

Beyond the Limit: The air pollution damages of overshooting temperature

Supplementary Material

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S1 Methodology details

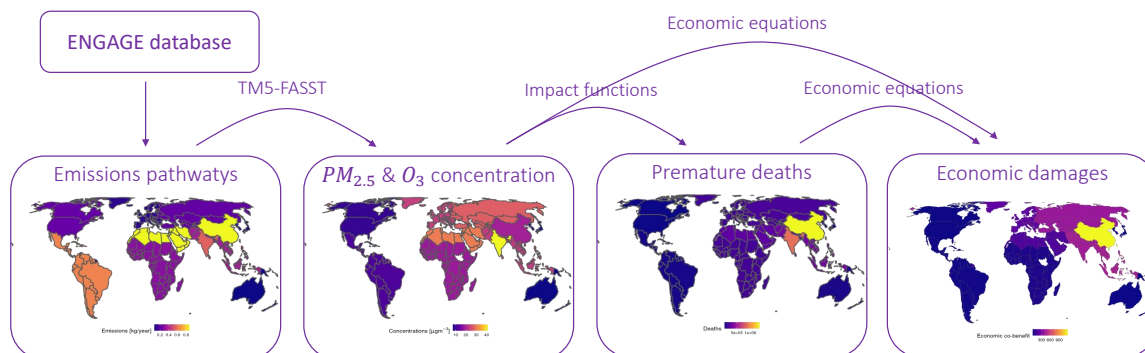


Figure S1: Methodology sketch

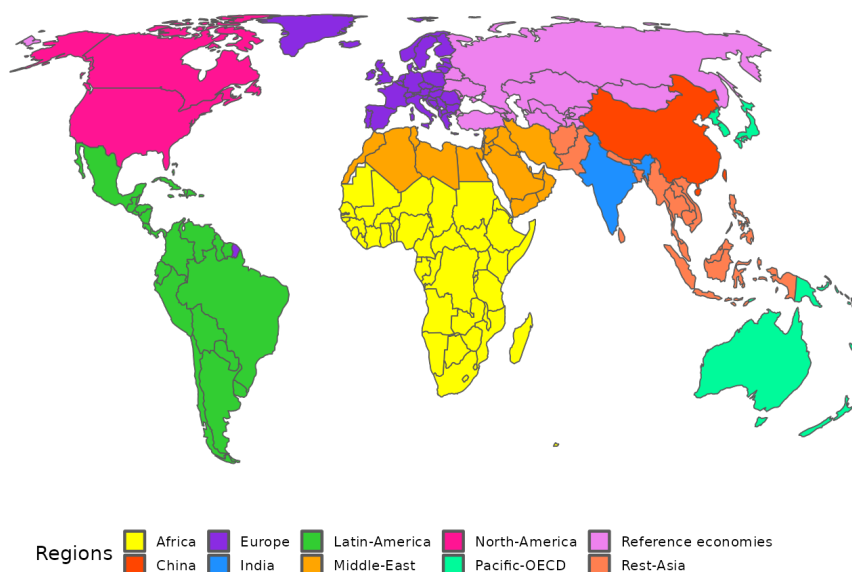


Figure S2: R10 World division

Table S1: R10 regional aggregation

Region	ISO code	Country name
Africa	ZAF	South Africa
Africa	DJI	Djibouti
Africa	COD	Congo, the Democratic Republic of the
Africa	CMR	Cameroon
Africa	LBR	Liberia
Africa	BDI	Burundi
Africa	CAF	Central African Republic
Africa	CPV	Cape Verde
Africa	COM	Comoros
Africa	BWA	Botswana
Africa	MDG	Madagascar
Africa	GHA	Ghana
Africa	RWA	Rwanda
Africa	GMB	Gambia
Africa	IOT	British Indian Ocean Territory
Africa	SEN	Senegal
Africa	COG	Congo
Africa	MWI	Malawi
Africa	MRT	Mauritania
Africa	GAB	Gabon
Africa	MLI	Mali
Africa	NAM	Namibia
Africa	LSO	Lesotho
Africa	ATF	French Southern Territories
Africa	TCD	Chad
Africa	AGO	Angola
Africa	ETH	Ethiopia
Africa	CIV	Côte d'Ivoire
Africa	STP	Sao Tome and Principe
Africa	GNB	Guinea-Bissau
Africa	GNQ	Equatorial Guinea
Africa	SHN	Saint Helena, Ascension and Tristan da Cunha
Africa	SWZ	Swaziland
Africa	MYT	Mayotte
Africa	SYC	Seychelles
Africa	UGA	Uganda
Africa	REU	Réunion
Africa	TZA	Tanzania, United Republic of
Africa	TGO	Togo

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Table S1: R10 regional aggregation (continued)

Region	ISO code	Country name
Africa	NGA	Nigeria
Africa	MOZ	Mozambique
Africa	SDN	Sudan
Africa	ZMB	Zambia
Africa	BEN	Benin
Africa	BFA	Burkina Faso
Africa	BVT	Bouvet Island
Africa	KEN	Kenya
Africa	SOM	Somalia
Africa	ERI	Eritrea
Africa	GIN	Guinea
Africa	NER	Niger
Africa	ZWE	Zimbabwe
Africa	MUS	Mauritius
Africa	SSD	South Sudan
Africa	SLE	Sierra Leone
China	MAC	Macao
China	CHN	China
China	TWN	Taiwan, Province of China
China	HKG	Hong Kong
Europe	ALA	Åland Islands
Europe	GRC	Greece
Europe	ALB	Albania
Europe	GRL	Greenland
Europe	SVK	Slovakia
Europe	LUX	Luxembourg
Europe	SWE	Sweden
Europe	CHE	Switzerland
Europe	LTU	Lithuania
Europe	AUT	Austria
Europe	CZE	Czech Republic
Europe	DEU	Germany
Europe	AND	Andorra
Europe	HUN	Hungary
Europe	DNK	Denmark
Europe	IMN	Isle of Man
Europe	BGR	Bulgaria
Europe	MKD	Macedonia, the former Yugoslav Republic of
Europe	IRL	Ireland
Europe	GGY	Guernsey

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Table S1: R10 regional aggregation (continued)

Region	ISO code	Country name
Europe	MNE	Montenegro
Europe	ESP	Spain
Europe	EST	Estonia
Europe	ITA	Italy
Europe	FIN	Finland
Europe	BEL	Belgium
Europe	NOR	Norway
Europe	FRA	France
Europe	FRO	Faroe Islands
Europe	SJM	Svalbard and Jan Mayen
Europe	ROU	Romania
Europe	GBR	United Kingdom
Europe	LVA	Latvia
Europe	SMR	San Marino
Europe	NLD	Netherlands
Europe	GIB	Gibraltar
Europe	SRB	Serbia
Europe	MCO	Monaco
Europe	SVN	Slovenia
Europe	JEY	Jersey
Europe	ISL	Iceland
Europe	LIE	Liechtenstein
Europe	BIH	Bosnia and Herzegovina
Europe	HRV	Croatia
Europe	POL	Poland
Europe	MLT	Malta
Europe	PRT	Portugal
Europe	VAT	Holy See (Vatican City State)
Europe	CYP	Cyprus
India	IND	India
Latin-America	BRA	Brazil
Latin-America	ECU	Ecuador
Latin-America	ANT	Netherlands Antilles
Latin-America	GLP	Guadeloupe
Latin-America	GTM	Guatemala
Latin-America	ATA	Antarctica
Latin-America	VGB	Virgin Islands, British
Latin-America	VEN	Venezuela, Bolivarian Republic of
Latin-America	CYM	Cayman Islands
Latin-America	BLZ	Belize

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Table S1: R10 regional aggregation (continued)

Region	ISO code	Country name
Latin-America	CUB	Cuba
Latin-America	ATG	Antigua and Barbuda
Latin-America	BRB	Barbados
Latin-America	FLK	Falkland Islands (Malvinas)
Latin-America	BMU	Bermuda
Latin-America	BOL	Bolivia, Plurinational State of
Latin-America	COL	Colombia
Latin-America	GRD	Grenada
Latin-America	VIR	Virgin Islands, U.S.
Latin-America	SLV	El Salvador
Latin-America	ABW	Aruba
Latin-America	GUY	Guyana
Latin-America	CHL	Chile
Latin-America	AIA	Anguilla
Latin-America	HND	Honduras
Latin-America	HTI	Haiti
Latin-America	SUR	Suriname
Latin-America	LCA	Saint Lucia
Latin-America	ARG	Argentina
Latin-America	PRY	Paraguay
Latin-America	TTO	Trinidad and Tobago
Latin-America	MAF	Saint Martin (French part)
Latin-America	CRI	Costa Rica
Latin-America	TCA	Turks and Caicos Islands
Latin-America	BLM	Saint Barthélemy
Latin-America	PRI	Puerto Rico
Latin-America	DMA	Dominica
Latin-America	NIC	Nicaragua
Latin-America	JAM	Jamaica
Latin-America	KNA	Saint Kitts and Nevis
Latin-America	PER	Peru
Latin-America	DOM	Dominican Republic
Latin-America	SGS	South Georgia and the South Sandwich Islands
Latin-America	MSR	Montserrat
Latin-America	BHS	Bahamas
Latin-America	GUF	French Guiana
Latin-America	PAN	Panama
Latin-America	MTQ	Martinique
Latin-America	VCT	Saint Vincent and the Grenadines
Latin-America	URY	Uruguay

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Table S1: R10 regional aggregation (continued)

Region	ISO code	Country name
Latin-America	MEX	Mexico
Middle-East	DZA	Algeria
Middle-East	BHR	Bahrain
Middle-East	YEM	Yemen
Middle-East	MAR	Morocco
Middle-East	LBN	Lebanon
Middle-East	OMN	Oman
Middle-East	ARE	United Arab Emirates
Middle-East	ISR	Israel
Middle-East	PSE	Palestinian Territory, Occupied
Middle-East	IRN	Iran, Islamic Republic of
Middle-East	EGY	Egypt
Middle-East	ESH	Western Sahara
Middle-East	KWT	Kuwait
Middle-East	SAU	Saudi Arabia
Middle-East	QAT	Qatar
Middle-East	LBY	Libyan Arab Jamahiriya
Middle-East	JOR	Jordan
Middle-East	TUN	Tunisia
Middle-East	SYR	Syrian Arab Republic
Middle-East	IRQ	Iraq
North-America	CAN	Canada
North-America	SPM	Saint Pierre and Miquelon
North-America	USA	United States
Pacific-OECD	PRK	Korea, Democratic People's Republic of
Pacific-OECD	KOR	Korea, Republic of
Pacific-OECD	JPN	Japan
Pacific-OECD	ASM	American Samoa
Pacific-OECD	SLB	Solomon Islands
Pacific-OECD	NIU	Niue
Pacific-OECD	NZL	New Zealand
Pacific-OECD	FJI	Fiji
Pacific-OECD	HMD	Heard Island and McDonald Islands
Pacific-OECD	PYF	French Polynesia
Pacific-OECD	TKL	Tokelau
Pacific-OECD	MHL	Marshall Islands
Pacific-OECD	TLS	Timor-Leste
Pacific-OECD	FSM	Micronesia, Federated States of
Pacific-OECD	COK	Cook Islands
Pacific-OECD	WLF	Wallis and Futuna

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Table S1: R10 regional aggregation (continued)

