The supplementary information consists of one file entitled:

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This contains Supplementary Methods, Supplementary Discussion, Supplementary Figures S1-S4 and Supplementary Tables S1-S4.

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Supplementary Information for:

Quantifying the benefit of early climate change mitigation in avoiding biodiversity loss

Warren, R*., VanDerWal, J., Price, J., Welbergen, J.A, Atkinson, I., Ramirez-Villegas, J., Osborn, T.J., Jarvis, A., Shoo, L.P., Williams, S.E, Lowe, J.

*To whom correspondence should be addressed. E-mail: r.warren@uea.ac.uk

This Supplementary Information contains:

- Supplementary Methods

- Supplementary Discussion

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- References

Supplementary Methods

Our approach is based on an efficient linkage of climate and bioclimatic envelope modelling tools within the Community Integrated Assessment System CIAS[1] and the Wallace Initiative (http://wallaceinitiative.org), using the MaxEnt model to project the movement of climate envelopes.

Climate modelling. Global climate change modelling was carried out by driving the MAGICC4.1 climate model[2,3] with 21st century emissions time series to create a projection of 21st century climate change, based on an exploration of uncertainties in three key parameters:

climate sensitivity, ocean mixing rate, and a climate-carbon cycle feedback factor that amplifies the temperature dependent climate-carbon cycle feedbacks in MAGICC. Climate sensitivity is examined with a widely-used probability distribution[4]. A log-normal distribution of ocean mixing rates was fitted to the general circulation models employed in IPCC[4]. The climate-carbon cycle amplification parameter follows a normal distribution whose parameters were derived to allow MAGICC's atmospheric carbon dioxide concentrations to closely match that of the earth system models in the C4MIP analysis[5]. This probabilistic analysis provides outputs in the form of percentiles of likely annual global mean near-surface temperature change over the 21st century, under each emissions scenario (see below). We used the median projections to drive a pattern-scaling module ClimGEN (developed from[6]); see also[1,7] in which scaled climate change patterns diagnosed from GCM simulations are combined with a baseline climate (CRU TS 3.0 for 1961-1990, updated from[8]). We produced spatially-specific projections of monthly mean, minimum and maximum temperatures, and total precipitation, downscaled to a resolution of 0.5° x 0.5°. Patterns from seven GCMs from the CMIP3 archive were used, specifically UKMO-HadCM3, CCCMA-CGCM3.1, IPSL-CM4, MPI-ECHAM5, UKMO-HadGEM1, CSIRO-Mk3.0, and NCAR-CCSM3.0[7]. ClimGEN was used to produce projected monthly time series for 30-year periods centered on the 2020s (2011-2040), 2050s (2041-2070) and 2080s (2071-2100). These were then averaged to produce representative monthly climates for each 30 year period, using four indicators: monthly mean temperature, monthly maximum temperature (defined as the average of the daily maximum temperatures during a month), monthly minimum temperature and precipitation. This approach was necessary because GCMs have not been run for the mitigation scenarios we wanted to examine in our study. The models MAGIC4.1 and ClimGEN are designed explicitly to emulate the behaviour of the more

complex models so that impact modelers can study emission scenarios that have not been simulated by the GCM modelers.

Emission scenarios used in our analysis included a baseline - SRES A1B[9], and several mitigation scenarios developed for the AVOID project[10]. In the mitigation scenarios, greenhouse gas emissions initially follow the baseline scenario before transitioning over seven years so that emissions peak globally in either 2016 or 2030, and are reduced subsequently at rates of between 2 and 5% annually, until they reach a hypothetical lower limit designed to represent emissions that might be difficult to eliminate, e.g. from the agricultural system. Combining our emission scenarios with seven alternative GCM-derived change patterns produced 42 projected climates consistent with the IPCC[11].

Downscaled climate data were post-processed to produce the maximum of eight bioclimatic indices required by MaxEnt[12,13] used in this study. The average maximum temperature of warmest month of the year (MTW), the average minimum temperature of coldest month of the year (MTC), annual mean temperature (AMT), temperature seasonality (TS), total annual rainfall (ATR), rainfall seasonality (RS) and rainfall of the wettest quarter (RWQ) and rainfall of the driest quarter (RDQ) were calculated directly from the average climates of the aforementioned 30-year periods.

MAGICC4.1 climate model. MAGICC4.1 is a probabilistic version of the simple climate module, MAGICC.TAR, which was used to illuminate the consequences of the SRES scenarios in the IPCC Third Assessment Report[14]. The model[15] was thus tuned to emulate seven state-of-the-art coupled Atmosphere-Ocean Global Circulation Models (AOGCMs[16]) and used to extend the model results to the 35 IPCC Special Report on Emissions Scenarios (SRES)[9]. It simulates greenhouse gas cycles, radiative forcing, temperature change, and ice

melt. Gas cycle models are used to convert emissions of gases (including ozone precursors) to atmospheric concentrations[15]. Climate feedback on the carbon cycle is included; the resulting CO_2 concentration depends on the forcing, the climate sensitivity and the ocean heat uptake efficiency. Radiative forcing is then calculated from the concentrations. Sulphate aerosol forcing is scaled directly with the emissions because of the short residence time in the atmosphere. The total forcing then drives an upwelling diffusion energy balance model to estimate future climate changes. Thus the model allows the user to determine changes in CO_2 concentration, global-mean surface air temperature and sea level between the years 2000 and 2100 resulting from anthropogenic emissions of CO_2, CH_4, N_2O, HFCs, CFCs and PFCs, as well as SO_2. It is also possible to determine the sensitivity of these results to the variation in key model parameters, specifically the climate sensitivity, the ocean diffusivity, the aerosol forcing and uncertainties in the carbon cycle[15], and this is applied in the probabilistic version used here. MAGICC4.1 has been widely used in integrated modelling studies of mitigation scenarios[e.g. 17] because it is capable of reproducing global mean warming from more complex global circulation models (GCMs)[see also 18]. Use of MAGICC4.1 is necessary because GCMs have yet to be run and analysed for many stringent mitigation scenarios such as those considered within this study.

ClimGEN model. ClimGEN is a tool for generating fields of climate data using the method of pattern scaling, and thus in the tradition of CLIMAPS[18], and SCENGEN[19], and was developed from methods described in Mitchell *et al*[8]. ClimGEN uses GCM datasets obtained from the IPCC Data Distribution Centre at www.ipcc-data.org to produce interpolated patterns of climate change per degree Kelvin of global warming. The GCM outputs currently incorporated in ClimGEN were used in the IPCC Third Assessment Report[14]: ClimGEN combines these change patterns with the observed climatology to yield patterns of mean

absolute climate, and then combines them with observed time series of deviations from climatology to yield realisations of climate change with realistic year-to-year variability superimposed. It provides month-by-month climate variations for both observed climate from 1901 to 2002 (CRU TS 2.1) and future climate scenarios over 2001 to 2100, at a resolution of 0.5° latitude by 0.5° longitude, for the entire terrestrial land surface except Antarctica[8]. Climate fields can be generated for 8 climate variables based on GCM outputs, specifically: mean, maximum and minimum temperature; precipitation, vapour pressure, cloud cover, and wet day frequency. In the case of precipitation changes in pattern-scaled GCM precipitation expressed as fractional changes from present-day precipitation that are combined with the observed climatology by multiplication. To simulate future changes in precipitation variability as well as mean precipitation, ClimGEN includes a gamma shape method in which the pattern of changes in a gamma shape parameter output by the GCM models which represents the temporal distribution of precipitation, is scaled by the required global-mean temperature change. Further details are provided in Warren *et al*[1,20].

