effects in ecosystems whose services, including cultural ones, fundamentally depend on water availability in rivers and lakes [23].

However, services and biomes are not uniform in their dependence on water and how ecosystem services are changed. Value loss from failure of water retention increases flows reducing the potential for water deprivation. This is complicated, however, by the timing of water availability – lost services from forest and mountain ecosystem services my increase flow overall but have reduced water storage capacity to mediate flows for seasonal requirements of agriculture. Increase in erosion as well as flow may reduce useable water, increasing stress which is a component of water damage costs. Human intervention of natural flow to reduce water stress and reduce the damage costs of water withdrawal has reduced flow to inland wetlands with adverse consequences, which may increase the cost of lost services. Dam building and alteration of natural flows has consequences including fragmentation of habitat, reduction in the value of services from loss of species and alteration of transport of nutrient and sediments to coastal ecosystems [24].

Other interactions in the impact pathway of a joint unit of water withdrawal and effective ha loss of ecosystem services are mixed. Malnutrition and loss of crop value from damage to water resource from water withdrawal, can be mitigated with enhanced agricultural productivity and technology, which in turn are associated to more degraded ecosystem services [25]. On the other hand, loss of wild food and other provisioning and regulating services, will increase incidence of malnutrition.

Overall, the complexity of interactions between water deprivation and mitigation of its effects, and mixed responses across ecosystem services means that we would use a moderate positive correlation. The explicit components of water damage costs in Annex A – Water lack an ecosystem component, hence, factoring only through malnutrition and crop losses from water deprivation, we use a weak positive correlation.

Marginal damage costs of nitrogen emissions and loss of ecosystem value per ha per year
Higher than expected damage costs from nitrogen emissions (per kg of NH3 to air, per kg NOx to air, per kg Nr surface run-off) are expected to coincide with higher-than-expected costs per ha from ecosystem value loss as described in Annex A – Nitrogen. Nitrogen induced acidification damages in the nitrogen cascade are widely distributed across biomes by air to land deposition and surface water run-off, including export of Nr to coastal systems and coral reefs. Acidification and eutrophication of terrestrial and aquatic biomes generally result in damage to biodiversity and ecosystem structure and hence service provision per ha [26].

Nr emissions have a complex interaction with terrestrial, aquatic, and coastal habitats, but net effects are expected to be positive. Excess nitrogen has increased biotic growth, resulting in increased carbon sequestration per ha and in some cases increased provision of materials, e.g., fibres and wood. The value of increases in yield per ha of materials and sequestration is expected be outweighed by loss of other services (cultural, water provisioning, fish and high tropic level mortality, etc. from algal blooms). It is unclear how air pollution regulation per ha is impacted by loss of biodiversity but increased biotic growth.

About half of nitrogen damage costs per kg come from human health losses due to inhalation of particulate matter originating from NH3 and NOx emission (mostly, with a smaller amount from nitrate in drinking water). Population density, distance of population to agricultural emission, and health condition of the population are the main covariate factors for the component of nitrogen damage costs from air pollution, which are not correlated with the same factors for ecosystem service value per ha.

From the component of air pollution and the combination of positive and negative effects, we use a moderate positive correlation.

Marginal damage costs from NCDs due to dietary intake and loss of ecosystem value per ha per year
NonCommunicable Disease (NCD) costs are higher without co-factors such as exercise and mental health [27, 28]. Higher estimates of losses of recreation services (exercise [29]) and cultural value (mental health [30]) from would be expected to correlate to higher health costs. Lost opportunities for recreation and cultural activities through loss of an ha of ecosystem services will therefore have a greater cost the higher the associated cost of the same dietary intake. Higher than expected costs of ecosystem services may include undervalued or not-valued additional services to human health [31]. The strength of correlation depends on covariates. Exercise and mental health factors are provided by other socio-economic factors such as income, social network, and advancing medical care. There is a lack of data on controlled covariance studies to estimate the contribution of ecosystems services compared to socio-economic factors [31, 32].

Given the lack of evidence on the strength of the contribution of ecosystem services compared to variation in socio-economic factors, we use no correlation to indicate the dominance of potential variation in socio-economic factors.

Poverty gaps and loss of ecosystem value per ha per year

Since we are considering block correlation coefficients, we must consider the effect of a country level increase in the poverty gap. In most countries with high levels of extreme poverty this will correlate to an increase in the value or extent of agricultural services, or a transition to higher value employment in urban areas.

An increase in the extent of agricultural services or industrialisation has predominately implied an increase in the loss of ecosystem services [32, 33]. Though there is potential for poverty alleviation in the provision of ecosystem services outside food and fibre, it is unrealised [33]. While research suggest that the extreme poor are more dependent on loss of value from ecosystem system services [34-36], there is little evidence on the strength of the correlation between the value of ecosystem services outside food and fibre and poverty alleviation [36] and that it would outweigh poverty alleviation through agricultural production or structural transition.

Though evidence suggests a negative correlation between poverty gap and value losses from ecosystem services, it is not clear whether the proportion of the value loss is due to changes in the effective ha loss (the quantity) or to changes in the value loss per ha per year. Effective ha loss is the more important quantity, as direct conversion of land for agricultural area is generally plateauing as productivity increases (https://ourworldindata.org/land-use). The tertiary relationship is negative (poverty gap decrease, implies ha effective loss increase, creating scarcity, implying increase in the value loss per ha per year), but it is unclear what the strength of a secondary effect is except factoring through agricultural nitrogen emissions and industrial resource use.

We assume that most of the negative relationship between poverty gap and loss of ecosystem value is due to effective ha lost (change in quantity of service), and that there are significant other social factors related to poverty alleviation that are weakly connected to the value per ha per year of ecosystem services. We assume a weak negative correlation.