Region	ISO code	Country name
Pacific-OECD	AUS	Australia
Pacific-OECD	PNG	Papua New Guinea
Pacific-OECD	NFK	Norfolk Island
Pacific-OECD	TON	Tonga
Pacific-OECD	NRU	Nauru
Pacific-OECD	MNP	Northern Mariana Islands
Pacific-OECD	UMI	United States Minor Outlying Islands
Pacific-OECD	GUM	Guam
Pacific-OECD	VUT	Vanuatu
Pacific-OECD	CXR	Christmas Island
Pacific-OECD	KIR	Kiribati
Pacific-OECD	PLW	Palau
Pacific-OECD	NCL	New Caledonia
Pacific-OECD	PCN	Pitcairn
Pacific-OECD	WSM	Samoa
Pacific-OECD	TUV	Tuvalu
Reforming economies	TUR	Turkey
Reforming economies	TKM	Turkmenistan
Reforming economies	AZE	Azerbaijan
Reforming economies	KAZ	Kazakhstan
Reforming economies	ARM	Armenia
Reforming economies	KGZ	Kyrgyzstan
Reforming economies	BLR	Belarus
Reforming economies	GEO	Georgia
Reforming economies	MNG	Mongolia
Reforming economies	RUS	Russian Federation
Reforming economies	UKR	Ukraine
Reforming economies	TJK	Tajikistan
Reforming economies	MDA	Moldova, Republic of
Reforming economies	UZB	Uzbekistan
Rest-Asia	IDN	Indonesia
Rest-Asia	PAK	Pakistan
Rest-Asia	LKA	Sri Lanka
Rest-Asia	NPL	Nepal
Rest-Asia	MDV	Maldives
Rest-Asia	BGD	Bangladesh
Rest-Asia	BTN	Bhutan
Rest-Asia	AFG	Afghanistan
Rest-Asia	THA	Thailand
Rest-Asia	LAO	Lao People's Democratic Republic

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Table S1: R10 regional aggregation (continued)

Region	ISO code	Country name
Rest-Asia	BRN	Brunei Darussalam
Rest-Asia	MYS	Malaysia
Rest-Asia	PHL	Philippines
Rest-Asia	SGP	Singapore
Rest-Asia	MMR	Myanmar
Rest-Asia	KHM	Cambodia
Rest-Asia	CCK	Cocos (Keeling) Islands
Rest-Asia	VNM	Viet Nam

Table S2: Temperature increase and carbon budget relation.

Temperature increase	Carbon budgets (GtCO ₂)
Range around 1.5°C	200, 300, 400, 500, 600, 700, 800, 900 (< 1000)
Range between 1.5-2°C	1000, 1200, 1400, 1600, 1800, 2000
Paris non-compliant	(> 2000) 2500, 3000

S2 Premature mortality computation

Taking as input the concentration of each pollutant per region and year, it is possible to estimate several health metrics. For instance, the premature deaths, the years of life lived with disability (YLDs), the years of life lost (YLLs), or the disability-adjusted life years (DALYs), among others [18]. All of them need the Population Attributable Fraction (PAF) value, that links the concentrations with the health risks. Subsequently, the impact made by it is the same on each health metric, and hence, it is only necessary to study one of them to understand the uncertainty given by this sensitive factor. In this project, the focus is on premature deaths.

To compute the premature deaths due to air pollution we consider the following formula:

$$\Delta Mort = y_0 \cdot PAF \cdot pop \quad (1)$$

provided by several references such as [3] and widely used in worldwide studies. The variable y_0 refers to the baseline mortality, whereas pop accounts for the exposed population. PAF is the acronym for Population Attributable Fraction. Consequently, $\Delta Mort$ is the proportional reduction in population mortality that would occur if exposure to a risk factor were reduced to an alternative ideal exposure scenario [23].

As previously explained, $PM_{2.5}$ is responsible for IHD, STROKE, LC, COPD, and ALRI. On the other hand, O_3 has a direct impact on COPD. Except for ALRI, which affects children (< 5 years old), the other causes of death are studied among the adult population (considered as ≥ 25 for the sake of consistency). Therefore, the exposed population value will be different for ALRI than for the rest of the illnesses.

The PAF can be obtained as

$$PAF = \frac{RR - 1}{RR} \quad (2)$$

as described in [26], where RR refers to Relative Risk, which is the ratio of the probability of an outcome in an exposed group to the probability of an outcome in an unexposed group. This value is different for each disease and concentration exposure. Importantly, there are multiple ways to compute it, especially for $PM_{2.5}$ exposure. The selected parameters to compute them and the methods chosen for the analysis are gathered in Table S3.

One of the simplest and more traditional methods to compute the relative risk for both $PM_{2.5}$ and O_3 is the Log-Linear (LL) model, developed approximately one-decade ago [21]:

$$LL(X) = \exp\{\beta(X - X_0)\}, \quad (3)$$

where β is the parameter that characterises its shape, X is the concentrations exposure, and X_0 is the counterfactual value. This formulation has some difficul-

ties when dealing with high levels of outdoor $\text{PM}_{2.5}$ since it is usually assumed no additional risk beyond $30 \mu\text{g m}^{-3}$ [6].

This function only depends on the difference in concentrations, $X - X_0$, not on their individual magnitudes. This fact is also present in other RR functions. There is a large consensus to use this function for O_3 exposure [9]. Since the GBD used it in 2010, it was reported by many authors [19, 21].

At the same moment, *Cohen et al.* [8] suggested a rational function for $\text{PM}_{2.5}$ exposure:

$$RR(X) = \left(\frac{X + 1}{X_0 + 1} \right)^\beta, \quad (4)$$

where the coefficient β is chosen according to the disease, the region, the educational level, and the economic status among others.

The Integrated Exposure-Response (IER) model, developed by the GBD, has become the state-of-the-art exposure-response model for estimating the $\text{PM}_{2.5}$ mortality relative risk since its introduction in 2013 [6, 7, 13]. It has the following formulation,

$$IER(X) = 1 - \nu(1 - \exp\{-\omega z^\delta\}), \quad z = \max(0, X - X_0), \quad (5)$$

where the parameters (ν, ω, δ) are estimated using non-linear regression methods. This formulation allows us to deal with arbitrary high $\text{PM}_{2.5}$ expositions while considering other sources of $\text{PM}_{2.5}$, particularly, secondhand and active smoking [6]. However, it assumes equal toxicity per unit dose across these non-outdoor sources, as well as presumes a counterfactual value, which adds uncertainty to the model [5].

To relax these assumptions, the Global Exposure Mortality Model (GEMM) [6] was developed, aiming to model the mortality due to $\text{PM}_{2.5}$ using data within any specific cohort.

$$GEMM(z) = \exp \left\{ \frac{\theta \log \left(\frac{z}{\alpha + 1} \right)}{1 + \exp\left\{-\frac{z - \mu}{\nu}\right\}} \right\}, \quad z = X - \min(X). \quad (6)$$

The parameters (θ, μ, τ) are estimated from data [6] α controls the amount of curvature, with less curvature for larger values of α . The parameters are constrained such that the change in relative risk for higher concentrations declined as concentrations increased. Thus, the predictions of relative risk beyond the observed exposure range have a logarithmic form with diminishing changes in relative risk as exposure increases [6]. This formulation endogenizes the counterfactual value, considering it simply as the minimum concentration of $\text{PM}_{2.5}$ in the study set.

In this study, when the counterfactual value was not specified, we followed the guidance of the GBD 2019 for $\text{PM}_{2.5}$, that is, a uniform distribution $U(2.4\text{--}5.9) \mu\text{g m}^{-3}$; and the uniform distribution defined by the GBD 2017 for O_3 , which is $U(33.3\text{--}41.9)$ ppb.

Following the literature, for the premature mortality estimates, we used the $\text{PM}_{2.5}$ annual average daily exposure and the O_3 sixth-month or three-months (depending on the equation) hourly maximum concentration.

There are two extra points that we considered: on the one hand, the GEMM model considered by [5] calibrated the parameters considering the results of a study where 15 research groups independently conducted analyses to characterize the shapes of $\text{PM}_{2.5}$ –mortality associations in their respective cohorts. Among these 15 cohorts was a study of Chinese men with long-term outdoor $\text{PM}_{2.5}$ exposures up to $84 \mu\text{g m}^{-3}$, thus greatly extending the range of exposures observed in cohort studies conducted in high-income countries in Europe and North America. Therefore, they did the study both including and not including them, and consequently, in this project, two separate sets are considered. On the other hand, in 2016, the GBD together with the WHO [24] re-calibrated the IER model’s parameters 5 from the 2013 ones. The provided data was especially extensive since they used a spatial resolution ($1^\circ \times 1^\circ$) globally to estimate the exposures of $\text{PM}_{2.5}$. Therefore, 1000 values were present for each cause of death and age group. We determine to split the data using the counterfactual exposure. In particular, three groups are created according to the GBD $\text{PM}_{2.5}$ -counterfactual distribution:

$$\text{LOW} = (2.4, 3.56), \quad \text{MEDIUM} = (3.57, 4.73), \quad \text{HIGH} = (4.74, 5.9).$$

Then, by illness, the median of each parameter and the counterfactual value was considered.

Table S3: Relative Risk parameters with 95% CI

Ref.	Publication's year	Pollutant	Method	Levels	Counterfactual value	Parameter	ALRI	LC	IHD	STROKE	COPD	CP
Burnett et al. 2018 [5]	2018	PM _{2.5}	GEMM	6	WITH	2.40 µg m ⁻³	θ	0.2942 (0.23273,0.35567)	0.2969 (0.27903,0.31477)	0.2720 (0.19503,0.34897)	0.2510 (0.18338,0.31862)	
							α	6.2	1.9	6.2	6.5	
							μ	9.3	12.0	16.7	2.5	
							ν	29.8	40.2	23.7	32.0	
					WITHOUT	2.40 µg m ⁻³	θ	0.2626 (0.18411,0.34109)	0.2543 (0.20841,0.30019)	0.1873 (0.10299,0.27161)	0.2095 (0.14225,0.27675)	
							α	6.7	4.9	6.2	7.2	
							μ	11.0	-21.1	14.5	2.0	
							ν	16.5	17.7	14.4	14.7	
					HIGH	5.29 µg m ⁻³ (5.27,5.31)	α	73.1 (65.5,80.3)	6.40 (6.04,6.72)	2.73 (2.62,2.84)	16.3 (14.6,18.0)	
							β	0.000195 (0.000174,0.000215)	0.0123 (0.0117,0.0131)	0.0141 (0.0135,0.0147)	0.0023 (0.00204,0.00264)	
							δ	0.773 (0.766,0.779)	0.334 (0.331,0.337)	0.432 (0.427,0.437)	0.579 (0.564,0.589)	
					MEDIUM	4.18 µg m ⁻³ (4.17,4.21)	α	71.5 (64.7,76.1)	6.16 (5.91,6.50)	2.72 (2.61,2.83)	15.4 (14.0,18.1)	
							β	0.000213 (0.000196,0.000239)	0.0131 (0.0124,0.0138)	0.0141 (0.0137,0.0147)	0.00228 (0.00206,0.00250)	
							δ	0.773 (0.766,0.782)	0.332 (0.329,0.335)	0.429 (0.425,0.435)	0.579 (0.568,0.589)	
Burnett et al. 2014 [7]	2014	PM _{2.5}	IER	5	LOW	3.00 µg m ⁻³ (2.92,3.05)	α	70.4 (63.4,75.6)	6.61 (6.31,6.97)	2.86 (2.75,2.99)	14.8 (13.6,16.1)	
							β	0.000205 (0.000185,0.000225)	0.0123 (0.0116,0.0129)	0.0142 (0.0136,0.0147)	0.00229 (0.00210,0.00254)	
							δ	0.777 (0.767,0.786)	0.333 (0.330,0.335)	0.425 (0.419,0.430)	0.575 (0.560,0.591)	
							ALRI: 5.553867502 (3.175877368,10.65856447)					
					STROKE	7.261807718 (6.53033859,8.921692107)	α	1.97378648 (1.436904185,2.935465288)	15.67636977 (12.30776596,47.47159043)	1.190330928 (0.947050981,1.228481327)	1.16632796 (1.410432389,1.780359822)	14.10220781 (7.440843463,14.99199458)
							β	0.002847675 (0.001440037,1.373370217)	0.001073919 (0.000864294,0.000131904)	0.0750978 (0.025256397,0.05795739)	0.011865371 (0.016309476,0.018028539)	0.001206578 (0.002112071,0.000493862)
							δ	1.209294599 (0.879980508,1.373370217)	0.765861621 (0.659865243,1.020917868)	0.374809182 (0.4164409,0.934215573)	1.202946339 (0.477576651,1.210566232)	0.680348423 (0.648260937,0.851276683)
							COPD: 5.787549667 (4.999997811,6.759656531)					
					COPD	U[2.4,5.9] µg m ⁻³	β	0.0104360 (0.00392207,0.0165514)	0.010436 (0.01043600,0.0182322)	0.0139762	0.0086178 (0.00582689,0.0113329)	
							δ	0.23218 (0.08563,0.37873)			0.15515 (0.0562,0.2541)	
							0.0083382 (0.0030459,0.013926)					
Jernett et al. 2009 [19]	2009	O ₃	LL	3	U[33.3,41.9] ppb	β	0.0039221 (0.00099503,0.0064851)					