Biodiversity Data. Primary biodiversity data were obtained from the Global Biodiversity Information Facility (GBIF)[21]. GBIF facilitates discovery of data from many datasets worldwide, exposed via the Internet, indexed centrally and accessible through a common portal[22]. This totalled 170 million occurrence records from 200 data providers. Whilst there are gaps in the available data, GBIF provides a source to allow researchers to identify the potential patterns of change across the widest range of species and areas possible. We verified locational consistency of all records in the database using an established automated process[23]. Specifically, we removed records with no location data or that did not fall within land areas using a high resolution (~90m) coastal layer derived from the SRTM Digital

Elevation Model[24]. We compared the location of each record with the reported country of collection in the database and discarded all records with conflicting values. We analyzed the environmental niche of each of the 48,786 species that remained in our database following these necessary procedures. Species records considered as outliers were further examined and cleaned. This involved a Tukey outlier test[25] that determined the environmental niche represented as a bioclimatic limit of species localities and 18 bioclimatic indices[26] derived using the WorldClim dataset at 30 arc-seconds[27] plus elevation (our 19th index)[24]; all occurrences considered as outliers in 80% or more of the 19 indices for each species were discarded. In spite of potential statistical correlations among these indices, we used all of them for the filtering due to the wide geographic coverage of our analyses, and the spatial variations in variable relationships. This also allowed us to use a relatively high threshold (80%) for filtering out outlying occurrences. For the modelling (see below) we used a reduced set of variables to minimize potential issues with autocorrelation and in order to prevent overfitting of the Maxent model species distributions. This last step was performed as a final correction for potentially erroneously geocoded information, and the level chosen was a compromise between potentially missing information leading to a reduced current climatic range versus including erroneously geocoded information leading to a potentially inflated current climatic range.

Climate envelope modelling. In developing MaxEnt models we first performed a training procedure to estimate a probabilistic representation of the current geographic distribution of each species using the observed species distributions held in the GBIF network and by deriving a relationship between the observations and the observed current climate. We then projected this relationship onto present-day climate (1961-1990) to map estimates of the

potential geographic distribution of the species for all global land areas at a spatial resolution of 0.5 degrees. During the training process, we only used AMT, TS, ATR and RS as driving variables on taxa with 10 to 40 records while using the 8 bioclimatic variables (listed above) for species with >40 records; species with less than 10 records were not analysed. We performed 10 cross-validated runs to assess MaxEnt's accuracy for all models. All default settings were used in MaxEnt as these were optimized for broad groups of species globally[12,28]. Selection of background points involved 10 000 random points from each of the eight bio-geographic realms (defined by Olson et al.[29]) in which the species had been recorded. The background selection was from a broad geographic region (but not the globe) and therefore the predicted distribution would likely be representative of climatic range boundaries[30]. Given the scale of the climate data (~50km x 50km), the latter is a negligible issue and would still provide liberal estimates of species distribution.

The Area under the Receiver Operating Characteristic (ROC) curve (AUC) was used as a model performance indicator to select species models for projection over all climate scenarios. AUC >0.7 is generally an indicator of good performance in MaxEnt[31,32] and only species that met this criterion were used for further analysis. AUC is appropriate and commonly used to assess threshold-independent measures of model quality in species distribution modeling applications despite known assumptions and limitations[e.g.,30,33]. Here we applied a threshold defined as the minimum ROC distance[12,31] to the predicted climatic suitability to assess metrics of distributional area change. Given the application of a threshold, we show in Fig. S4 how several threshold dependent measures of model accuracy (Kappa, omission rate, sensitivity, specificity and proportion correct) correlate to the threshold-independent measure of AUC. The frequency distributions shown in Fig. S4 show that very few species (i.e. <5%

of the 48,786 species) had a sensitivity or specificity of less than 80%, and hence that the models perform well.

The predicted 'current' distributions were clipped by two factors: the eight bio-geographic realms for which all occurrence information for an individual species came, and a 2000 km buffer around the outermost occurrence records, because of the likely paucity of the data in some regions in the GBIF network and to minimize commission errors. Oceanic islands within this 2000 km range and within the relevant biogeographic region were included. The size of the buffer was set to be as large as practical to avoid omission errors (i.e., failure to identify a site as suitable owing to lack of records), while minimizing commission errors (i.e., identification of suitable climates in areas where a given species has never occurred owing to barriers or other biogeographic limitations). Commission errors often occur in global and continental scale analyses of this type where similar climates are found in widely separated regions (e.g., Mediterranean climates). Thus, the goal of the clipping was to reduce potential range inflation from commission errors while also trying to minimize range deflation from omission errors (much less common but still possible in some species). The current distribution was defined as the climatically suitable areas within this buffer region[12,31].

We used the projected climates and trained models to derive potential future climate space for each species in our future climate scenarios for 30-year periods centred on 2025, 2055 and 2085. To each future projection, we applied three class-specific 'dispersal' scenarios (referring to the rates at which species' ranges shift over time, see below) as a buffer (distance defined by the rate of movement and the number of years into the future) around this current distribution, given a continuous land surface and allowing dispersal to contiguous land areas[29]. Finally, we estimated proportions of species losing ≥50, ≥70, ≥90 or

≥99% of their climatically suitable range under these dispersal assumptions and future climate scenarios.

Dispersal Scenarios. There are many different ways in which the term dispersal is used in the ecological and paleoecological literature. Dispersal often refers to natal dispersal, post-breeding dispersal, or even to vagrancy. Within a short-term, metapopulation dynamics definition, the importance of repeated colonization and extinction events, and rescue effects, is important to the long-term persistence of metapopulations of taxa[e.g. 34]. In this study the dispersal rate refers to the average long-term shift of an entire species' range (taken from the published literature of current observed changes and paleoecological changes) taking into account potential repeated colonization and extinction events until a species' entire range catches up with the new 'environmental space'. We included a zero dispersal rate as one scenario, in common with many previous studies e.g. [35]. However, contrary to many studies, we did not look at a "full" dispersal scenario, where species are allowed to fully move into the newly available climate space regardless of the rate of climate change. We feel that such a dispersal scenario is unrealistic and unsupported by the paleoecological literature. The typical dynamics of range shifts (through multiple dispersal, colonization, extirpation and rescue events), barriers to movements, lack of instant availability of suitable soils or habitats, as well as lack of a stabilized climate (within the timeframes of this study) are just some of the factors making a 'full' dispersal scenario unlikely within the timeframe of this study in the absence of assisted movement. Instead, we looked at two further dispersal scenarios, based on long-term average dispersal rates found in the literature. In these scenarios, we allow species to move to fill their new climate envelope at the rate specified, provided they do not move across sea or ocean barriers[36]. Hence, we focus on dispersal to contiguous areas

in the same manner as Petersen *et al.*[37] as well as constrain species to remain within their native biogeographic zones. If a species can disperse at a rate of 1.5 km/yr, then in 100 years it can move 150 km. As grid cell size is approximately 30-50 km depending on location, this species would be simulated to cross 2-4 grid cell boundaries to track the climate. Our approach does not include the potential response of species movements to changes in the frequency of magnitude extremes resulting from inter-decadal and inter-annual climate variability, which can constrain dispersal rates[38] by introducing gaps in climate suitable pathways even in barrier-free situations. Dispersal can also be strongly affected by a species' ability to persist during short periods of unfavourable climate[38]. We recognize that dispersal rates can also vary significantly within taxa, with some individual species in some areas possibly moving at far greater rates (and others moving at reduced rates). Nevertheless, our approach is a balanced compromise between the more extreme approaches of no and full dispersal that are typically used in this field.

While the mean natal dispersal of European bird species is 22.8 km for migrants and 15.6 km for residents (the range for all species is 0.7–44.5 km)[39] this is not indicative of how well birds may track a shifting climate. Similar, longer distance dispersal rates can be found for many other taxa. However, these rates are best considered as applicable to meta-populations of species as they only represent colonization potential without considering extirpation events and as such are not representative of rates of long-term shifts in species' ranges (the long-term dispersal rate used here). Since dispersal occurs in many different directions, and first-year mortality is high, overall population movement would be expected to be slower than this. However, it is generally thought that changes in population density and dispersal in birds are rapid enough to keep communities of birds in equilibrium with climate[40]. In the UK, 12 bird species have been moving northwards at a rate of approximately 1

km/year[41]. Huntley[42] gives dispersal rates of 0.2-2 km/year for birds, whilst in Finland some species have been moving northwards about 19 km in 12 years (i.e. at 1.6 km/year[43]); whilst Devictor et al.[44] report that European bird communities are shifting at a rate of 37±3 km in an 18 year period, or approximately 2 km/year. Hence for birds we chose a realistic dispersal rate of 1.5 km/year, and an optimistic one of 3 km/year. The projected velocity of temperature change over the earth's surface is estimated to be 0.42 km/yr (0.11-0.46 km/yr)[45] for the 2050s, whilst observations over the period 1950-2009 already show median velocities of 2.7 km/yr (on land) and 2.2 km/yr (in the ocean) over the period 1950-2009[46]. While our dispersal rates suggests that birds may be able to keep up with climate change, with dispersal rates of 1.7 km/yr reported, recent work has found that even birds are lagging behind the climate change in some places[44,46,47]. The literature suggests that mammals have similar dispersal rates as birds, for example a rate of 2 km/year was estimated for deer[48]. Hence we use the same values for mammals as for birds.