Marginal costs of undernourishment and loss of ecosystem value per ha per year

Undernourishment and extreme poverty gap, generally, have a moderate positive relationship across countries (Annex A – Water), resulting in a weak negative factor between DALYs per undernourished person and ecosystem value loss per ha. Water filtering services and changing habitats for disease vectors have co-morbidities with DALYs from protein-energy malnutrition [37-39]. Higher value water filtering ecosystem services losses per ha would therefore be expected to correlate with higher mortality given malnutrition. Tertiary effects in mortality given malnutrition, i.e., through climate sequestration and regulation services correlated with reduced climate impacts and the co-effects of climate change with co-morbidities of malnutrition, would also be positive and relate to climate adaptation capacity and development level.

The strongest factor for differences in countries in DALYs per person in malnutrition is HDI (Annex A – Water). Presently, this is influenced more by development which degrades ecosystem services and their marginal value, than the positive effects of ecosystem services. We assume a weak negative factor between DALYs per undernourished person and ecosystem value loss per ha.

3.6 Consideration for use

3.6.1 Costs of subsidies and subsidy reform

Since subsidies are largely social welfare policies, economic arguments for subsidy reform should be framed as costs to society.

Global subsidy reform will involve potentially large changes in spatial distribution of agricultural production and volumes of commodities. Price effects change non-food consumption and/or demand change for agricultural commodities, with a secondary correction to production distribution and volumes. Competition for land-use and spatial changes in production have effects on labour and inputs. General equilibrium modelling of changes to the economy, resulting in quantities associated to impacts, are appropriate for studies of subsidy reform. Economic losses framed as costs to society are appropriate for comparisons with general equilibrium modelling output.

Agricultural subsidy reform will likely change agricultural use of land considerably, and in countries (Brazil, China, etc.) traditionally associated to deforestation (conversion) or ecosystem stress from nitrogen emissions (effective ha lost), particularly of aquatic systems emission sources. Costs of lost ecosystem services are used in the costs assessment of subsidy reform in land-use change (forest converted to agricultural land, agriculture land abandoned) and in assessment of the cost of Nr emissions.

Land-use changes and ecosystem effects post-farm gate are unlikely to be largely changed from spatial re-distribution of production. The different biomes effected directly by conversion, and indirectly through Nr emissions provide rationale for costing the range of biomes examined.

Implicit in exogenous scenarios are trajectories of subsidy reform and land-use change. If setting exogenous scenarios, there should be some consideration whether the marginal costs of lost ecosystem services need adjustment over the timeline of the scenario, as discussed in Section 3.4.2.

3.7 References

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3.8 Appendix

3.8.1 Tables of results

Caveats from the main text: Assignment of Ecosystem Service Value (ESV) per ha per year to countries is done by HDI tier. Landlocked countries without territories and without coral reef of coastal systems still are given an ESV. In a valuation the quantity of change in ha or effective ha lost of ecosystems that a country or its territories does not possess can only be zero. Hence there will be no change in value despite being assigned an ecosystem service value per ha per year if the country or its territories were to possess ha of the given ecosystem.

The values in Table 6 and their uncertainty Table 7 were determined by a statistical analysis of the ESVD dataset, they represent lower mean values for biomes than Figure 1. The lower values originate from the assumption of the number of ecosystem services provided by an ecosystem. The valuation assumed only that an ecosystem provides provisioning, regulating, and cultural services, sampled from the ESVD studies on what the value might be for each service. The summation in Figure 1 is across all ecosystem services that are not removed as outliers, so there are more summands. Including more summands, especially for services with low numbers of valuations which are not weighted to account for their statistical certainty, adds artificial certainty in the summand of random numbers. There are mutual exclusions between the ecosystem services (e.g., food and fibre) and variation between ecosystems within biomes that need to be taken into account in order to justify additional summands.

Despite having lower mean values, the uncertainty represented in Table 7 spans several orders of magnitude due to the highly uncertain nature of the value of ecosystems given present data, and the epistemological uncertainty of assigning a country level value to a spatially explicit connection of an ecosystem to local and national economy, environmental conditions, and socio-economical stressors. It is not recommended to use the mean values in Table 6 separate from the uncertainty estimates in Table 7.

Annex A

Table 6: Valuation of 202 countries based on HDI tier and provisioning, regulating and cultural ecosystem services from the ESVD dataset (Table 4). Using the biome id code of the ESVD, k=2 represents coral reefs, k=3 coastal systems including wetlands, k=4 represents inland wetlands, k=5 lakes and rivers, k=6 tropical forest, k=7 temperate forest, k=8 woodland and shrubland and k=9 grassland and rangeland (Table 1).Measured in US$2020 purchasing power parity (international dollars) per hectare per year. It is not recommended to use the mean values in this table separate from the uncertainty estimates in Table 7. The column of values (bold) provide the mean of the log-normal distributed value ESV.

				ESV US$2020 per ha per yr							
Country	**ISO3166-1**	**UN-M49**	**HDI**	**k=2**	**k=3**	**k=4**	**k=5**	**k=6**	**k=7**	**k=8**	**k=9**
Afghanistan	AFG	4	0.511	1692	1886	1083	13975	764	1766	222	218
Angola	AGO	24	0.581	1692	1886	1083	13975	764	1766	222	218
Albania	ALB	8	0.795	31897	20960	5294	20474	764	1766	222	218
Andorra	AND	20	0.868	31897	20960	5294	20474	764	1766	222	218
United Arab Emirates	ARE	784	0.89	31897	20960	5294	20474	764	1766	222	218
Argentina	ARG	32	0.845	31897	20960	5294	20474	764	1766	222	218
Armenia	ARM	51	0.776	31897	20960	5294	20474	764	1766	222	218
American Samoa	ASM	16	0.827	31897	20960	5294	20474	764	1766	222	218
Antigua and Barbuda	ATG	28	0.778	31897	20960	5294	20474	764	1766	222	218
Australia	AUS	36	0.944	4502	9450	7047	20474	764	1766	222	218
Austria	AUT	40	0.922	4502	9450	7047	20474	764	1766	222	218
Azerbaijan	AZE	31	0.756	31897	20960	5294	20474	764	1766	222	218
Burundi	BDI	108	0.433	1692	1886	1083	13975	764	1766	222	218
Belgium	BEL	56	0.931	4502	9450	7047	20474	764	1766	222	218
Benin	BEN	204	0.545	1692	1886	1083	13975	764	1766	222	218
Burkina Faso	BFA	854	0.452	1692	1886	1083	13975	764	1766	222	218
Bangladesh	BGD	50	0.632	31897	11545	39863	5109	764	1766	222	218
Bulgaria	BGR	100	0.816	31897	20960	5294	20474	764	1766	222	218
Bahrain	BHR	48	0.852	31897	20960	5294	20474	764	1766	222	218
Bahamas, The	BHS	44	0.814	31897	20960	5294	20474	764	1766	222	218
Bosnia and Herzegovina	BIH	70	0.78	31897	20960	5294	20474	764	1766	222	218