S3 Economic damages computation

The economic damage can be estimated by taking into account either the concentrations of each pollutant or the premature deaths. *Economic damage* refers to the policy damage, i.e., the economic gain derived from applying certain policies p (NZ or EoC) in contrast with the reference. We compute it by each region i and year t . All values were homogenized to US\$ 2010.

One of the most extended ways to compute the economic damage derived from premature mortalities is the Value of Statistical Life (VSL) [15] [25, Chapter 2.3] [29]. It is the local trade-off rate between fatality risk and money. When the trade-off values are derived from choices in market contexts, the VSL serves as both a measure of the population's willingness to pay for risk reduction and the marginal cost of enhancing safety. This equation contains an elasticity constant, which its choice derives uncertainty as well [28].

The VSL values were down-scaled by year and region from the EU 2005 GDP (PPP) per capita value published by the OCED.

$$VSL_{i,t,p} = VSL_{R10EUROPE,2005} \cdot \left(\frac{GDPperCapita_{i,t,p}}{GDPperCapita_{R10EUROPE,2005}} \right)^\alpha, \quad \alpha \in \{0.8, 1, 1.2\}, \quad (7)$$

This value allowed us to estimate the avoided economic damage for each region, year, and climate policy:

$$AvoidedDamage_{i,t,p} = VSL_{i,t,p} \cdot \Delta Mort_{i,t,p} - VSL_{i,t,REF} \cdot numDeaths_{i,t,REF}, \quad (8)$$

where $numDeaths_{i,t,p}$ refers to the number of premature deaths due to air pollution in the region i in year t following policy p .

Recently, *Dechezleprêtre et al.* [10] established an econometric model with data from the European region. It focuses on the impact of air pollution on the GDP value per capita. It considers some other factors, such as weather covariates and thermal inversions, which have been wiped off for our purpose. Thus, the equation is simply

$$\Delta \ln GDP_{i,t} = \gamma \Delta AP_{i,t}, \quad (9)$$

where $AP_{i,t}$ represents the concentration of $PM_{2.5}$ $\mu g m^{-3}$ population-weighted of region i in year t , and γ is interpreted as a growth rate. Like in the VSL case, it is possible to specifically obtain the parameter γ for any region i , year t , and policy p using a down-scaling procedure:

$$\gamma_{i,t,p} = \gamma_{R10EUROPE} \cdot \left(\frac{GDPperCapitaEngage_{i,t,p}}{GDPperCapitaEngage_{R10EUROPE}} \right)^\alpha, \quad \alpha \in \{0.8, 1, 1.2\}, \quad (10)$$

where $\gamma = -0.8$ for R10EUROPE between 2010 and 2015 according to the literature [10]. Thus, we considered the mean of the GDP per capita in the ENGAGE database for those years for the down-scaling.

Using the Taylor approximation of order one, we re-wrote equation 9:

$$\log(y_t) - \log(x_t) \approx \frac{y_t - x_t}{x_t}. \quad (11)$$

Through Dechezleprêtre equation's interpretation, we directly computed the avoided damage between a policy p and the reference policy REF for the same year t and region i .

$$AvoidedDamage_{i,t,p} = GDP_{i,t,REF} \cdot \gamma \cdot (AP_{i,t,p} - AP_{i,t,REF}). \quad (12)$$

In 2021, *Dong et al.* [11] developed another econometric model, this time, based on China. The aim of the model is to estimate the economic growth considering air pollution and other factors. Like in Dechezleprêtre's model, we only account for the air pollution factor since we aim to see the impact of this item solely. Thus, the GDP growth equation for region i , year t , and policy p is

$$GDPgrowthNew_{i,t,p} = GDPgrowthBasis_{i,t,p} + \beta AP_{i,t,p}, \quad (13)$$

where AP represents the $PM_{2.5} \mu g m^{-3}$ concentration population-weighted, β is the air pollution impact coefficient, and $GDPgrowthBasis_{i,t,p}$ refers to the standard growth rate of the GDP per capita, without considering the air pollution effects. Notice that the last term ($\beta AP_{i,t}$) reduces the GDP growth since β is always negative. Hence, as higher the air pollution concentration, the more severe the GDP growth reduction is. Once again, the parameter β was down-scaled by region and year based on the literature data from China between 2010 and 2015:

$$\beta_{i,t,p} = \beta_{R10CHINA} \cdot \left(\frac{GDPperCapitaEngage_{i,t,p}}{GDPperCapitaEngage_{R10CHINA}} \right)^\alpha, \quad \alpha \in \{0.8, 1, 1.2\}, \quad (14)$$

setting $\beta_{R10CHINA} = -0.02108$ and considering the $GDPperCapitaEngage_{R10CHINA}$ as the mean of the GDP per capita in China between 2010 and 2015. Then, using equation 13 we obtain the GDP (PPP) per capita considering the air pollution impact:

$$GDPnew_{i,t,p} = GDPengage_{i,t,p} \cdot (1 + GDPgrowthNew_{i,t,p}). \quad (15)$$

Finally, the avoided economic damage is

$$AvoidedDamage_{i,t,p} = GDPnew_{i,t,p} - GDPnew_{i,t,REF}. \quad (16)$$

The last method we considered is the Human Capital Loss (HCL), extensively used in other air pollution studies [30, 22]. It refers to the loss of human capital due to severe illness or premature death due to PM_{2.5} pollution. The equation is

$$HCL_{i,t,p} = HC_{i,t,p} \cdot \Delta Mort_{i,t,p}, \quad (17)$$

where $\Delta Mort_{i,t,p}$ are the premature deaths of adult population due to air pollution and HC refers to the Human Capital, computed as

$$HC_{i,t,p} = \sum_{i=1}^t GDP_{i,t,p} \cdot \left(\frac{1+\alpha}{1+\gamma} \right)^i, \quad (18)$$

where $GDP_{i,t,p}$ is the GDP per capita, α represents the annual GDP growth rate, γ is the elasticity value (0.06, 0.08, and 0.1 for this study), and t indicates the remaining life expectancy.

Using this equation, the avoided economic damage is

$$AvoidedDamage_{i,t,p} = (GDP_{i,t,REF} - HCL_{i,t,REF}) - (GDP_{i,t,p} - HCL_{i,t,p}). \quad (19)$$

S4 Kolmogorov-Smirnov test

We consider the Kolmogorov-Smirnov two-sample test, which is an adaptation of the non-parametric Kolmogorov-Smirnov one-sample test. It compares the empirical distribution function of two samples. Intuitively, the test answers the question “What is the probability that these two sets of samples were drawn from the same (but unknown) probability distribution?”

Consider two data samples of size m and n from continuous populations F_X and F_Y denoted by

$$X_1, X_2, \dots, X_m, \quad \text{and} \quad Y_1, Y_2, \dots, Y_n.$$

Their respective empirical continuous distribution functions, denoted by $S_m(x)$ and $S_n(x)$, are defined as

$$S_i(x) = \begin{cases} 0 & \text{if } x < X_1 \\ \frac{k}{i} & \text{if } X_k \leq x < X_{k+1}, \quad k = 1, 2, \dots, i-1, \\ 1 & \text{if } x \geq X_i, \end{cases} \quad \text{where } i = m, n.$$

The hypotheses of the test are the following:

$$\begin{cases} H_0 : F_X(x) = F_Y(x) \quad \forall x, \\ H_1 : F_X(x) \neq F_Y(x) \quad \text{for some } x, \end{cases}$$

which means that if the null hypothesis is true, both population distributions are identical and the samples are from the same population. Thanks to Glivenko-Cantelli theorem [16], we know that as m (analogously n) increases, the step function $S_m(x)$ approaches the true distribution function $F_X(x)$. Therefore, for large samples' size, the deviations between the true function and its statistical image, $|S_m(x) - F_X(x)|$, should be small for all values of x . This result suggests that the statistic

$$D_{m,n} = \max_x |S_m(x) - S_n(x)|$$

is, for any m and n , a reasonable measure of the accuracy of our estimate, and the rejection region is in the upper tail, defined by

$$D_{m,n} \geq c_\alpha, \quad \text{where } P(D_{m,n} \geq c_\alpha | H_0) \leq \alpha.$$

Once again, as a consequence of Glivenko-Cantelli theorem [16], the test is consistent and the p-value is

$$p = P(D_{m,n} \geq D_0 | H_0),$$

where D_0 is the observed value of the two-sample K-S statistic [16].

For our purpose, the significance level is set to 0.05, and the two data samples considered are the values of emissions, concentrations, premature deaths, and economic damages estimated by the NZ and EoC climate policies. Remark each test is run by grouping the regions, pollutants, carbon budget intervals, year, and method (relative risk function or economic damage function).