For reptiles and amphibians, the literature on dispersal rates is sparse. However, Segura et al.[49] found that snakes have limited dispersal abilities, and Araujo et al.[50] consider that snakes are poor dispersers and highly philopatric. Dispersal rates of 19-51 m vertical distance upslope in 10 years (equivalent to about 100 m horizontally) have been found for 30 reptiles and amphibians in the Tsaratanana Massif in northern Madagascar[51], keeping pace with the observed temperature change, and thus providing a lower limit to the potential dispersal rate. However, dispersal in lizards could be inhibited by temperature rise[52]. Based on this very limited information we set 'realistic' dispersal rates for amphibians and reptiles to 0.1 km/year, and assumed that amphibians would also be thus constrained. We also created an 'optimistic' scenario in which these animals have dispersal rates of 0.5 km/year.

Plant seed dispersal rates vary widely. Some plants, such as those dispersed by creeping of stems (blastochory), disperse on average only 0.1 m per year (1 m/decade), whilst those dispersed by animals can move on average 500 m/year (5 km/decade). Other types of dispersal result in intermediate dispersal rates, with estimates of 40-300 m/year (0.4-3 km/decade) for plants with wind-dispersed seeds[53,54] or 100 m/year (1 km/decade) for ant and rodent dispersed plants[54]. Thuiller *et al.*[54] consider that trees cannot move faster than 5 km/decade and present-day migration rates of 83-126 and 50-81 m/year (approx. 1 km/decade) respectively have been observed for oaks (which are bird dispersed) and Southern pines (which are wind dispersed)[55,56] whilst other sources suggest tree migration rates of 0.05 to 1 km/year. Thus we chose the highest value quoted, 5 km/decade, as our optimistic scenario for plant dispersal. We selected a value representative of the lower values, 0.1 km/year, as our realistic scenario.

Supplementary Discussion

Limitations of correlative species distribution modelling. Correlative species distribution modelling is a common tool for gaining ecological and evolutionary insight into how species are distributed across a landscape, and how this may change in space and time. The models often build statistical relationships between species occurrences and environmental data, assuming that where a species occurs provides useful information on the species' physiological and ecological requirements. The assumptions and limitations of species distribution modelling has been largely reviewed in the literature[e.g., 57] and references therein. Common to species distribution modelling exercises are several assumptions, including that the observations for each species represent the full environmental range of the species; that there is little-to-no bias in observations; and that background selection excludes areas that

have not been searched. We sought to minimize potential violation of these assumptions by i) using the most robust global data for species observations (GBIF) to represent the full range of species; ii) reducing biases associated with spatial aggregation of observations by using only a single observation record per ~10 km pixel for model training (removing potential for high bias in prevalence); and iii) selecting background points from biogeographic realms appropriate to observed species records.

Other factors of potential importance in our analysis. Our findings result from the most comprehensive global analysis to date of projected losses in the climatic ranges of plants and animals; nevertheless, we were unable to consider all factors of potential importance in our analysis. Many factors could lead to either under- or overestimation of potential climatic range shifts[58]. For example, it is unclear how and to what extent species might utilize novel climates, as they need to be able to disperse to them and furthermore it is likely that some species' reshuffling will occur resulting in undesirable no-analog communities[59]. Changes in the severity of extremes of atmospheric weather and climate variables, such as temperature and precipitation extremes, might exceed the survivability thresholds of some species before the mean climate becomes unsuitable[60]. Changes in fire regimes, while not considered directly are included indirectly as fire frequency is also strongly related to bioclimatic variables[61], and can potentially lead to major changes in biodiversity. There is an expectation[62] that overall there will be more increases than decreases in extreme events with concomitant negative impacts on biodiversity.

The direct biotic effects of increases in CO_2 concentrations (e.g., earlier stomatal closing, protein or phytochemical changes leading to increases/decreases in herbivory) were not included as it would not be practical in a large-scale study such as this. Similarly, the

potential effects of biotic interactions, such as climate-change-mediated decoupling of trophic levels or of mutualistic relationships e.g., [63,64], or the potential spread of various disease vectors, pathogens and invasive species might also impact species but were also included here. To some extent, the overall Wallace Initiative database can be used for specific studies on such effects, something that has hitherto been difficult to accomplish.

While species might persist in suitable microclimates (e.g., at higher elevations, protected micro-habitats) within areas otherwise apparently climatically unsuitable at a large scale, their overall range would still be smaller than currently. Similarly, species might be absent from apparently climatically suitable areas due to unsuitable microclimates. Thus, over the entire range of the species we would expect these two opposing effects to cancel out, especially for more broadly distributed species.

Analyses of paleoecological data showed that the response of many species to past climatic changes has been range shifts. Nevertheless, there is the potential for genetic variability that might provide adaptive potential for some species. Although the magnitude of this potential is unknown, it is likely to be limited given the rate with which anthropogenic climate change is expected to proceed.

Since the completion of this study it has become evident that emissions are in fact increasing faster than our baseline scenario[65], and that it is therefore conceivable that a business as usual scenario that does not consider climate change mitigation could have significantly higher emissions than the A1B scenario, matching for example, the radiative forcing trajectory associated with the new Representative Concentration Pathway (RCP) 8.5 in which global temperatures exceed 4°C by 2100[66]. Our comparison between climate policies including mitigation with those containing no mitigation may therefore underestimate the potential benefits.

Thus, although future research incorporating the above factors may refine our results, we believe that, on balance, our overall conclusions are likely conservative at the scale of our analysis because when taken altogether these factors are more likely to exacerbate than reduce the projected impacts of climate change.

Supplementary Figures
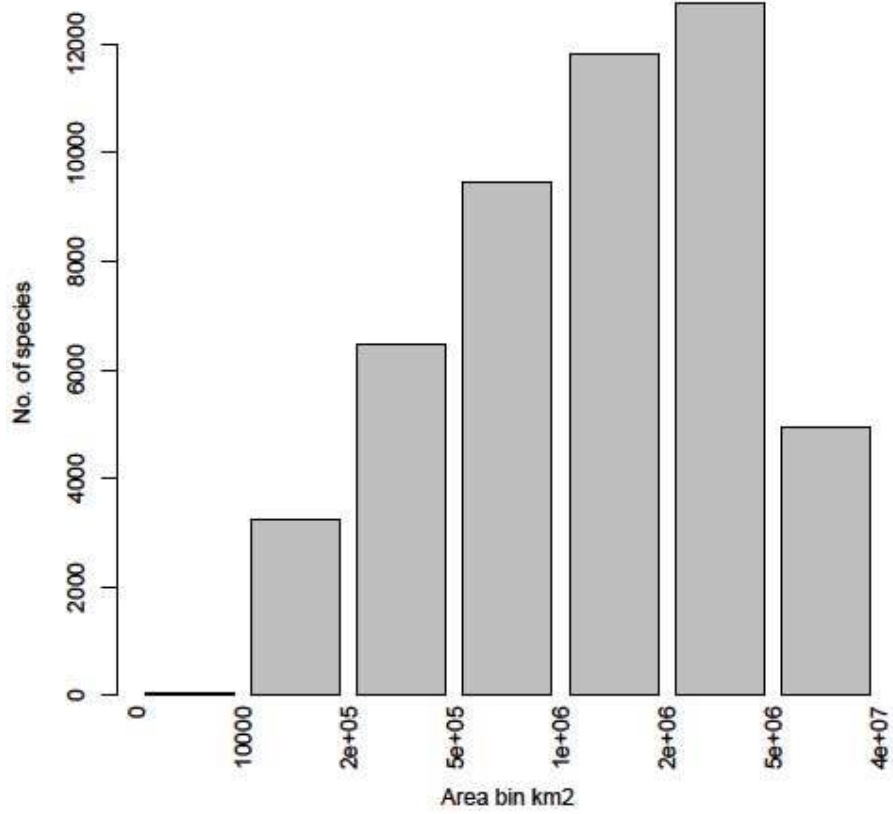
Fig. S1. Range sizes of the 48,786 species analysed