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Belarus	BLR	112	0.823	31897	20960	5294	20474	764	1766	222	218
Belize	BLZ	84	0.716	31897	11545	39863	5109	764	1766	222	218
Bermuda	BMU	60	0.981	4502	9450	7047	20474	764	1766	222	218
Bolivia	BOL	68	0.718	31897	11545	39863	5109	764	1766	222	218
Brazil	BRA	76	0.765	31897	20960	5294	20474	764	1766	222	218
Barbados	BRB	52	0.814	31897	20960	5294	20474	764	1766	222	218
Brunei Darussalam	BRN	96	0.838	31897	20960	5294	20474	764	1766	222	218
Bhutan	BTN	64	0.654	31897	11545	39863	5109	764	1766	222	218
Botswana	BWA	72	0.735	31897	11545	39863	5109	764	1766	222	218
Central African Republic	CAF	140	0.397	1692	1886	1083	13975	764	1766	222	218
Canada	CAN	124	0.929	4502	9450	7047	20474	764	1766	222	218
Switzerland	CHE	756	0.955	4502	9450	7047	20474	764	1766	222	218
Chile	CHL	152	0.851	31897	20960	5294	20474	764	1766	222	218
China	CHN	156	0.761	31897	20960	5294	20474	764	1766	222	218
Cote d'Ivoire	CIV	384	0.538	1692	1886	1083	13975	764	1766	222	218
Cameroon	CMR	120	0.563	1692	1886	1083	13975	764	1766	222	218
Congo, Dem. Rep.	COD	180	0.48	1692	1886	1083	13975	764	1766	222	218
Congo, Rep.	COG	178	0.574	1692	1886	1083	13975	764	1766	222	218
Colombia	COL	170	0.767	31897	20960	5294	20474	764	1766	222	218
Comoros	COM	174	0.554	1692	1886	1083	13975	764	1766	222	218
Cabo Verde	CPV	132	0.665	31897	11545	39863	5109	764	1766	222	218
Costa Rica	CRI	188	0.81	31897	20960	5294	20474	764	1766	222	218
Cuba	CUB	192	0.783	31897	20960	5294	20474	764	1766	222	218
Cyprus	CYP	196	0.887	31897	20960	5294	20474	764	1766	222	218
Czech Republic	CZE	203	0.9	4502	9450	7047	20474	764	1766	222	218
Germany	DEU	276	0.947	4502	9450	7047	20474	764	1766	222	218
Djibouti	DJI	262	0.524	1692	1886	1083	13975	764	1766	222	218

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Dominica	DMA	212	0.742	31897	11545	39863	5109	764	1766	222	218
Denmark	DNK	208	0.94	4502	9450	7047	20474	764	1766	222	218
Dominican Republic	DOM	214	0.756	31897	20960	5294	20474	764	1766	222	218
Algeria	DZA	12	0.748	31897	11545	39863	5109	764	1766	222	218
Ecuador	ECU	218	0.759	31897	20960	5294	20474	764	1766	222	218
Egypt, Arab Rep.	EGY	818	0.707	31897	11545	39863	5109	764	1766	222	218
Eritrea	ERI	232	0.459	1692	1886	1083	13975	764	1766	222	218
Spain	ESP	724	0.904	4502	9450	7047	20474	764	1766	222	218
Estonia	EST	233	0.892	4502	9450	7047	20474	764	1766	222	218
Ethiopia	ETH	231	0.485	1692	1886	1083	13975	764	1766	222	218
Finland	FIN	246	0.938	4502	9450	7047	20474	764	1766	222	218
Fiji	FJI	242	0.743	31897	11545	39863	5109	764	1766	222	218
France	FRA	250	0.901	4502	9450	7047	20474	764	1766	222	218
Micronesia, Fed. Sts.	FSM	583	0.62	1692	1886	1083	13975	764	1766	222	218
Gabon	GAB	266	0.703	31897	11545	39863	5109	764	1766	222	218
United Kingdom	GBR	826	0.932	4502	9450	7047	20474	764	1766	222	218
Georgia	GEO	268	0.812	31897	20960	5294	20474	764	1766	222	218
Ghana	GHA	288	0.611	1692	1886	1083	13975	764	1766	222	218
Guinea	GIN	324	0.477	1692	1886	1083	13975	764	1766	222	218
Gambia, The	GMB	270	0.496	1692	1886	1083	13975	764	1766	222	218
Guinea-Bissau	GNB	624	0.48	1692	1886	1083	13975	764	1766	222	218
Equatorial Guinea	GNQ	226	0.592	1692	1886	1083	13975	764	1766	222	218
Greece	GRC	300	0.888	31897	20960	5294	20474	764	1766	222	218
Grenada	GRD	308	0.779	31897	20960	5294	20474	764	1766	222	218
Guatemala	GTM	320	0.663	31897	11545	39863	5109	764	1766	222	218
Guam	GUM	316	0.901	4502	9450	7047	20474	764	1766	222	218
Guyana	GUY	328	0.682	31897	11545	39863	5109	764	1766	222	218