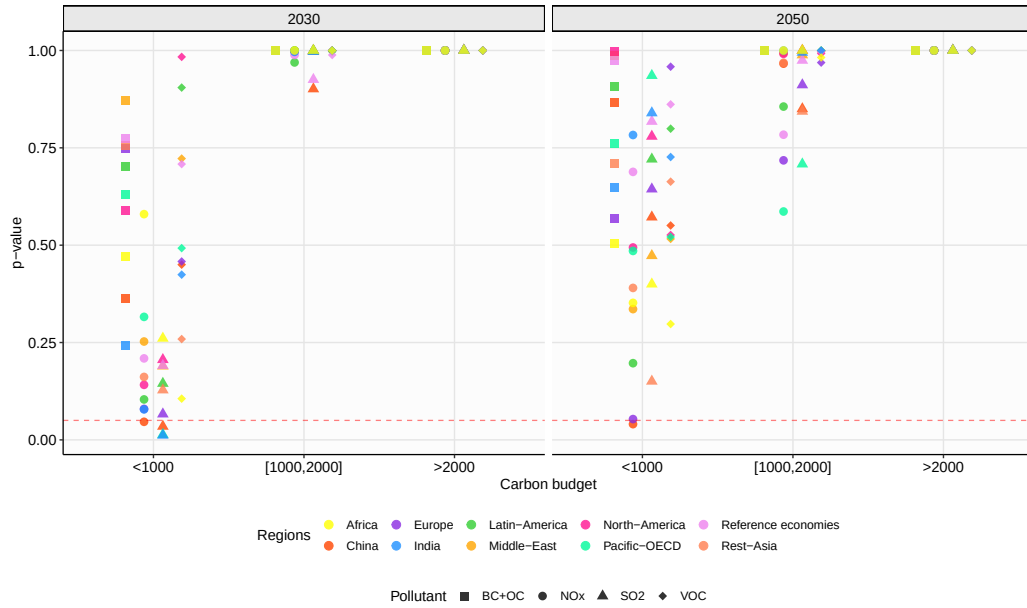
Precisely, our hypotheses are:

$$\begin{cases} H_0 : & \text{NZ and EoC climate policies have the same distribution function,} \\ H_1 : & \text{NZ and EoC climate policies have different distribution functions,} \end{cases}$$

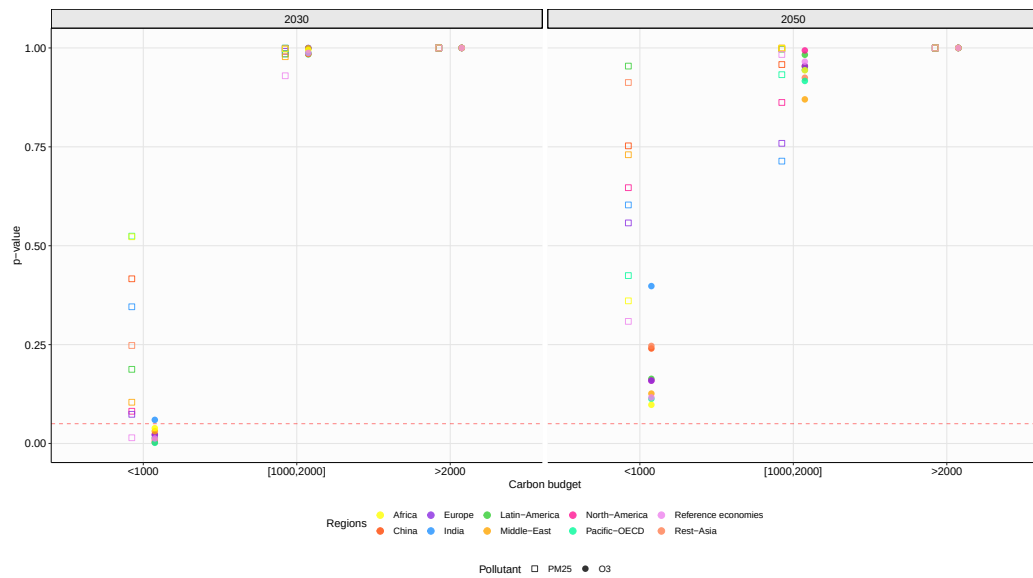
and we look for statistical evidence to reject the H_0 .

Thus, for high p-values no difference due to the climate policy is expected, while for low p-values we can state that the climate policy plays some role. Remark that if a p-value is lower than the significance level we can state, with a 95% of assurance, that the climate policy is decisive, whereas if it's higher than 0.95, we can say that it has no influence on the data.

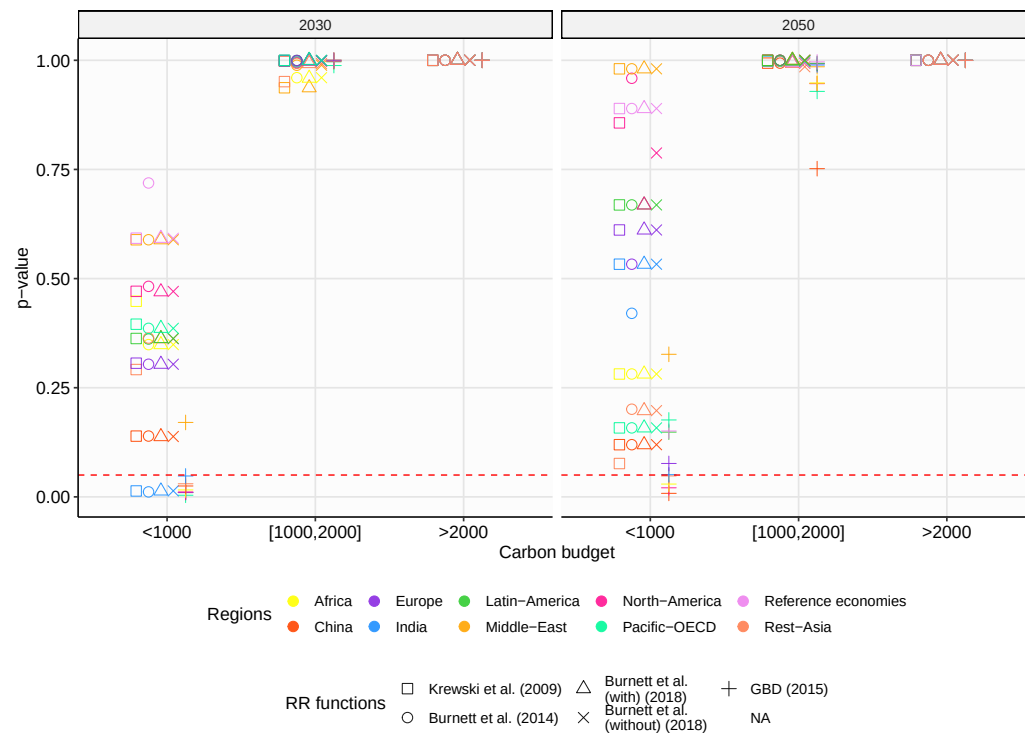
The results are the following:



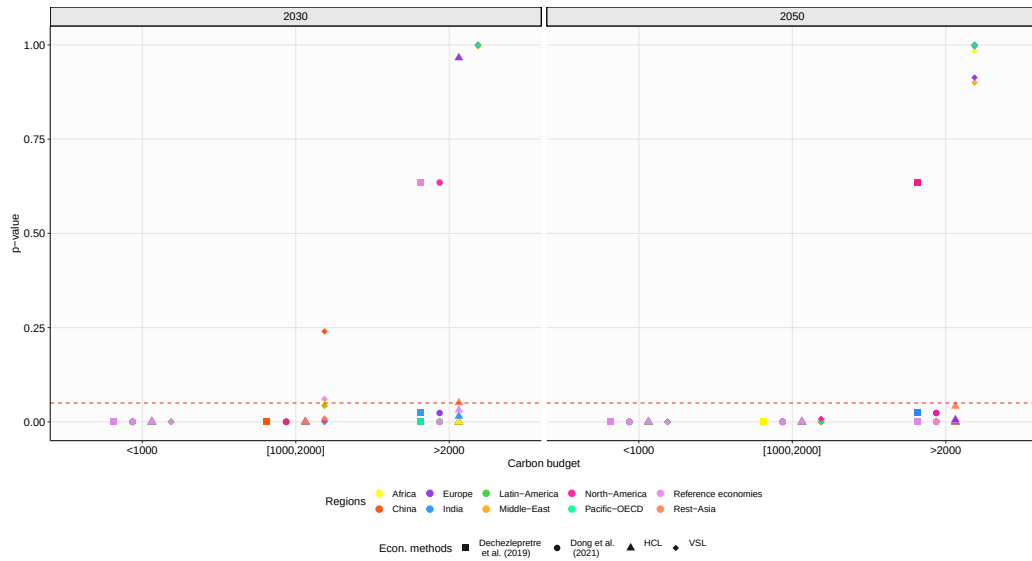
(a) Pollutants precursors' emissions K-S test result.



(b) Pollutant's concentrations K-S test result.



(c) Premature mortalities K-S test result.



(d) Economic damages K-S test result.

Figure S3: Climate policy dependence by region, year, and carbon budget. On the Y-axis there is the p-value of the K-S two-sample test done separately by pollutant, region, year, carbon budget, and method (in the case of the premature mortalities and economic damages). The dashed red line indicates the significance level threshold (0.05).

S5 Individual and propagated uncertainty

There are two different kinds of uncertainty: the individual uncertainty and the propagated uncertainty. The first one refers to the uncertainty given by each uncertainty source, while the second one applies to the reiterative use of uncertainty sources, which makes the overall uncertainty grow. Besides, there exists also a general uncertainty, given by the different outcomes throughout regions, short-term policies (NDC and NPi), and carbon budgets.

To compute the individual uncertainty, we can consider the quantile values (5%, 25%, 50%, 75%, and 95%) for each factor of uncertainty. For example, in the case of the uncertainty given by the IAMs, we can consider the quantile values for each IAM model separately. Then, we compute the median among all values that refer to the 25%, the 50%, and the 75% percentile across the different IAMs, and we consider the maximum value of the 95% percentile as well as the minimum value of the 5% percentile. In this way, we can see the uncertainty given by the considered factor, in this case, the IAMs, in its whole range, since the other uncertainty sources are being set to their median.

To assess the propagated uncertainty, one can do the previous argument by adding a new uncertainty source each time. This means, that the new considered uncertainty source is no longer considered optimal throughout the median, but modifiable thanks to the modeler choice; and it adds uncertainty to the overall uncertainty.

All in all, to compute the premature mortality, the IAMs, the RR function, and the parameters and counterfactual value choice are the uncertainty sources. To compute the economic damage, the IAMs, the economic method, the elasticity value, the RR function, the parameters of the RR function, and the counterfactual value of the RR function are the uncertainty sources. Notice that in this case, the RR functions are only relevant for the VSL and HCL equations (figure S4).