Fig. S2a-f. Proportion of plants (a), animals (b), mammals(c), birds (d), reptiles (e) and amphibians (f) losing ≥50%, ≥70%, ≥90% and ≥99% of their ranges in the 2080s under (i) no (ii) realistic (iii) optimistic dispersal. Red lines show trends for emission pathway SRES A1B without mitigation, whilst green and blue pathways show those with mitigation in which global greenhouse gas emissions peak in 2030 and in 2016, respectively. The vertical axes labelled '<x% current' refer to species losing ≥(100-x)% of their range (e.g. <1% current refers to species losing ≥99% of their range) .
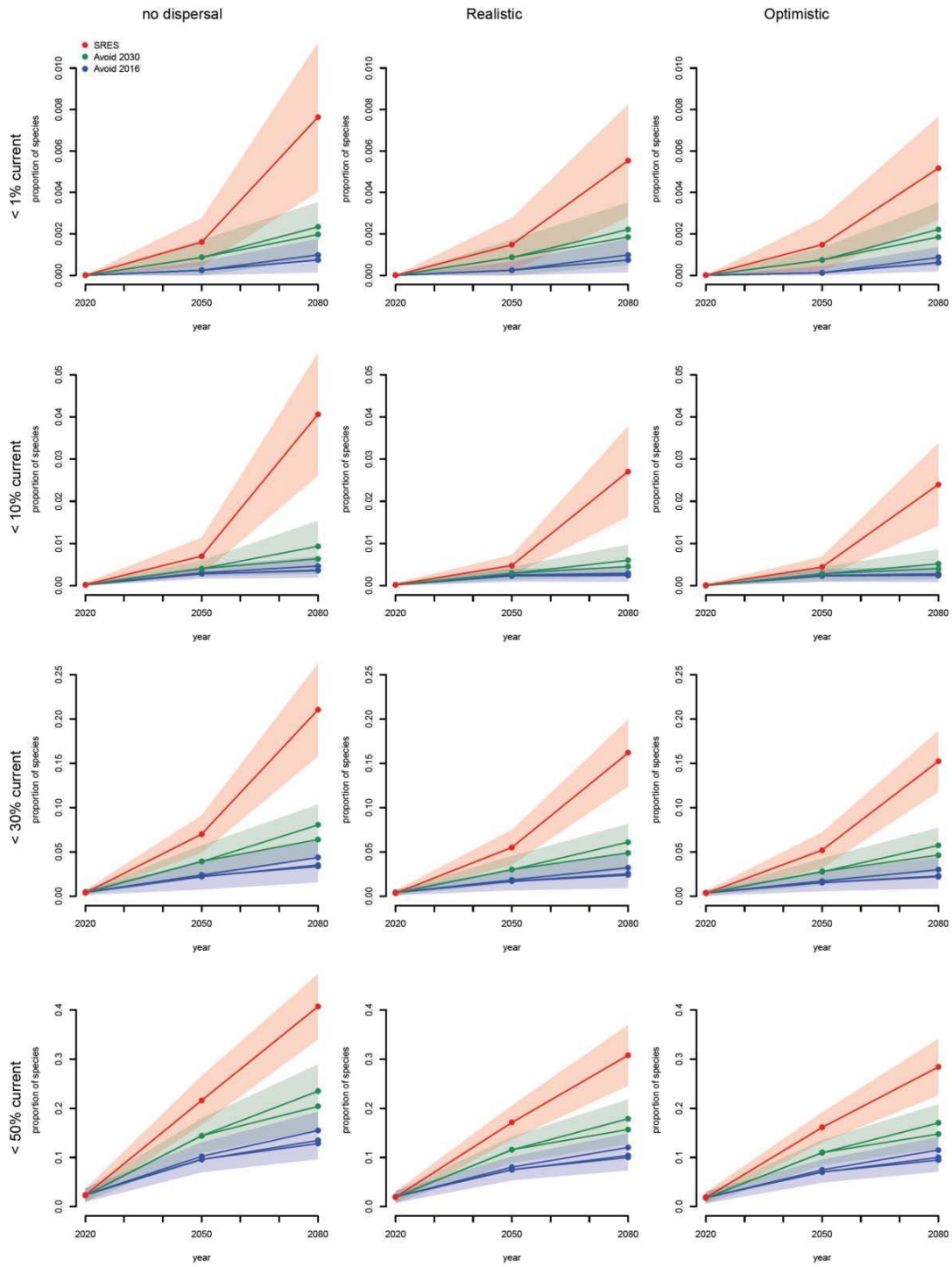
(a) Plants
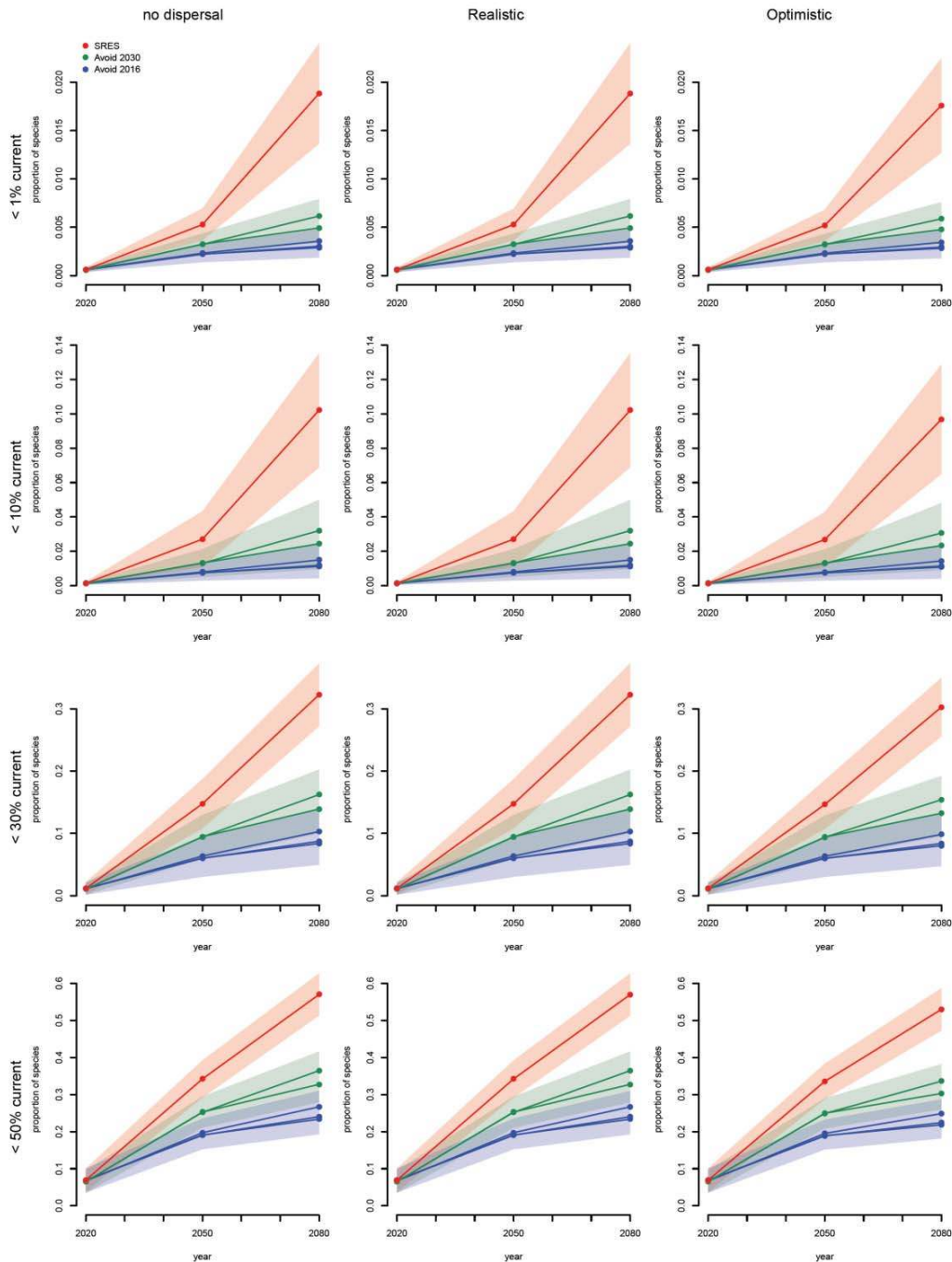
(b) Animals
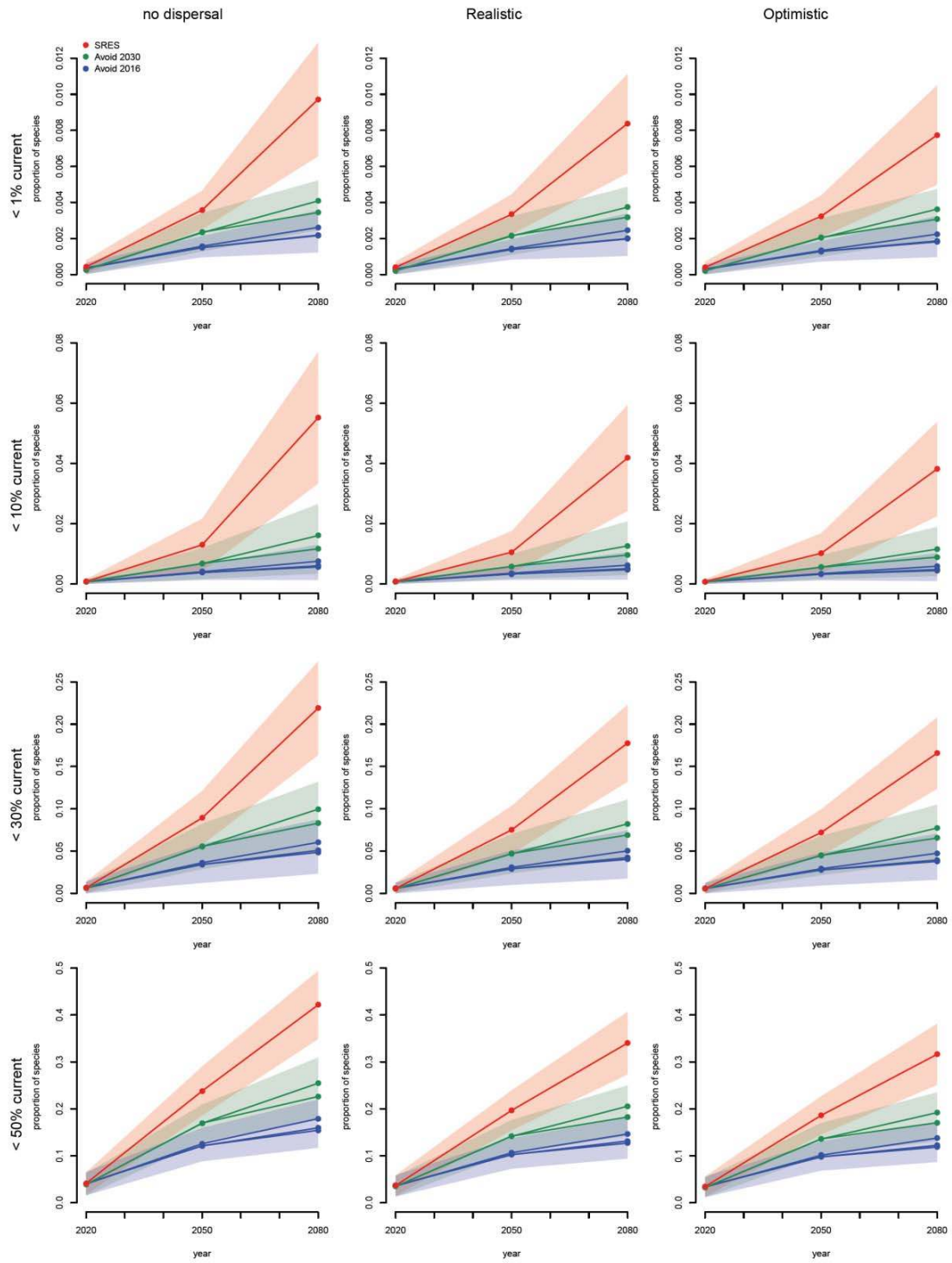
(c) Mammals