Hong Kong SAR, China	HKG	344	0.949	4502	9450	7047	20474	764	1766	222	218
Honduras	HND	340	0.634	31897	11545	39863	5109	764	1766	222	218
Croatia	HRV	191	0.851	31897	20960	5294	20474	764	1766	222	218
Haiti	HTI	332	0.51	1692	1886	1083	13975	764	1766	222	218
Hungary	HUN	348	0.854	31897	20960	5294	20474	764	1766	222	218
Indonesia	IDN	360	0.718	31897	11545	39863	5109	764	1766	222	218
India	IND	356	0.645	31897	11545	39863	5109	764	1766	222	218
Ireland	IRL	372	0.955	4502	9450	7047	20474	764	1766	222	218
Iran, Islamic Rep.	IRN	364	0.783	31897	20960	5294	20474	764	1766	222	218
Iraq	IRQ	368	0.674	31897	11545	39863	5109	764	1766	222	218
Iceland	ISL	352	0.949	4502	9450	7047	20474	764	1766	222	218
Israel	ISR	376	0.919	4502	9450	7047	20474	764	1766	222	218
Italy	ITA	380	0.892	4502	9450	7047	20474	764	1766	222	218
Jamaica	JAM	388	0.734	31897	11545	39863	5109	764	1766	222	218
Jordan	JOR	400	0.729	31897	11545	39863	5109	764	1766	222	218
Japan	JPN	392	0.919	4502	9450	7047	20474	764	1766	222	218
Kazakhstan	KAZ	398	0.825	31897	20960	5294	20474	764	1766	222	218
Kenya	KEN	404	0.601	1692	1886	1083	13975	764	1766	222	218
Kyrgyz Republic	KGZ	417	0.697	31897	11545	39863	5109	764	1766	222	218
Cambodia	KHM	116	0.594	1692	1886	1083	13975	764	1766	222	218
Kiribati	KIR	296	0.63	31897	11545	39863	5109	764	1766	222	218
St. Kitts and Nevis	KNA	659	0.779	31897	20960	5294	20474	764	1766	222	218
Korea, Rep.	KOR	410	0.916	4502	9450	7047	20474	764	1766	222	218
Kuwait	KWT	414	0.806	31897	20960	5294	20474	764	1766	222	218
Lao PDR	LAO	418	0.613	1692	1886	1083	13975	764	1766	222	218
Lebanon	LBN	422	0.744	31897	11545	39863	5109	764	1766	222	218
Liberia	LBR	430	0.48	1692	1886	1083	13975	764	1766	222	218

Libya	LBY	434	0.724	31897	11545	39863	5109	764	1766	222	218
St. Lucia	LCA	662	0.759	31897	20960	5294	20474	764	1766	222	218
Liechtenstein	LIE	438	0.919	4502	9450	7047	20474	764	1766	222	218
Sri Lanka	LKA	144	0.782	31897	20960	5294	20474	764	1766	222	218
Lesotho	LSO	426	0.527	1692	1886	1083	13975	764	1766	222	218
Lithuania	LTU	440	0.882	31897	20960	5294	20474	764	1766	222	218
Luxembourg	LUX	442	0.916	4502	9450	7047	20474	764	1766	222	218
Latvia	LVA	428	0.866	31897	20960	5294	20474	764	1766	222	218
Macao SAR, China	MAC	446	0.922	4502	9450	7047	20474	764	1766	222	218
Morocco	MAR	504	0.686	31897	11545	39863	5109	764	1766	222	218
Monaco	MCO	492	1	4502	9450	7047	20474	764	1766	222	218
Moldova	MDA	498	0.75	31897	20960	5294	20474	764	1766	222	218
Madagascar	MDG	450	0.528	1692	1886	1083	13975	764	1766	222	218
Maldives	MDV	462	0.74	31897	11545	39863	5109	764	1766	222	218
Mexico	MEX	484	0.779	31897	20960	5294	20474	764	1766	222	218
Marshall Islands	MHL	584	0.704	31897	11545	39863	5109	764	1766	222	218
North Macedonia	MKD	807	0.774	31897	20960	5294	20474	764	1766	222	218
Mali	MLI	466	0.434	1692	1886	1083	13975	764	1766	222	218
Malta	MLT	470	0.895	4502	9450	7047	20474	764	1766	222	218
Myanmar	MMR	104	0.583	1692	1886	1083	13975	764	1766	222	218
Montenegro	MNE	499	0.829	31897	20960	5294	20474	764	1766	222	218
Mongolia	MNG	496	0.737	31897	11545	39863	5109	764	1766	222	218
Mozambique	MOZ	508	0.456	1692	1886	1083	13975	764	1766	222	218
Mauritania	MRT	478	0.546	1692	1886	1083	13975	764	1766	222	218
Mauritius	MUS	480	0.804	31897	20960	5294	20474	764	1766	222	218
Malawi	MWI	454	0.483	1692	1886	1083	13975	764	1766	222	218
Malaysia	MYS	458	0.81	31897	20960	5294	20474	764	1766	222	218