In more technical terms: consider an output $X_{i_1, i_2, i_3, \dots, i_n}$ linked to n sources of uncertainty: $i_1, i_2, i_3, \dots, i_n$. This means that for a certain $i_1 = i_{1_1}$, $i_2 = i_{2_1}$, $i_3 = i_{3_1}$, $\dots$, $i_n = i_{n_1}$ the value $X_{i_{1_1}, i_{2_1}, i_{3_1}, \dots, i_{n_1}}$ is fixed. To study the uncertainty given by a single parameter, for instance i_1 , we consider the finite set of all possible values of this parameter, $I_1 = \{i_{1_1}, i_{1_2}, i_{1_3}, \dots, i_{1_{m_1}}\}$, where $m_1 = |I_1|$, and consider as well all the possible combinations of the rest of the parameters, $I_{2,3,\dots,n} = \{\{i_{2_1}, i_{3_1}, \dots, i_{n_1}\}, \{i_{2_2}, i_{3_1}, \dots, i_{n_1}\}, \{i_{2_3}, i_{3_1}, \dots, i_{n_1}\}, \dots, \{i_{2_{m_2}}, i_{3_1}, \dots, i_{n_1}\}, \dots, \{i_{2_{m_2}}, i_{3_{m_3}}, \dots, i_{n_{m_n}}\}\}$. For every element in $I_{2,3,\dots,n}$, we compute the median over I_1 :

$$\forall p \in I_{2,3,\dots,n}, X_p = \text{Median}(\{X_{k,p}\}_{k \in I_1}). \quad (20)$$

Computing the median of X_p over $p \in I_{2,3,\dots,n}$, we obtain the median output value over the parameter i_1 . Considering the same procedure but now accounting for the

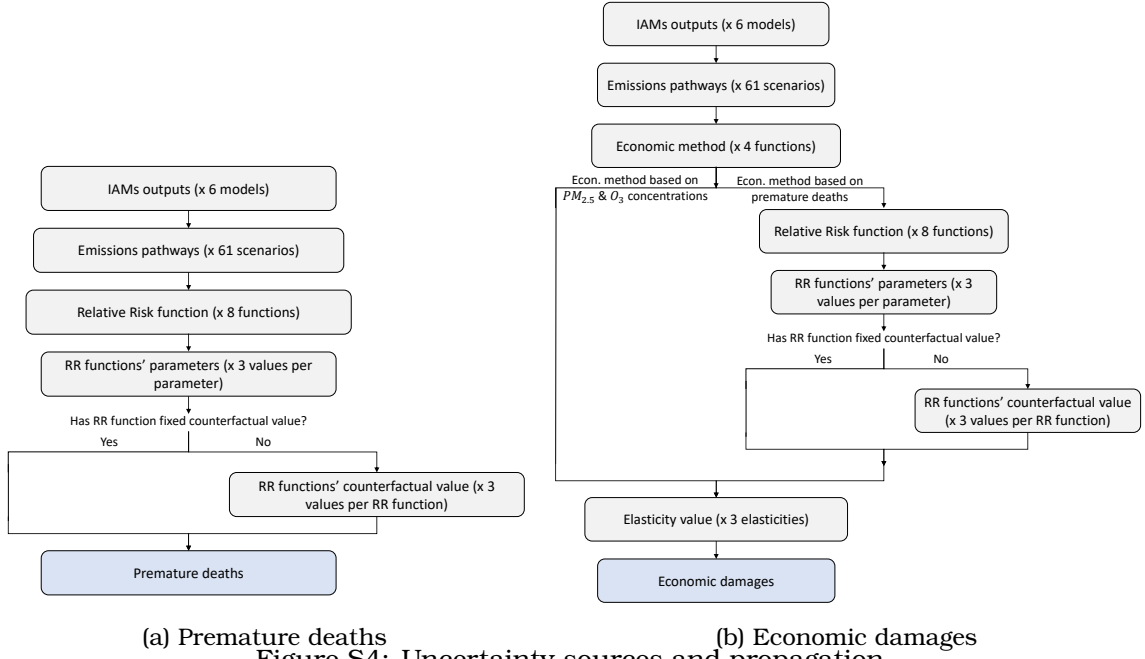


Figure S4: Uncertainty sources and propagation

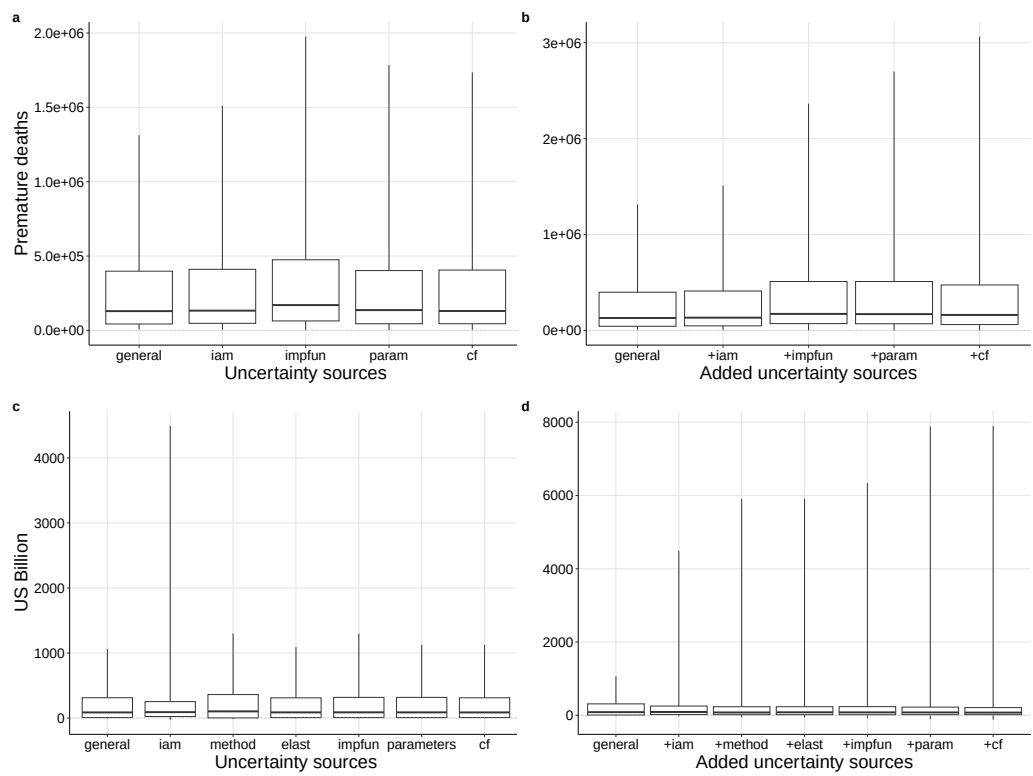
5%, 25%, 75%, and 95% percentiles instead of the median, we get the deviation due to parameter i_1 , which corresponds to the previously called *individual uncertainty*.

To estimate the propagated uncertainty due to the combination $i_1 \sim i_2$, we consider the same procedure until we obtain X_p , $\forall p \in I_{2,3,\dots,n}$ through equation 20. Then, we reduce again the dimension taking into account I_2 and the set of the rest of the parameters, $I_{3,4,\dots,n}$. Similarly to equation 20, we compute X_q :

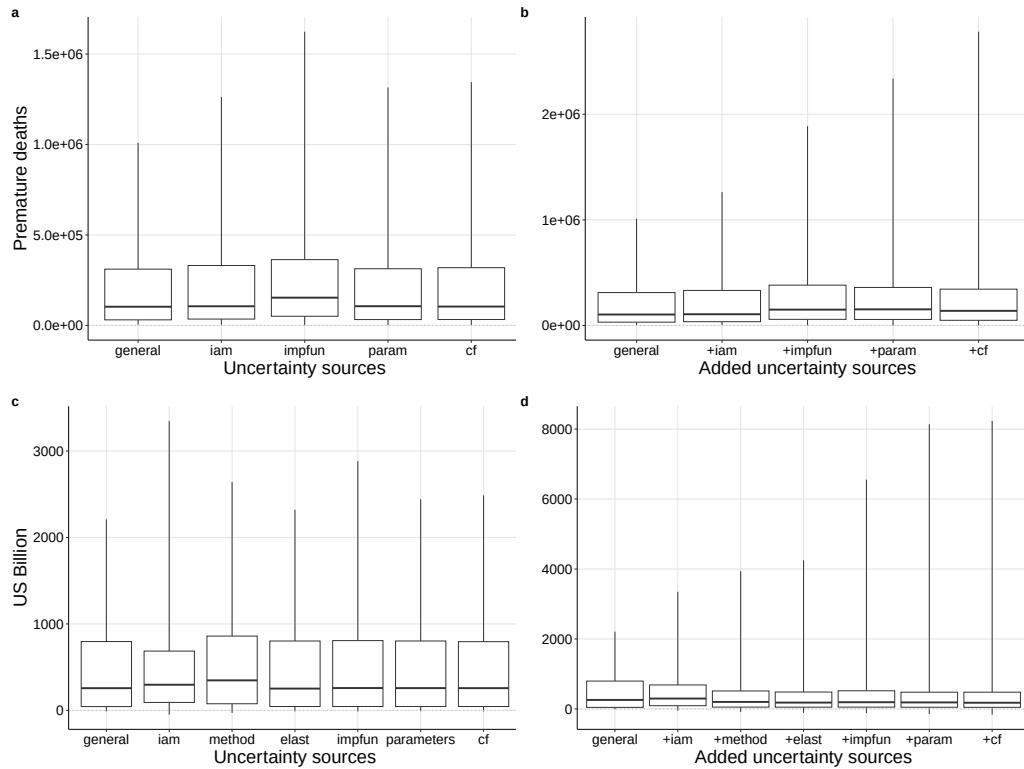
$$\forall q \in I_{3,4,\dots,n}, X_q = \text{Median}(\{X_{k,q}\}_{k \in I_2}). \quad (21)$$

Computing the median of X_q over $q \in I_{3,4,\dots,n}$, we obtain the median output value over the parameters' combination $i_1 \sim i_2$. Considering again the same procedure for the 5%, 25%, 75%, and 95% percentiles instead of the median, we get the deviation due to parameters' combination $i_1 \sim i_2$, which corresponds to the previously called *propagated uncertainty*. To study the propagated uncertainty regarding more parameters, we simply need to repeat the previous steps reducing the dimension to one each time.

Considering this procedure, the results are the following:



(a) 2030 results



(b) 2050 results

Figure S5: 5th, 25th, 50th, 75th, and 95th percentile in 2030 and 2050 for low carbon budgets of **a)** Individual health impact uncertainty sources. Values are expressed in number of people. **b)** Propagated health impact uncertainty sources. Values are expressed in number of people. **c)** Individual avoided damages uncertainty source. Values expressed in US\$ (Billion/2010). **d)** Propagated avoided damages uncertainty sources. Values expressed in US\$ (Billion/2010).

S6 Tail heaviness analysis

There is no unique definition of a heavy-tailed distribution. Indeed, this notion only makes sense in the context of each considered model. What we usually expect when we talk about heavy-tailed phenomena is some kind of different qualitative behavior of the underlying model, i.e., some deviation from the “normal behavior” which is caused by the extremes of the sample [4]. Precisely because of that, heavy-tailed distributions tend to have many outliers with very high values. The heavier the tail, the larger the probability to have one or more disproportionate values in a sample; and in our case, the larger probability of high mortality outcomes.

Although it does not exist a universal definition, there is a general consensus and acceptance of the following one:

Definition S6.1. [14] A probability distribution $F(x)$ is **heavy-tailed** if and only if

$$\int_{\mathbb{R}} e^{\lambda x} F(x) dx = \infty, \quad \forall \lambda > 0. \quad (22)$$

Analogously, a probability distribution $F(x)$ is **light-tailed** if and only if

$$\int_{\mathbb{R}} e^{\lambda x} F(x) dx < \infty, \quad \text{for some } \lambda > 0. \quad (23)$$

Intuitively, a probability distribution is called *heavy-tailed* if it has a tail that's heavier than an exponential distribution [4]. In other words, a distribution that is heavy-tailed goes to zero slower than one with exponential tails. On the contrary, if a function is *light-tailed*, it goes to zero quicker than one with exponential tails.

One way of measuring the tail heaviness is computing the tail index [17]. However, for a given impact function, year, region, and pollutant we do not have enough data to obtain reliable estimates. Thus, we proceed as in [12] exploiting a finite sample argument relative to the binomial random behavior of threshold exceedances.

Specifically, for a given region and pollutant, we focus on the sequence of premature deaths, represented by the random variable X_t , where $t = 2020, \dots, 2050$ is the time index. Then, we consider a “high” threshold h given by the 90th percentile obtained from all premature death or economic co-benefit values by region and pollutant available with the NZ data. This threshold value has been chosen since it represents the mortality extremeness. Now, we consider the exceeding probability

$$p = P(X_t > h), \quad t = 2020, \dots, 2050.$$

In this way, for each year we have n premature death values, obtained through different carbon budgets and impact functions. For simplicity, it can be assumed

that these values are observations generated from the independent random variables $X_t^{(i)}$, $i = 1, 2, \dots, n$. Since $\mathbb{1}(X_t > h)$ is a Bernoulli random variable, then

$$\sum_{i=1}^n \mathbb{1}(X_t^{(i)} > h) \sim \text{Bin}(n, p),$$

i.e., the number of exceedances on n trials follows a binomial distribution with success probability p . This probability provides an indication of the heaviness of the tail distribution. In particular, as p increases, fatter is the distribution's tail. Although with this procedure we can not obtain a precise indication of the tail heaviness, we do identify the distribution with the heavier tail, which fits exactly our analysis aim.