(d) Birds
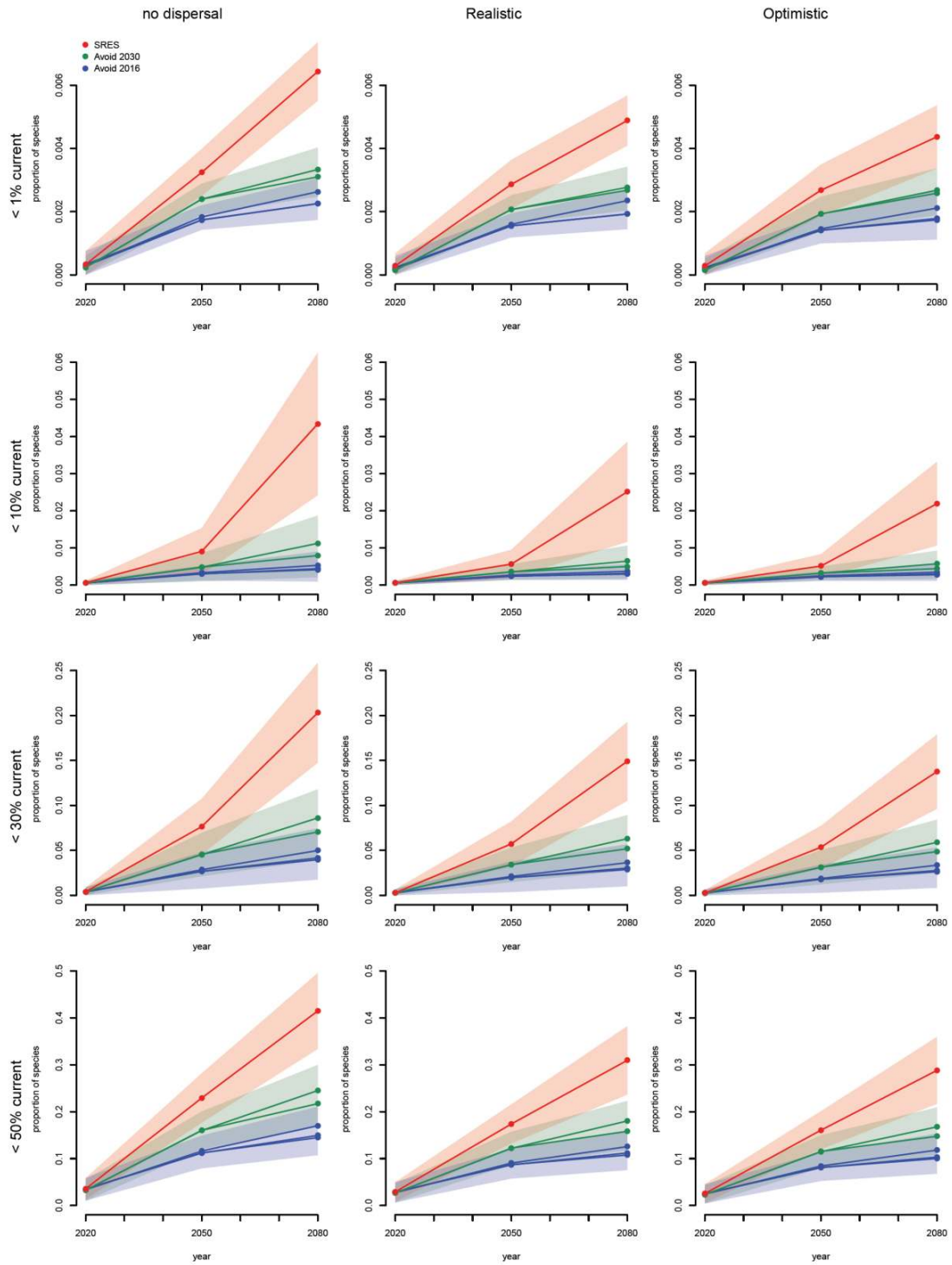
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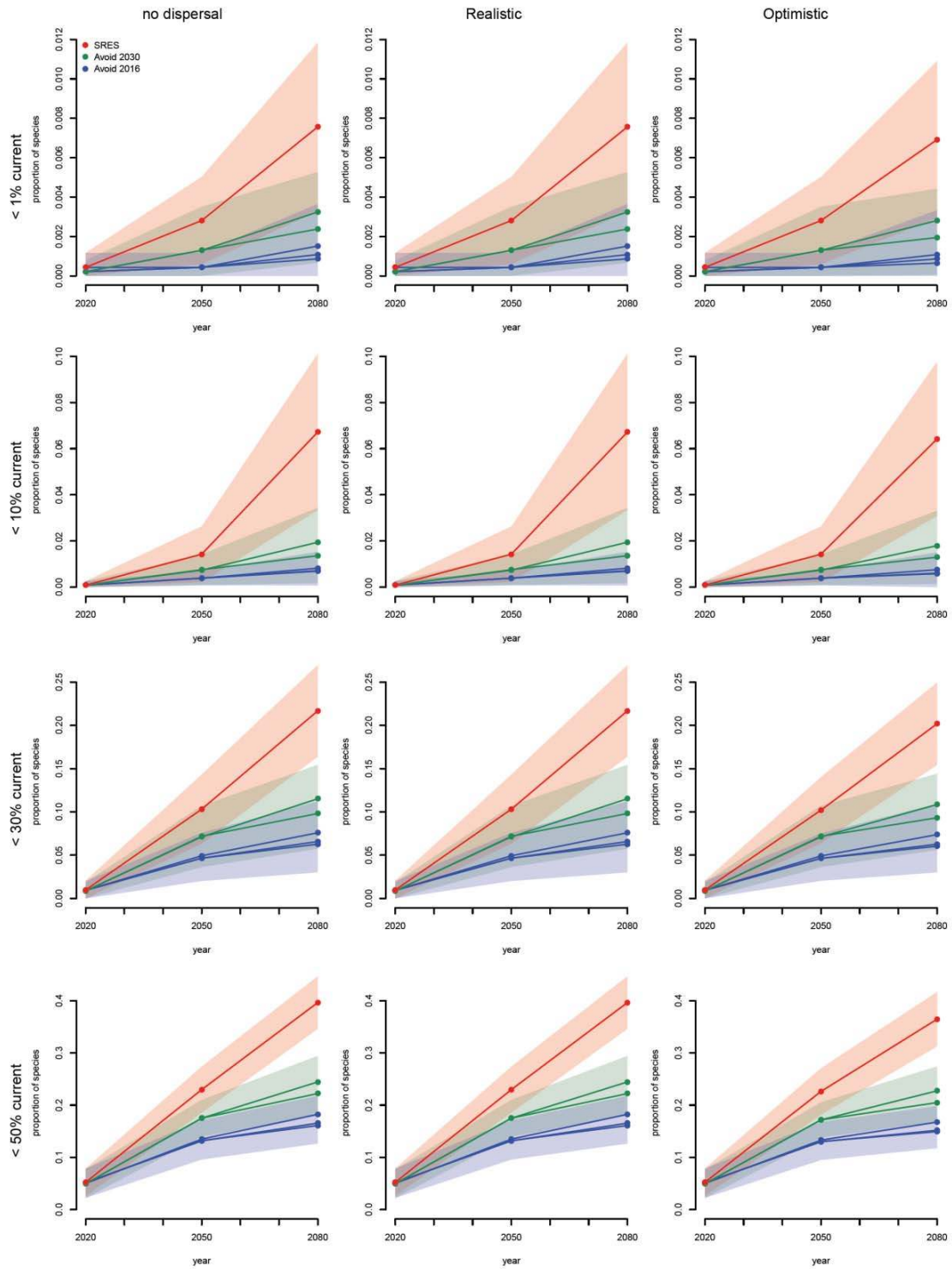
(f) Amphibians
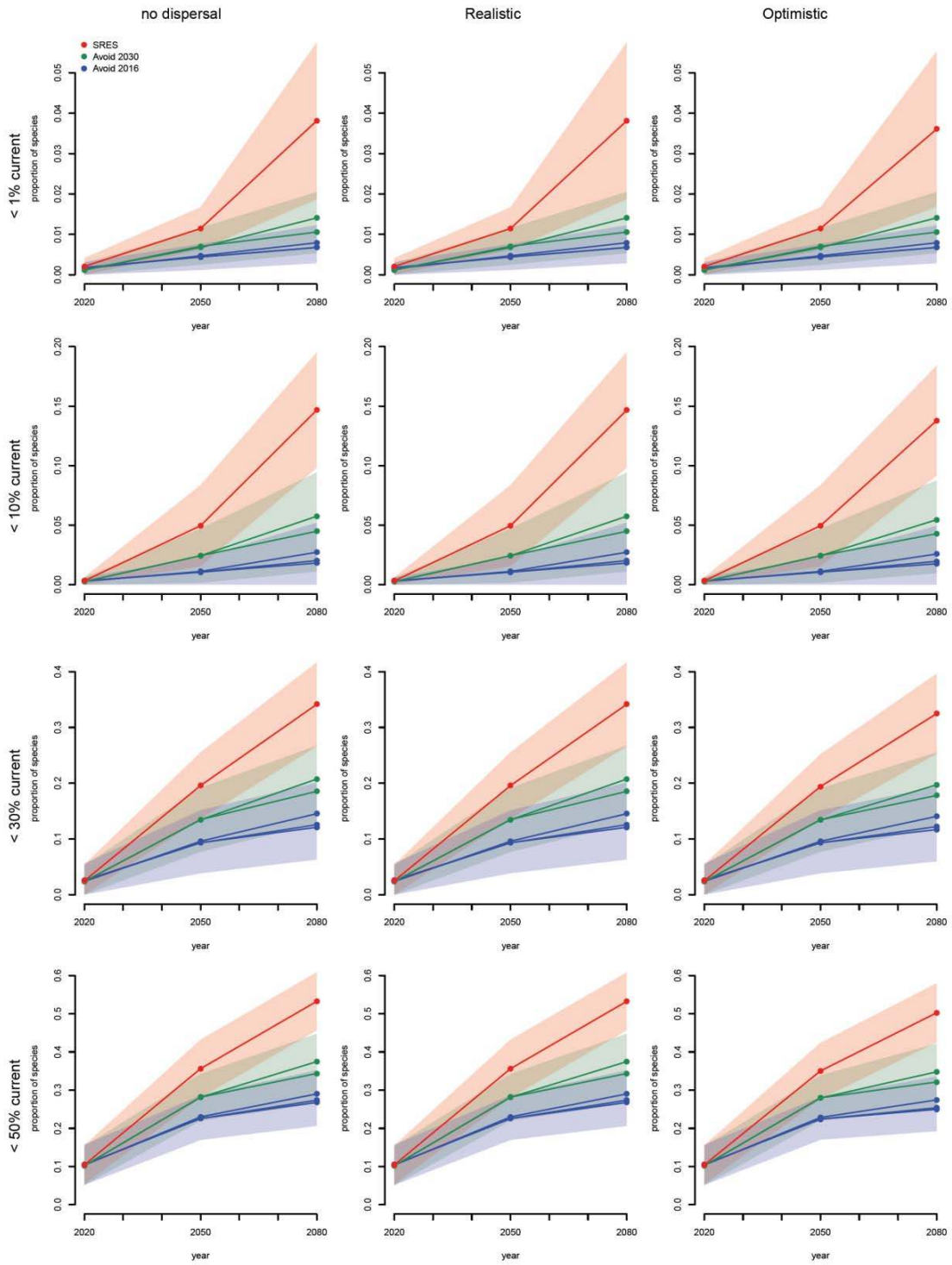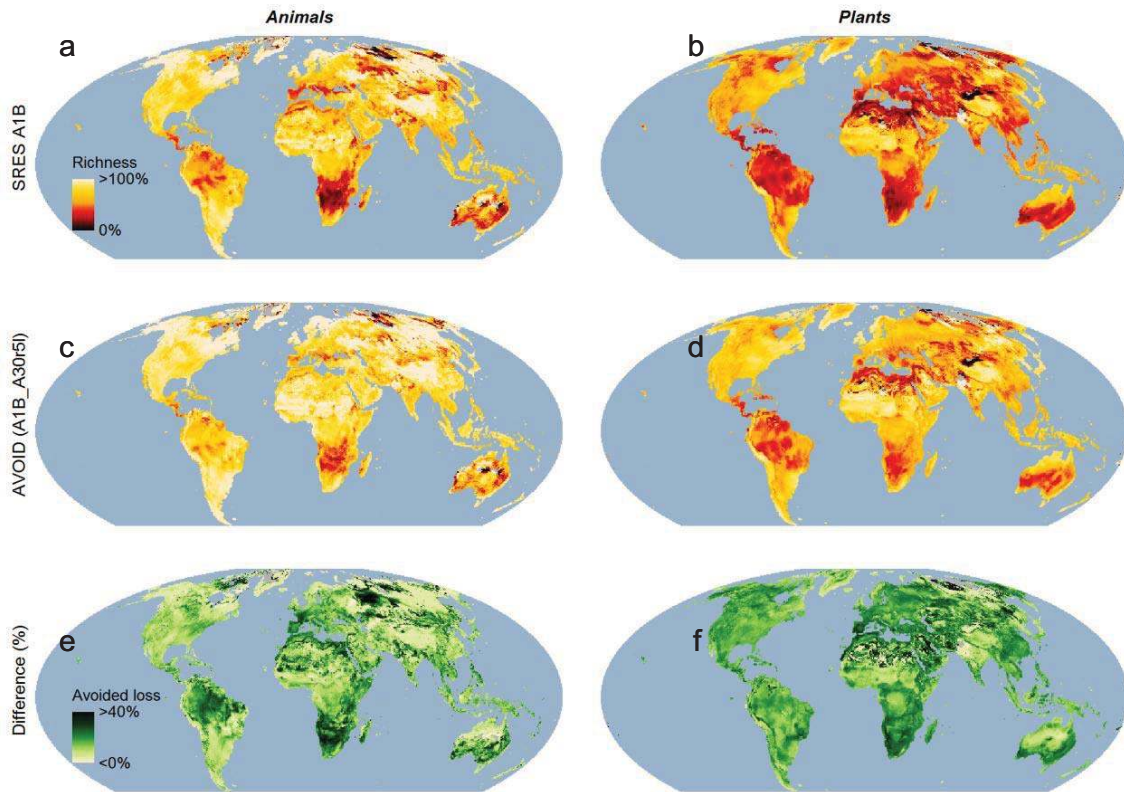
Fig. S3a-f. Species richness of animals (a, c) and plant (b, d) species present in the GBIF network in the 2080s under realistic dispersal for the stringent mitigation case in which global greenhouse gas emissions peak in 2030 and are subsequently reduced at 5% annually (c, d) compared