Namibia	NAM	516	0.646	31897	11545	39863	5109	764	1766	222	218
New Caledonia	NCL	540	0.813	31897	20960	5294	20474	764	1766	222	218
Niger	NER	562	0.394	1692	1886	1083	13975	764	1766	222	218
Nigeria	NGA	566	0.539	1692	1886	1083	13975	764	1766	222	218
Nicaragua	NIC	558	0.66	31897	11545	39863	5109	764	1766	222	218
Netherlands	NLD	528	0.944	4502	9450	7047	20474	764	1766	222	218
Norway	NOR	578	0.957	4502	9450	7047	20474	764	1766	222	218
Nepal	NPL	524	0.602	1692	1886	1083	13975	764	1766	222	218
Nauru	NRU	520	0.721	31897	11545	39863	5109	764	1766	222	218
New Zealand	NZL	554	0.931	4502	9450	7047	20474	764	1766	222	218
Oman	OMN	512	0.813	31897	20960	5294	20474	764	1766	222	218
Pakistan	PAK	586	0.557	1692	1886	1083	13975	764	1766	222	218
Panama	PAN	591	0.815	31897	20960	5294	20474	764	1766	222	218
Peru	PER	604	0.777	31897	20960	5294	20474	764	1766	222	218
Philippines	PHL	608	0.718	31897	11545	39863	5109	764	1766	222	218
Palau	PLW	585	0.826	31897	20960	5294	20474	764	1766	222	218
Papua New Guinea	PNG	598	0.555	1692	1886	1083	13975	764	1766	222	218
Poland	POL	616	0.88	31897	20960	5294	20474	764	1766	222	218
Puerto Rico	PRI	630	0.845	31897	20960	5294	20474	764	1766	222	218
Korea, Dem. People's Rep.	PRK	408	0.733	31897	11545	39863	5109	764	1766	222	218
Portugal	PRT	620	0.864	31897	20960	5294	20474	764	1766	222	218
Paraguay	PRY	600	0.728	31897	11545	39863	5109	764	1766	222	218
West Bank and Gaza	PSE	275	0.708	31897	11545	39863	5109	764	1766	222	218
French Polynesia	PYF	258	0.895	4502	9450	7047	20474	764	1766	222	218
Qatar	QAT	634	0.848	31897	20960	5294	20474	764	1766	222	218
Romania	ROU	642	0.828	31897	20960	5294	20474	764	1766	222	218
Russian Federation	RUS	643	0.824	31897	20960	5294	20474	764	1766	222	218

Rwanda	RWA	646	0.543	1692	1886	1083	13975	764	1766	222	218
Saudi Arabia	SAU	682	0.854	31897	20960	5294	20474	764	1766	222	218
Sudan	SDN	729	0.51	1692	1886	1083	13975	764	1766	222	218
Senegal	SEN	686	0.512	1692	1886	1083	13975	764	1766	222	218
Singapore	SGP	702	0.938	4502	9450	7047	20474	764	1766	222	218
Solomon Islands	SLB	90	0.567	1692	1886	1083	13975	764	1766	222	218
Sierra Leone	SLE	694	0.452	1692	1886	1083	13975	764	1766	222	218
El Salvador	SLV	222	0.673	31897	11545	39863	5109	764	1766	222	218
San Marino	SMR	674	0.961	4502	9450	7047	20474	764	1766	222	218
Somalia	SOM	706	0.285	1692	1886	1083	13975	764	1766	222	218
Serbia	SRB	688	0.806	31897	20960	5294	20474	764	1766	222	218
South Sudan	SSD	728	0.433	1692	1886	1083	13975	764	1766	222	218
Sao Tome and Principe	STP	678	0.625	31897	11545	39863	5109	764	1766	222	218
Suriname	SUR	740	0.738	31897	11545	39863	5109	764	1766	222	218
Slovak Republic	SVK	703	0.86	31897	20960	5294	20474	764	1766	222	218
Slovenia	SVN	705	0.917	4502	9450	7047	20474	764	1766	222	218
Sweden	SWE	752	0.945	4502	9450	7047	20474	764	1766	222	218
Eswatini	SWZ	748	0.611	1692	1886	1083	13975	764	1766	222	218
Seychelles	SYC	690	0.796	31897	20960	5294	20474	764	1766	222	218
Syrian Arab Republic	SYR	760	0.567	1692	1886	1083	13975	764	1766	222	218
Chad	TCD	148	0.398	1692	1886	1083	13975	764	1766	222	218
Togo	TGO	768	0.515	1692	1886	1083	13975	764	1766	222	218
Thailand	THA	764	0.777	31897	20960	5294	20474	764	1766	222	218
Tajikistan	TJK	762	0.668	31897	11545	39863	5109	764	1766	222	218
Turkmenistan	TKM	795	0.715	31897	11545	39863	5109	764	1766	222	218
Timor-Leste	TLS	626	0.606	1692	1886	1083	13975	764	1766	222	218
Tonga	TON	776	0.725	31897	11545	39863	5109	764	1766	222	218

Trinidad and Tobago	TTO	780	0.796	31897	20960	5294	20474	764	1766	222	218
Tunisia	TUN	788	0.74	31897	11545	39863	5109	764	1766	222	218
Turkey	TUR	792	0.82	31897	20960	5294	20474	764	1766	222	218
Tuvalu	TUV	798	0.711	31897	11545	39863	5109	764	1766	222	218
Tanzania	TZA	834	0.529	1692	1886	1083	13975	764	1766	222	218
Uganda	UGA	800	0.544	1692	1886	1083	13975	764	1766	222	218
Ukraine	UKR	804	0.779	31897	20960	5294	20474	764	1766	222	218
Uruguay	URY	858	0.817	31897	20960	5294	20474	764	1766	222	218
United States	USA	840	0.926	4502	9450	7047	20474	764	1766	222	218
Uzbekistan	UZB	860	0.72	31897	11545	39863	5109	764	1766	222	218
St. Vincent and the Grenadines	VCT	670	0.738	31897	11545	39863	5109	764	1766	222	218
Venezuela, RB	VEN	862	0.711	31897	11545	39863	5109	764	1766	222	218
Virgin Islands (U.S.)	VIR	850	0.894	4502	9450	7047	20474	764	1766	222	218
Vietnam	VNM	704	0.704	31897	11545	39863	5109	764	1766	222	218
Vanuatu	VUT	548	0.609	1692	1886	1083	13975	764	1766	222	218
Samoa	WSM	882	0.715	31897	11545	39863	5109	764	1766	222	218
Yemen, Rep.	YEM	887	0.47	1692	1886	1083	13975	764	1766	222	218
South Africa	ZAF	710	0.709	31897	11545	39863	5109	764	1766	222	218
Zambia	ZMB	894	0.584	1692	1886	1083	13975	764	1766	222	218
Zimbabwe	ZWE	716	0.571	1692	1886	1083	13975	764	1766	222	218