All in all, we estimate the exceeding probability p by each sample group. Furthermore, applying the exact Pearson-Klopper method we can also estimate the 95% confidence interval for p . This method allows us to obtain the binomial confidence interval as follows:

$$p \in (p_L, p_U), \text{ where} \\ p_L = \left\{ p \mid P[\text{Bin}(n; p) \leq x] > \frac{\alpha}{2} \right\} \quad \text{and} \quad p_U = \left\{ p \mid P[\text{Bin}(n; p) \geq x] > \frac{\alpha}{2} \right\},$$

where α is the significance level and $0 \leq x \leq n$ is the number of successes observed in the sample [2].

To see if the estimated exceeding probability p is often higher with the EoC data than with the NZ one, we consider the binomial test with the following hypotheses:

$$\begin{cases} H_0 : p^{(EoC)} \leq p^{(NZ)}, \\ H_1 : p^{(EoC)} > p^{(NZ)}, \end{cases}$$

where $p^{(EoC)}$ is the exceeding probability of the EoC distribution and $p^{(NZ)}$ is the exceeding probability of the NZ distribution. Once again, we look for empirical evidence to reject the null hypothesis H_0 .

The binomial test follows the same idea as the Kolmogorov-Smirnov test. However, now the p-value is simply computed with the binomial probability function:

$$p = \sum_{i=0}^k P(X \leq i) = \sum_{i=0}^k \binom{n}{i} \pi_0^i (1 - \pi_0)^{n-i},$$

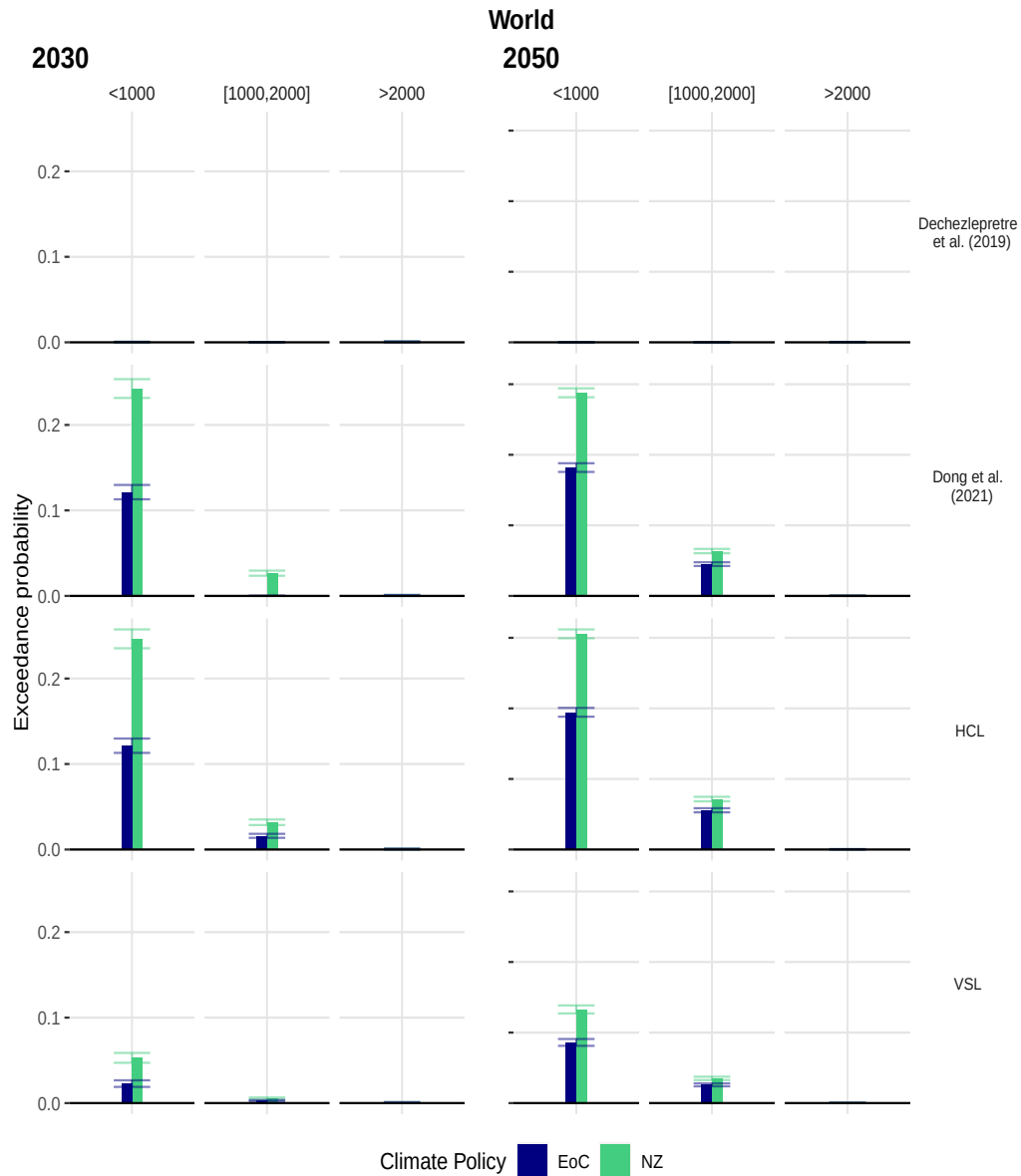
where k is the number of successes in the sample of size n , corresponding to $p^{(EoC)}$ in our specific case, and π_0 is the threshold value of the hypothesis, $p^{(NZ)}$ in our procedure [1].

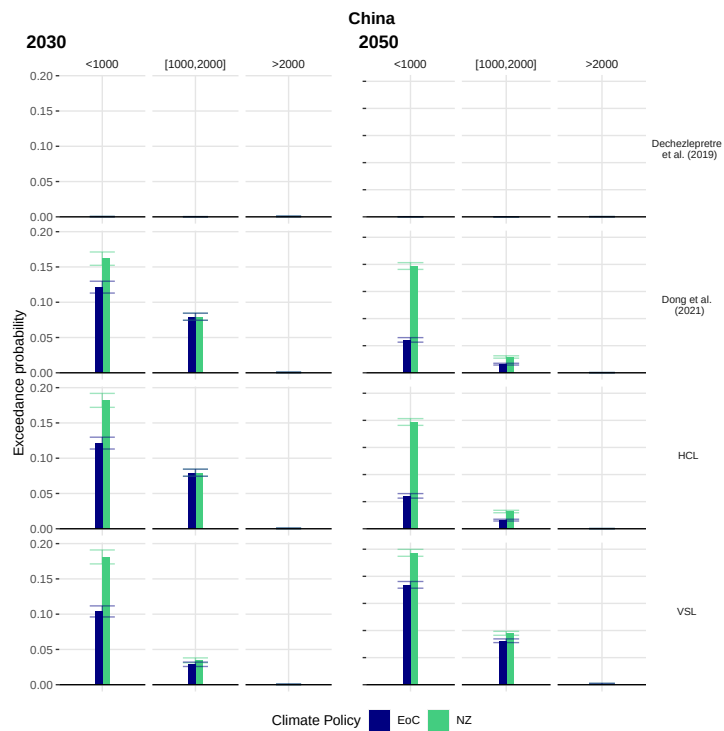
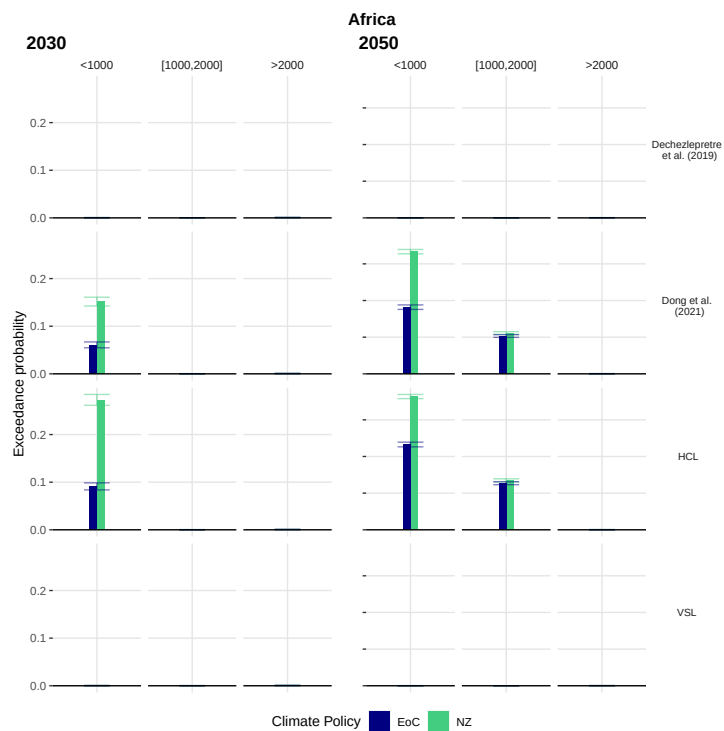
Finally, for the test to be coherent, we need the same amount of NZ and EoC data samples. However, not all models from the ENGAGE database are

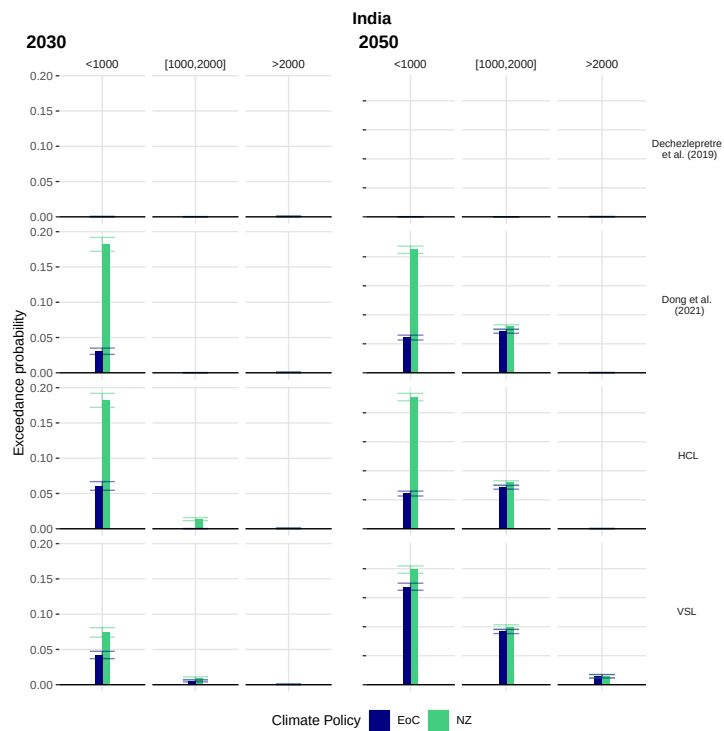
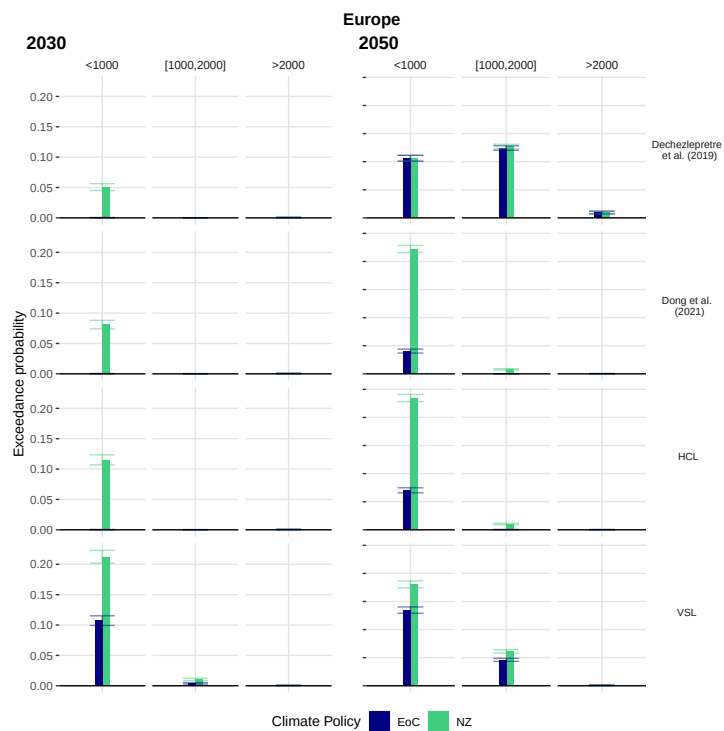
run with both climate policies for each carbon budget. Therefore, it is necessary to select only the ones that run both climate policy types before computing the test.