with the no mitigation case SRES A1B (a, b). Panels (e, f) show the species richness change that is avoided by such mitigation. White areas are those where no data exist in the GBIF network.
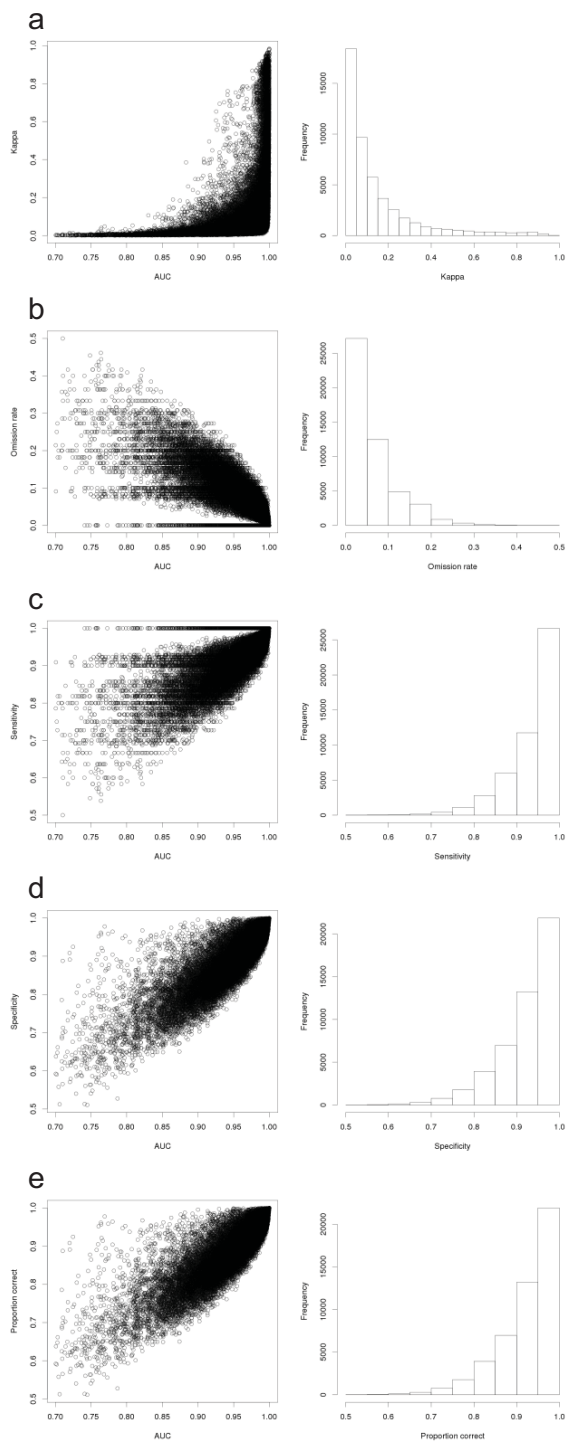
Fig. S4a-e. Threshold-dependent measures of model accuracy (Cohen's kappa (a), omission rate (b), sensitivity (c), specificity (d) and proportion correct (e)) compared with the threshold-independent measure of model accuracy used (AUC). Each plot is accompanied by a matching frequency distribution.