Annex A

Table 7: Valuation of 202 countries based on HDI tier and provisioning, regulating and cultural ecosystem services from the ESVD dataset (Table 4). Using the biome id code of the ESVD, k=2 represents coral reefs, k=3 coastal systems including wetlands, k=4 represents inland wetlands, k=5 lakes and rivers, k=6 tropical forest, k=7 temperate forest, k=8 woodland and shrubland and k=9 grassland and rangeland (Table 1). The parameters mu and sigma refer to the lognormal fit of ecosystem service value (ESV) as an uncertain value: log(ESV)~N(mu,sigma).

			log(ESV) mean parameter								log(ESV) standard deviation parameter							
			k=2	k=3	k=4	k=5	k=6	k=7	k=8	k=9	k=2	k=3	k=4	k=5	k=6	k=7	k=8	k=9
Country Name	**Country Code**	**M49**	**mu**	**mu**	**mu**	**mu**	**mu**	**mu**	**mu**	**mu**	**σ**	**σ**	**σ**	**σ**	**σ**	**σ**	**σ**	**σ**
Afghanistan	AFG	4	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Albania	ALB	8	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Algeria	DZA	12	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
American Samoa	ASM	16	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Andorra	AND	20	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Angola	AGO	24	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Antigua and Barbuda	ATG	28	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Azerbaijan	AZE	31	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Argentina	ARG	32	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Australia	AUS	36	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Austria	AUT	40	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Bahamas, The	BHS	44	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Bahrain	BHR	48	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Bangladesh	BGD	50	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Armenia	ARM	51	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Barbados	BRB	52	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Belgium	BEL	56	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Bermuda	BMU	60	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Bhutan	BTN	64	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849

Bolivia	BOL	68	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Bosnia and Herzegovina	BIH	70	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Botswana	BWA	72	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Brazil	BRA	76	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Belize	BLZ	84	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Solomon Islands	SLB	90	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Brunei Darussalam	BRN	96	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Bulgaria	BGR	100	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Myanmar	MMR	104	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Burundi	BDI	108	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Belarus	BLR	112	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Cambodia	KHM	116	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Cameroon	CMR	120	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Canada	CAN	124	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Cabo Verde	CPV	132	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Central African Republic	CAF	140	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Sri Lanka	LKA	144	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Chad	TCD	148	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Chile	CHL	152	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
China	CHN	156	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Colombia	COL	170	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Comoros	COM	174	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Congo, Rep.	COG	178	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849

Congo, Dem. Rep.	COD	180	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Costa Rica	CRI	188	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Croatia	HRV	191	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Cuba	CUB	192	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Cyprus	CYP	196	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Czech Republic	CZE	203	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Benin	BEN	204	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Denmark	DNK	208	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Dominica	DMA	212	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Dominican Republic	DOM	214	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Ecuador	ECU	218	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
El Salvador	SLV	222	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Equatorial Guinea	GNQ	226	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Ethiopia	ETH	231	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Eritrea	ERI	232	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Estonia	EST	233	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Fiji	FJI	242	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Finland	FIN	246	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
France	FRA	250	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
French Polynesia	PYF	258	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Djibouti	DJI	262	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Gabon	GAB	266	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Georgia	GEO	268	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Gambia, The	GMB	270	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849

West Bank and Gaza	PSE	275	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Germany	DEU	276	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Ghana	GHA	288	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Kiribati	KIR	296	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Greece	GRC	300	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Grenada	GRD	308	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Guam	GUM	316	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Guatemala	GTM	320	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Guinea	GIN	324	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Guyana	GUY	328	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Haiti	HTI	332	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Honduras	HND	340	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Hong Kong SAR, China	HKG	344	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Hungary	HUN	348	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Iceland	ISL	352	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
India	IND	356	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Indonesia	IDN	360	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Iran, Islamic Rep.	IRN	364	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Iraq	IRQ	368	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Ireland	IRL	372	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Israel	ISR	376	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Italy	ITA	380	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Cote d'Ivoire	CIV	384	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Jamaica	JAM	388	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Japan	JPN	392	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849

Kazakhstan	KAZ	398	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Jordan	JOR	400	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Kenya	KEN	404	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Korea, Dem. People's Rep.	PRK	408	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Korea, Rep.	KOR	410	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Kuwait	KWT	414	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Kyrgyz Republic	KGZ	417	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Lao PDR	LAO	418	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Lebanon	LBN	422	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Lesotho	LSO	426	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Latvia	LVA	428	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Liberia	LBR	430	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Libya	LBY	434	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Liechtenstein	LIE	438	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Lithuania	LTU	440	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Luxembourg	LUX	442	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Macao SAR, China	MAC	446	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Madagascar	MDG	450	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Malawi	MWI	454	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Malaysia	MYS	458	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Maldives	MDV	462	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Mali	MLI	466	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Malta	MLT	470	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Mauritania	MRT	478	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849

Mauritius	MUS	480	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Mexico	MEX	484	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Monaco	MCO	492	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Mongolia	MNG	496	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Moldova	MDA	498	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Montenegro	MNE	499	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Morocco	MAR	504	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Mozambique	MOZ	508	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Oman	OMN	512	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Namibia	NAM	516	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Nauru	NRU	520	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Nepal	NPL	524	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Netherlands	NLD	528	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
New Caledonia	NCL	540	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Vanuatu	VUT	548	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
New Zealand	NZL	554	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Nicaragua	NIC	558	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Niger	NER	562	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Nigeria	NGA	566	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Norway	NOR	578	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Micronesia, Fed. Sts.	FSM	583	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Marshall Islands	MHL	584	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Palau	PLW	585	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Pakistan	PAK	586	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Panama	PAN	591	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849

Papua New Guinea	PNG	598	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Paraguay	PRY	600	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Peru	PER	604	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Philippines	PHL	608	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Poland	POL	616	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Portugal	PRT	620	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Guinea-Bissau	GNB	624	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Timor-Leste	TLS	626	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Puerto Rico	PRI	630	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Qatar	QAT	634	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Romania	ROU	642	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Russian Federation	RUS	643	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Rwanda	RWA	646	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
St. Kitts and Nevis	KNA	659	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
St. Lucia	LCA	662	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
St. Vincent and the Grenadines	VCT	670	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
San Marino	SMR	674	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Sao Tome and Principe	STP	678	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Saudi Arabia	SAU	682	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Senegal	SEN	686	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Serbia	SRB	688	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Seychelles	SYC	690	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Sierra Leone	SLE	694	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849