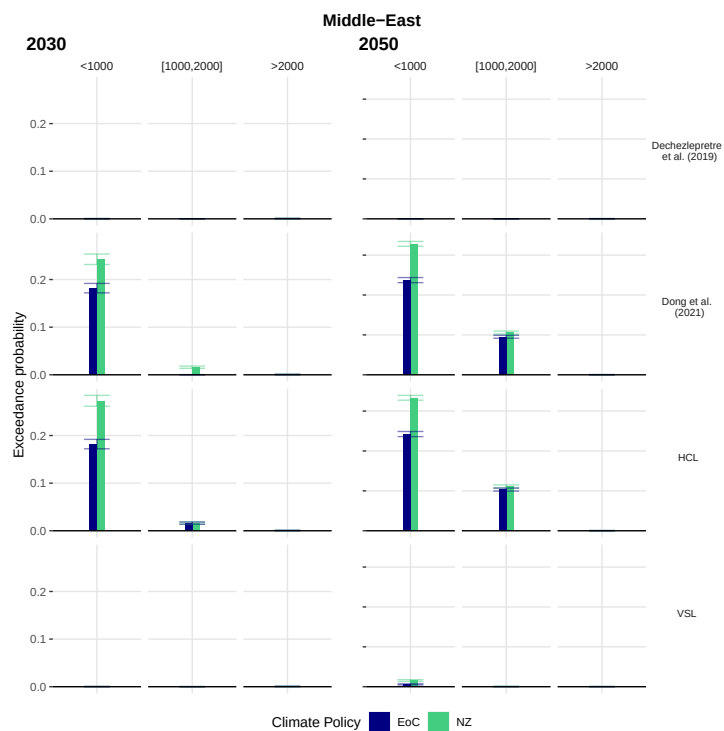
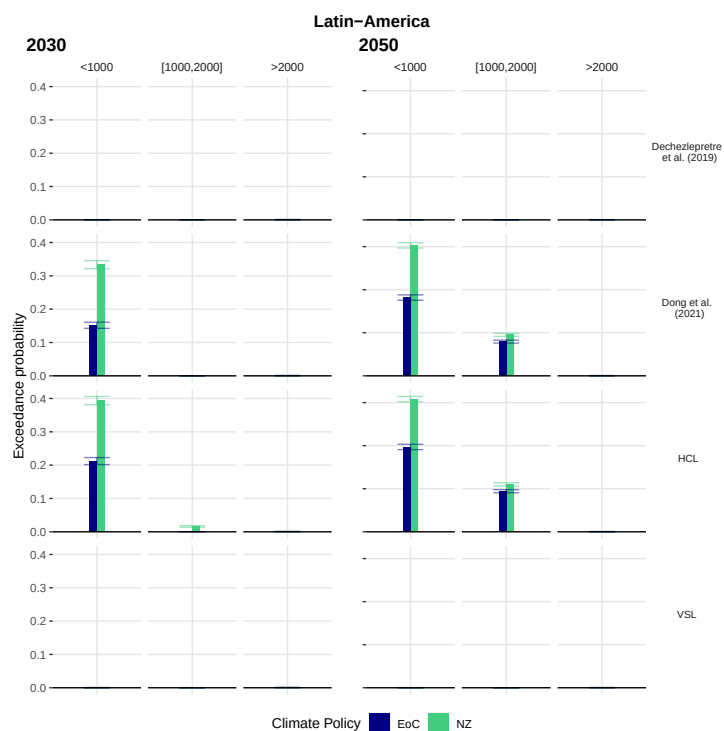
Considering the above methodology, the results by region are the following:

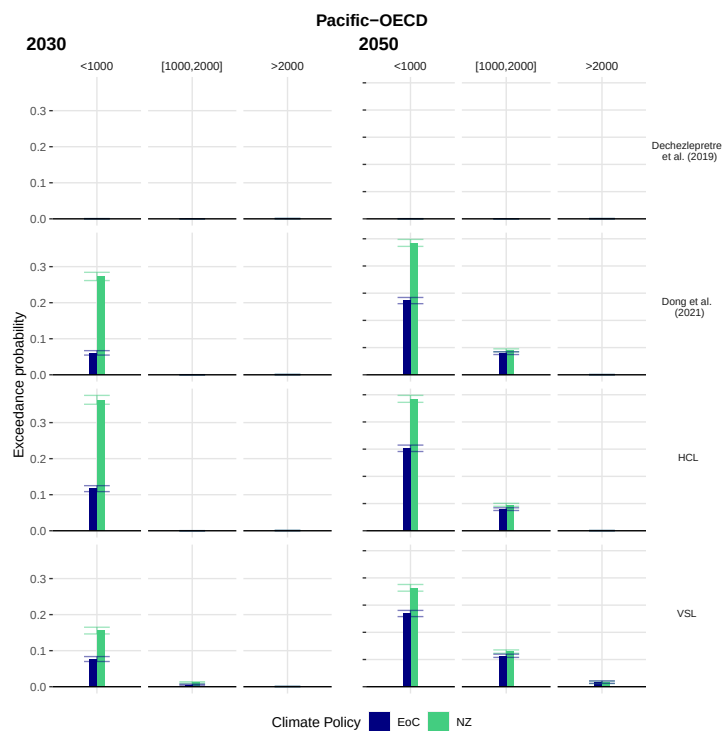
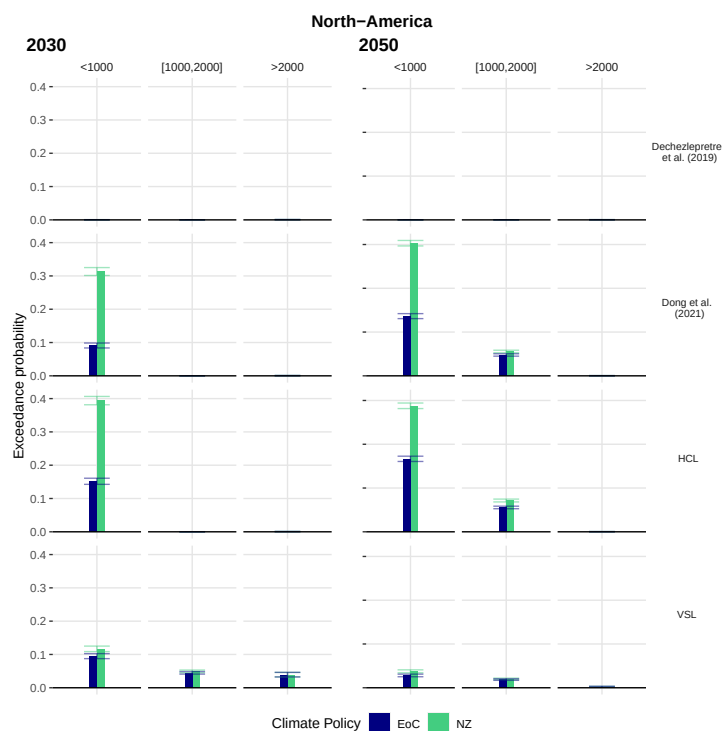
S6.1 Economical co-benefits sensitivity and uncertainty: tail heaviness probability graphs