Supplementary Tables

Table S1. Our dispersal scenarios showing dispersal rate assumptions for different taxonomic groups. Superscript numbers refer to the references used to determine the rates.

Dispersal Ability	Plants	Mammals	Birds	Reptiles	Amphibians
No dispersal[35]	0 km/yr	0 km/yr	0 km/yr	0 km/yr	0 km/yr
Realistic	0.1 km/yr[53-56]	1.5 km/yr[48]	1.5 km/yr[41-44]	0.1 km/yr[37,49]	0.1 km/yr[51]
Optimistic	0.5 km/yr[53-56]	3 km/yr[48]	3 km/yr[42-44,67]	0.5 km/yr[37,49]	0.5 km/yr[51]

Table S2a-c Relative importance of climatic driving variables across all taxa and species modelled in MaxEnt (a) proportion of species in each taxa which are more strongly driven by temperature related variables (b,c) relative importance of the climatic driving variables (% variance explained) for species with 10-40 data points for which models were based on 4 climatic variables (b) or more than 40 data points for which models were based on 8 climatic variables (c)

(a)

Taxon	Total number modeled	Number more strongly affected by temperature	% more strongly affected by temperature related factors
Plantae	43,578	27691	64
Mammalia	1,168	790	67
Aves	3,059	2285	54
Reptilia	663	423	63
Amphibia	492	270	55
ALL	48,960	31459	64

(b)

Taxon	AMT	TS	ATR	RS	ALL T-related
Plantae	25	32	25	18	57±23
Mammalia	24	38	22	17	61±24
Aves	24	41	20	14	65±24
Amphibia	21	35	25	29	56±23
Reptilia	20	38	23	19	58±22
ALL	24	33	25	17	57±24

(c)

Taxon	AMT	TS	MTW	MTC	ATR	RS	RWQ	RDQ	ALL T-related
Plantae	14	22	12	12	10	10	8	17	57±21
Mammalia	11	24	8	15	7	10	8	17	60±23
Aves	14	24	10	15	5	10	7	15	64±21
Reptilia	12	12	12	13	6	12	6	17	58±20
Amphibia	11	20	11	10	6	15	6	21	51±19
ALL	13	22	10	12	9	9	8	17	57±22

Table S3 Proportions of plants and animals gaining ≥50% of their current range due to climate change alone by the 2080s in the various emissions scenarios under no dispersal (ND) and realistic dispersal (RD) Ranges show variation arising from use of seven different GCM patterns for creating downscaled climate projections.

	Baseline A1B	Mitigation 2030-2-H	Mitigation 2030-5-L	Mitigation 2016-2-H	Mitigation 2016-4-L	Mitigation 2016-5-L
Most likely global mean temperature rise by 2100 (ºC)	*4.0*	*2.8*	*2.5*	*2.2*	*2.0*	*2.0*
Probability of constraining the temperature rise to 2ºC above pre-industrial levels	*<1%*	*7%*	*17%*	*30%*	*44%*	*45%*
Proportions of plants and animals **gaining 50%** or more of their current range						
Animals (ND)	0%	0%	0%	0%	0%	0%
Animals (RD)	4% (3-5%)	3%	3%	3%	3%	3%
Animals (OD)	8% (7-9%)	7% (6.5-7.5%)	7% (6.5-7.5%)	6% (5.5-6.5%)	6% (5.5-6.5%)	6% (5.5-6.5%)
Plants (ND)	0%	0%	0%	0%	0%	0%
Plants (RD)	0%	0%	0%	0%	0%	0%
Plants (OD)	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%

Table S4a Proportions of plants and animals losing ≥70% of their current range due to climate change alone by the 2080s in the various emissions scenarios under no dispersal (ND) and realistic dispersal (RD) Ranges show variation arising from use of seven different GCM patterns for creating downscaled climate projections.

	Baseline A1B	Mitigation 2030-2-H	Mitigation 2030-5-L	Mitigation 2016-2-H	Mitigation 2016-4-L	Mitigation 2016-5-L
Most likely global mean temperature rise by 2100 (ºC)	*4.0*	*2.8*	*2.5*	*2.2*	*2.0*	*2.0*
Probability of constraining the temperature rise to 2ºC above pre-industrial levels	*<1%*	*7%*	*17%*	*30%*	*44%*	*45%*
Proportions of plants and animals **losing 70%** or more of their current range						
Animals (ND)	22% (16-28%)	10% (7-13%)	8% (5-11%)	6% (3-9%)	5% (2-8%)	5% (2-8%)
Animals (RD)	18% (13-23%)	8% (5-11%)	7% (4-10%)	5% (2-8%)	4% (1-7%)	4% (1-7%)
Animals (OD)	17% (13-21%)	8% (5-11%)	7% (4-10%)	5% (3-7%)	4% (2-6%)	4% (2-6%)
Plants (ND)	32% (27-37%)	16% (12-20%)	14% (10-18%)	10% (6-14%)	9% (6-12%)	8% (5-11%)
Plants (RD)	32% (27-37%)	16% (12-20%)	14% (10-18%)	10% (6-14%)	9% (6-12%)	8% (5-11%)
Plants (OD)	30% (25-35%)	15% (11-19%)	13% (9-17%)	10% (7-13%)	8% (5-11%)	8% (5-11%)

Table S4b Proportions of plants and animals losing ≥90% of their current range due to climate change alone by the 2080s in the various emissions scenarios under no dispersal (ND) and realistic dispersal (RD) Ranges show variation arising from use of seven different GCM patterns for creating downscaled climate projections.

	Baseline A1B	Mitigation 2030-2-H	Mitigation 2030-5-L	Mitigation 2016-2-H	Mitigation 2016-4-L	Mitigation 2016-5-L
Most likely global mean temperature rise by 2100 (ºC)	4.0	2.8	2.5	2.2	2.0	2.0
Probability of constraining the temperature rise to 2ºC above pre-industrial levels	<1%	7%	17%	30%	44%	45%
Proportions of plants and animals **losing 90%** or more of their current range						
Animals (ND)	6% (4-8%)	2% (1-3%)	1% (0-2%)	1% (0.5-1.5%)	1% (0.5-1.5%)	1% (0.5-1.5%)
Animals (RD)	4% (2-6%)	1% (0-2%)	1% (0-2%)	0.6% (0.2-1%)	0.5% (0.1-0.9%)	0.5% (0.2-0.8%)
Animals (OD)	4% (2-6%)	1% (0-2%)	1% (0-2%)	0.6% (0.2-1%)	0.5% (0.1-0.9%)	0.4% (0-0.8%)
Plants (ND)	27% (25-29%)	1% (0-2%)	1% (0-2%)	1% (0.5-1.5%)	1% (0.5-1.5%)	1% (0.5-1.5%)
Plants (RD)	10% (7-13%)	3% (1-5%)	2% (0-4%)	1% (0-2%)	1% (0-2%)	1% (0-2%)
Plants (OD)	10% (7-13%)	3% (1-5%)	2% (1-3%)	1% (0.5-2.4%)	1% (0.3-1.8%)	1% (0.3-1.8%)

Table S4c Proportions of plants and animals losing ≥99% of their current range due to climate change alone by the 2080s in the various emissions scenarios under no dispersal (ND) and realistic dispersal (RD) Ranges show variation arising from use of seven different GCM patterns for creating downscaled climate projections.

	Baseline A1B	Mitigation 2030-2-H	Mitigation 2030-5-L	Mitigation 2016-2-H	Mitigation 2016-4-L	Mitigation 2016-5-L
Most likely global mean temperature rise by 2100 (ºC)	*4.0*	*2.8*	*2.5*	*2.2*	*2.0*	*2.0*
Probability of constraining the temperature rise to 2ºC above pre-industrial levels	*<1%*	*7%*	*17%*	*30%*	*44%*	*45%*
Proportions of plants and animals **losing 99%** or more of their current range						
Animals (ND)	1% (0.7-1.3%)	0.4 (0.3-0.5%)	0.3% (0.2-0.4%)	0.3% (0.2-0.4%)	0.2% (0.1-0.3%)	0.2% (0.1-0.3%)
Animals (RD)	0.8% (0.5-1.1%)	0.4% (0.3-0.5%)	0.3% (0.2-0.4%)	0.2% (0.1-0.3%)	0.2% (0.1-0.3%)	0.2% (0.1-0.3%)
Animals (OD)	0.8% (0.5-1.1%)	0.4% (0.3-0.5%)	0.3% (0.2-0.4%)	0.2% (0.1-0.3%)	0.2% (0.1-0.3%)	0.2% (0.1-0.3%)
Plants (ND)	2% (1.5-2.5%)	0.6% (0.4-0.8%)	0.5% (0.3-0.7%)	00.4% (0.3-0.5%)	0.3% (0.2-0.4%)	0.3% (0.2-0.4%)
Plants (RD)	2% (1.5-2.5%)	0.6% (0.4-0.8%)	0.5% (0.3-0.7%)	0.4% (0.3-0.5%)	0.3% (0.2-0.4%)	0.3% (0.2-0.4%)
Plants (OD)	2% (1.5-2.5%)	0.6% (0.4-0.8%)	0.5% (0.3-0.7%)	0.3% (0.2-0.4%)	0.3% (0.2-0.4%)	0.3% (0.2-0.4%)

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