Singapore	SGP	702	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Slovak Republic	SVK	703	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Vietnam	VNM	704	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Slovenia	SVN	705	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Somalia	SOM	706	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
South Africa	ZAF	710	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Zimbabwe	ZWE	716	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Spain	ESP	724	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
South Sudan	SSD	728	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Sudan	SDN	729	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Suriname	SUR	740	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Eswatini	SWZ	748	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Sweden	SWE	752	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Switzerland	CHE	756	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Syrian Arab Republic	SYR	760	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Tajikistan	TJK	762	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Thailand	THA	764	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Togo	TGO	768	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Tonga	TON	776	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Trinidad and Tobago	TTO	780	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
United Arab Emirates	ARE	784	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Tunisia	TUN	788	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Turkey	TUR	792	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Turkmenistan	TKM	795	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849

Tuvalu	TUV	798	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Uganda	UGA	800	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Ukraine	UKR	804	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
North Macedonia	MKD	807	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Egypt, Arab Rep.	EGY	818	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
United Kingdom	GBR	826	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Tanzania	TZA	834	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
United States	USA	840	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Virgin Islands (U.S.)	VIR	850	7.972	8.061	8.183	9.259	5.915	7.311	4.858	4.587	1.34	1.992	1.745	1.791	1.849	0.935	1.517	1.849
Burkina Faso	BFA	854	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Uruguay	URY	858	9.519	9.1	8.183	9.259	5.915	7.311	4.858	4.587	1.916	2.017	1.379	1.791	1.849	0.935	1.517	1.849
Uzbekistan	UZB	860	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Venezuela, RB	VEN	862	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Samoa	WSM	882	9.519	8.655	9.793	7.972	5.915	7.311	4.858	4.587	1.916	2.118	2.227	1.752	1.849	0.935	1.517	1.849
Yemen, Rep.	YEM	887	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849
Zambia	ZMB	894	7.099	7.108	6.123	8.994	5.915	7.311	4.858	4.587	1.402	1.51	2.006	1.633	1.849	0.935	1.517	1.849

3.8.2 Global Results

For perspective, the damage costs of average annual land conversion attributable to agriculture for 202 countries are estimated in Section 3.8.2. The damage costs are calculated by pairing the marginal damage costs for 202 countries (Table 6 and Table 7) with global land conversion data from the HILDA+ dataset [2].

The HILDA+ dataset includes global land use conversion data with a spatial resolution of approximately 1 square kilometre per year for the transitions:

- Cropland to forest
- Cropland to unmanaged grass/shrubland
- Pasture/rangeland to forest
- Pasture/rangeland to unmanaged grass/shrubland
- Forest to cropland
- Forest to pasture/rangeland
- Unmanaged grass/shrubland to cropland
- Unmanaged grass/shrubland to pasture/rangeland

The transition values in ha were assigned to the respective countries for a given year with borders according to the Natural Earth database [(https://www.naturalearthdata.com/downloads/50m-cultural-vectors/50m-admin-0-countries-2/)](https://www.naturalearthdata.com/downloads/50m-cultural-vectors/50m-admin-0-countries-2/) such that the average conversion per transition per country for the years 2015-2019 could be calculated. The forest conversation data included in HILDA+ was not further specified as being temperate and tropical forests. To obtain a ESV estimate for each country the values for temperate and tropical forests were multiplied by the ratio of both forest types to the total amount of forest within a specific country. The average annual amount over 2015-2019 was used as an estimate of 2020 conversion of forest and grassland biomes to and from agricultural use (Figure 31). Net increase in grassland and forest from abandonment of agricultural land were recorded in the US and China. The greatest decrease in forest from agriculture use was recorded in France, Brazil and Angola.

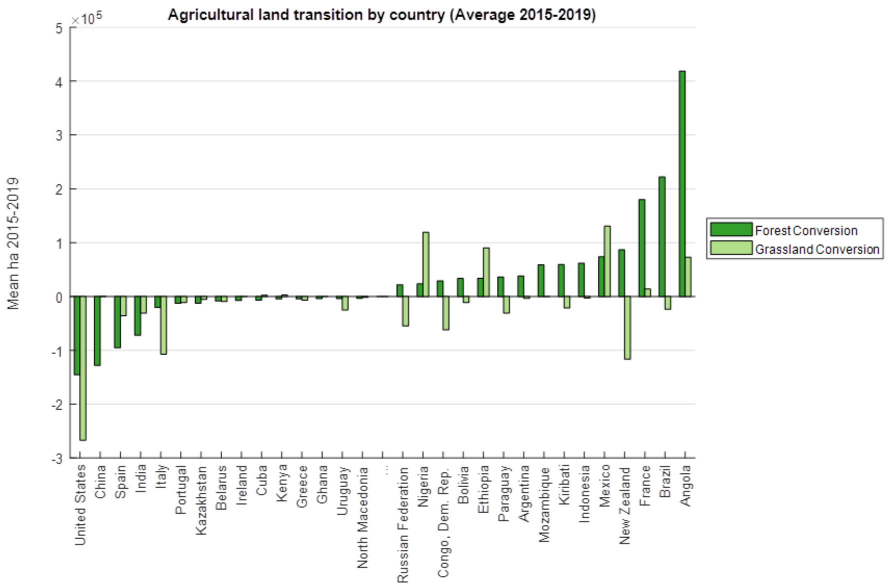

Figure 31: Ha of grassland and forest conversion attributable to agriculture for 202 countries. Calculated from the HILDA+ land use transitions dataset.

We estimated the value of the ecosystem services gain from cropland to forest or grassland to be equal to the value of ecosystem services coming from a ha of additional forest or grassland. Likewise, the value of ecosystem services gained from pasture/rangeland conversion to forest or grassland was estimated to be equal to the value of ecosystem services coming from a ha of additional forest or grassland. The value of ecosystem services lost due to forest conversion to cropland or pasture/rangeland was assumed to equal the value of services from one ha of forest lost. Equivalently, the value of ecosystem services lost due to unmanaged grassland conversion to cropland or pasture/rangeland was estimated as loss of services of one ha of grassland.

A ha of forest or grassland gained or lost was multiplied by a sample of the value of the ecosystem services of the ha drawn from the marginal distributions given in Table 6 and Table 7. This provided a sample of the total costs or benefits for that specific country and biome. This process was done for every country and every biome, and the samples were added across biomes and countries, resulting in one sample for the global total cost of land use conversion in 2020 attributable to agriculture. This procedure was repeated 10 000 times to generate 10 000 samples for global total cost of land use conversion attributional to agricultural activities (Figure 32).

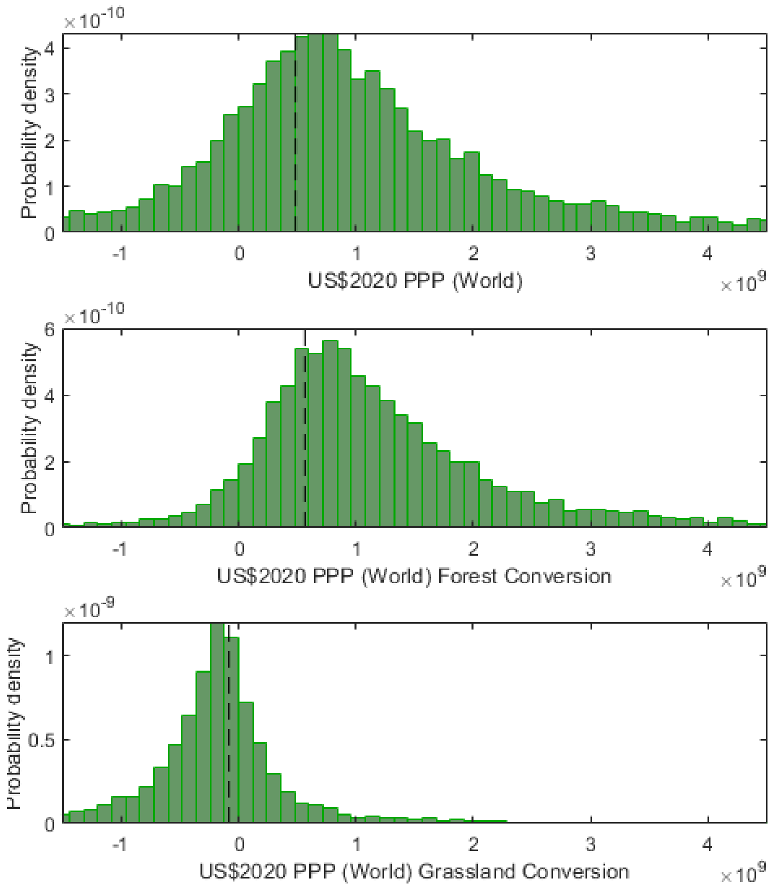

Figure 32: Top panel: Global costs of lost ecosystem services in US\$2020 PPP yr^{-1} from net land use conversion in 2020 attributed to agriculture. Net conversion of forest and grassland in 2020 estimated in ha from the average net forest and grassland conversion from 2015-2019. The marginal costs for ha of relevant biomes in each country were sampled 10000 times from the log-normal distributions in Table 7, and multiplied against ha of net forest or grassland conversion for each country. The top panel is the histogram of the sum of the samples of damage costs from each country. The mean (dotted black line) represents the expected costs of ~0.5 billion US\$2020 PPP yr^{-1}. Middle and bottom panel: Global costs from net forest and net grassland conversion attributed to agriculture in 2020, separately.

Expected economic loss in 2020 from net conversion attributable to agriculture in 2020 was US$2020 0.5 billion yr^{-1}, with a greater than 5% chance that losses are over US$2020 3 billion yr^{-1} (Figure 32). Net conversion of forest globally was ~5Mha (5 million hectares). Net conversion of grassland was ~-0.1 Mha - more agriculture land was abandoned in grassland biomes than grassland was converted, on average, over 2015-2019.

2020 GHG emissions from the global food system and 2020 reactive nitrogen emissions from global agricultural production have mean damage costs in the order of 1 trillion US$2020 PPP. Cost in 2020 of land conversion to or from agricultural use at 0.5 billion US$2020 PPP yr^{-1} is orders of magnitude smaller than the costs from the production activities on the land under agricultural use:

1) 2020 land conversion damage costs have been given in US$2020 PPP yr^{-1} rather than, as was done for GHG and Nr emissions in 2020, US$2020 PPP amounts over the full time of impacts. Trajectories of land-use are complicated to specify for a general costs dataset. Assuming a present value equivalent of 20 years of damage from lost ecosystem services from 2020 conversion would put expected economic loss at US$2020 10 billion.
2) Net conversions of agricultural land use (~5Mha yr^{-1}) compared to overall agricultural land use (~3Gha, or 3 billion ha) are small.
3) The opportunity cost of dietary change is more significant than the present rate of land conversion [40]. Dietary change could reduce agricultural land use by approximately 1 Gha for no calorie loss and healthier diets. Under the same assumptions in 1), if economies utilised the returned ecosystem services from the returned forest and grassland, then conversion from dietary change could yield ~US$2020 200 billion yr^{-1} in benefits.

How much of the estimated economic loss from land conversion can be recovered from transforming agricultural production and food systems is unclear without global modelling studies placing food system mitigation costs within the context of least cost abatement of land use change.

The middle and bottom panel in Figure 32 represent the contributions to the estimated total global damage costs of forest and grassland conversions separately. The net-conversion of forest is more likely to impose costs to society, whereas the grassland net-conversion is most often negative.

How much of this estimated economic loss can be recovered from transforming agricultural production and food systems is unclear without global modelling studies placing food system mitigation costs within the context of least cost abatement of land use change.