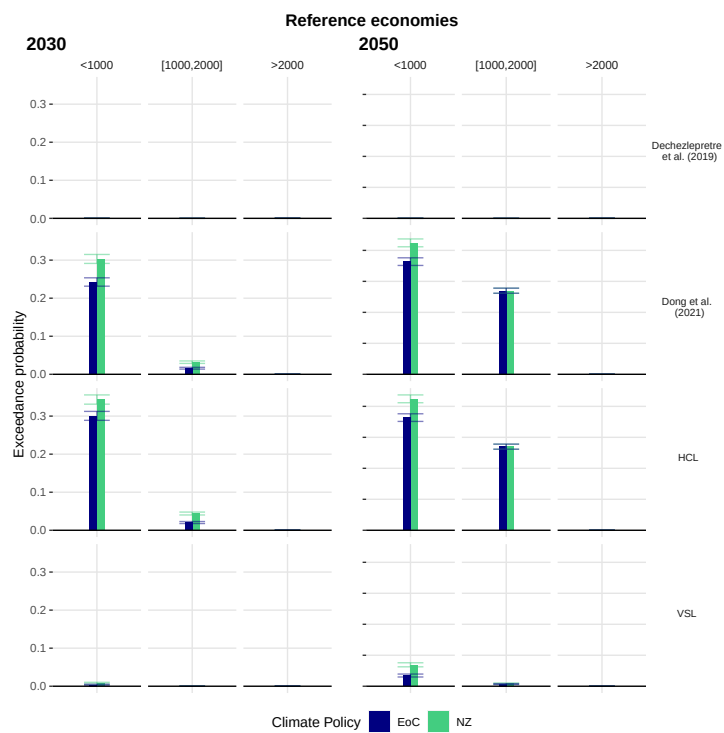












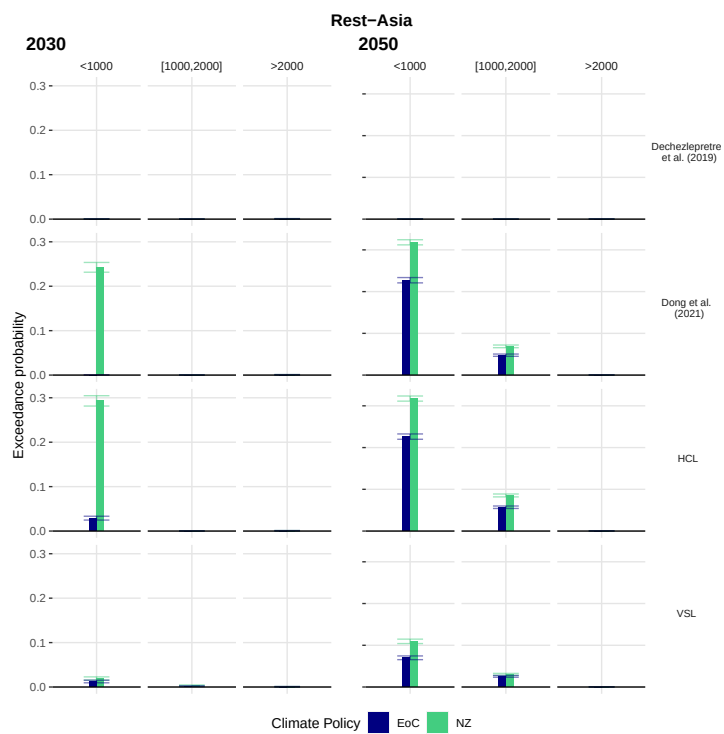
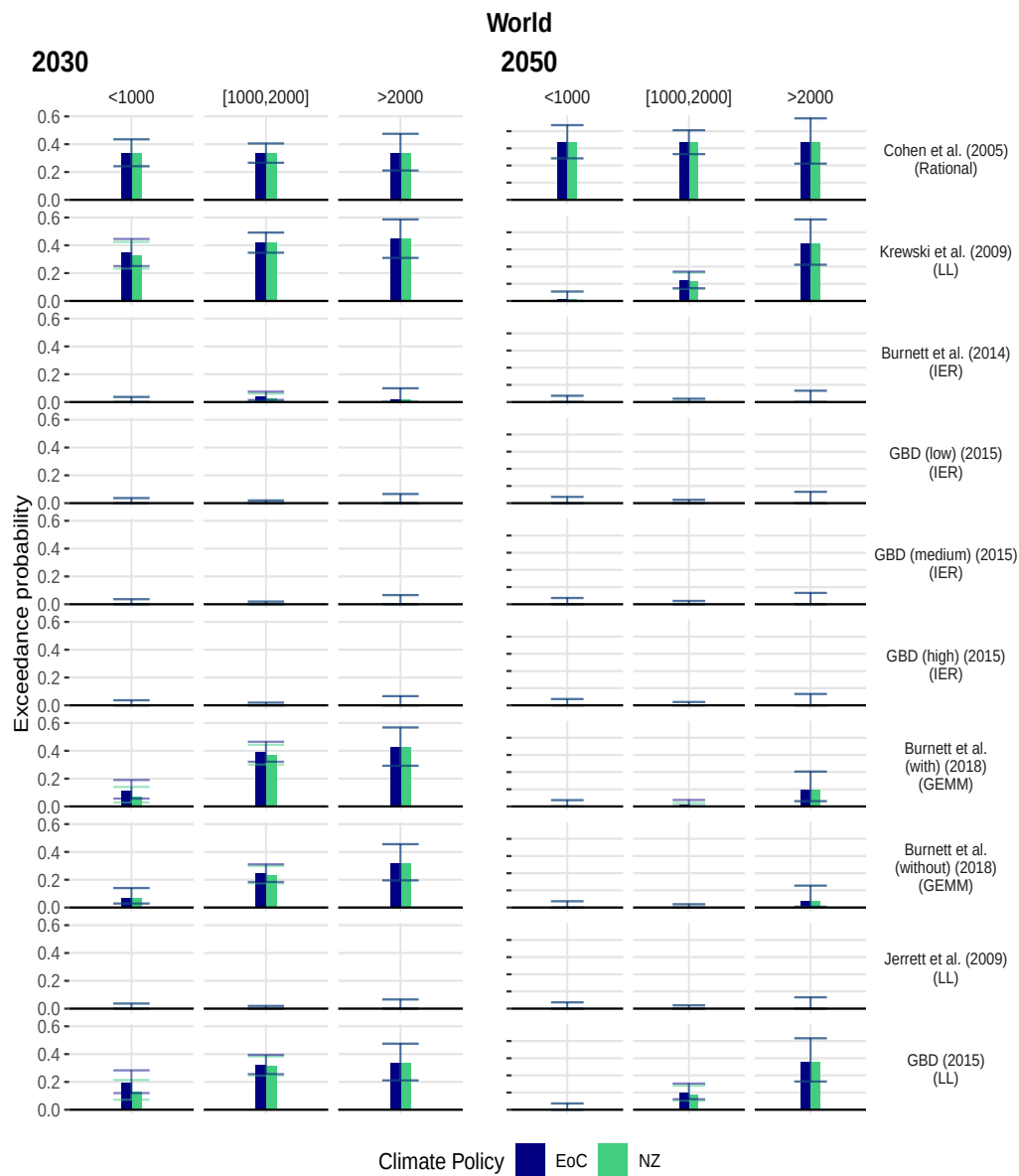
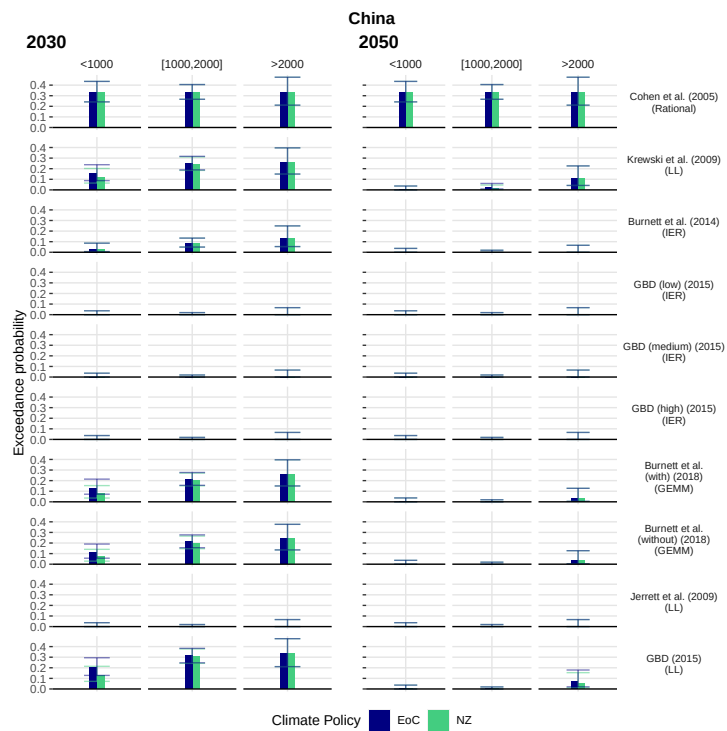
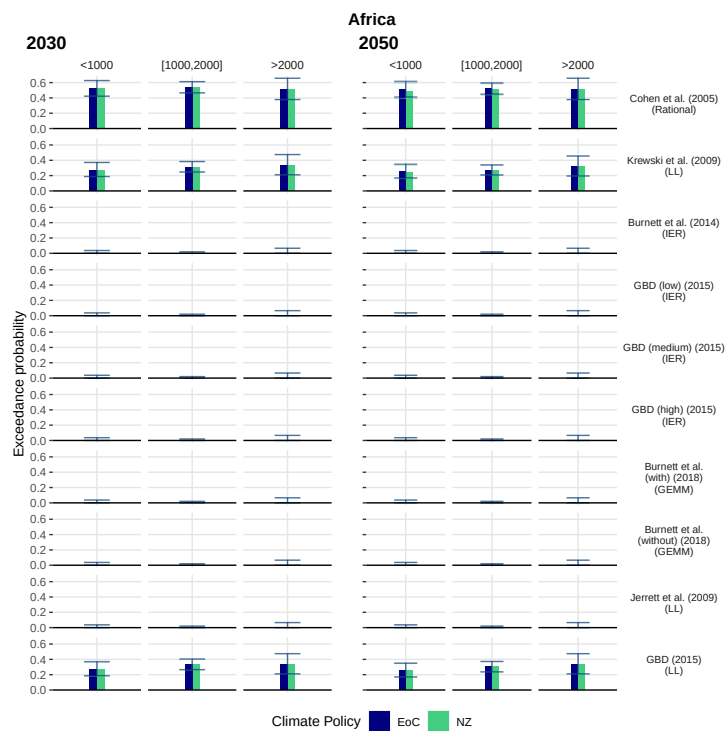
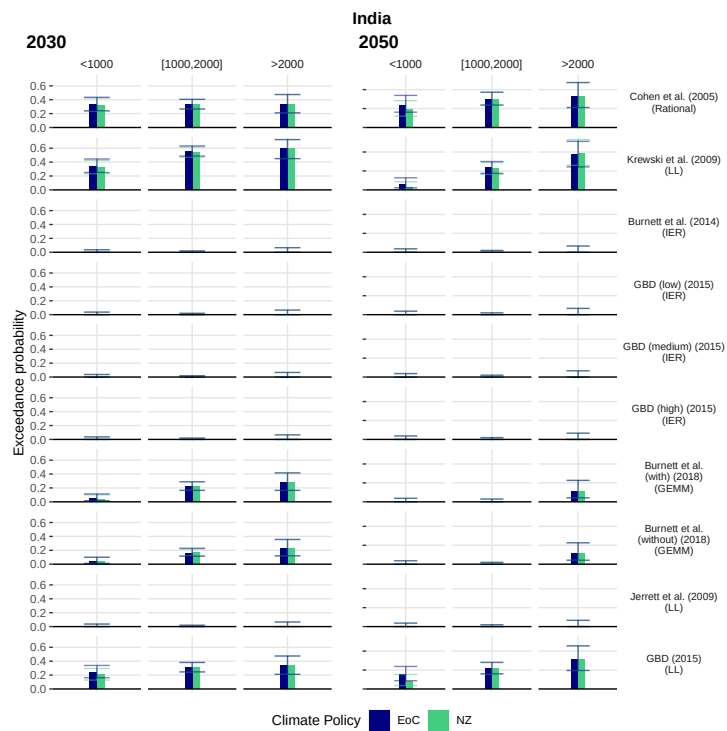
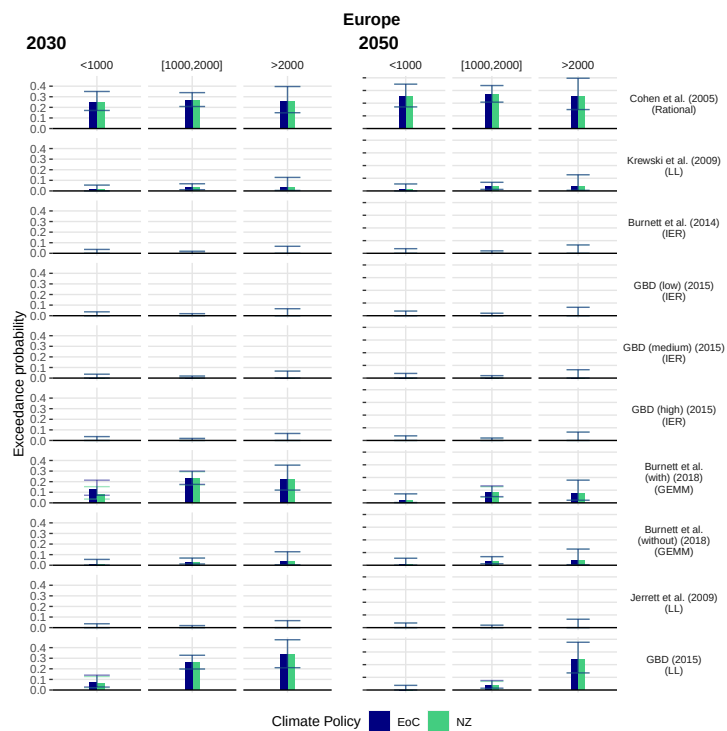


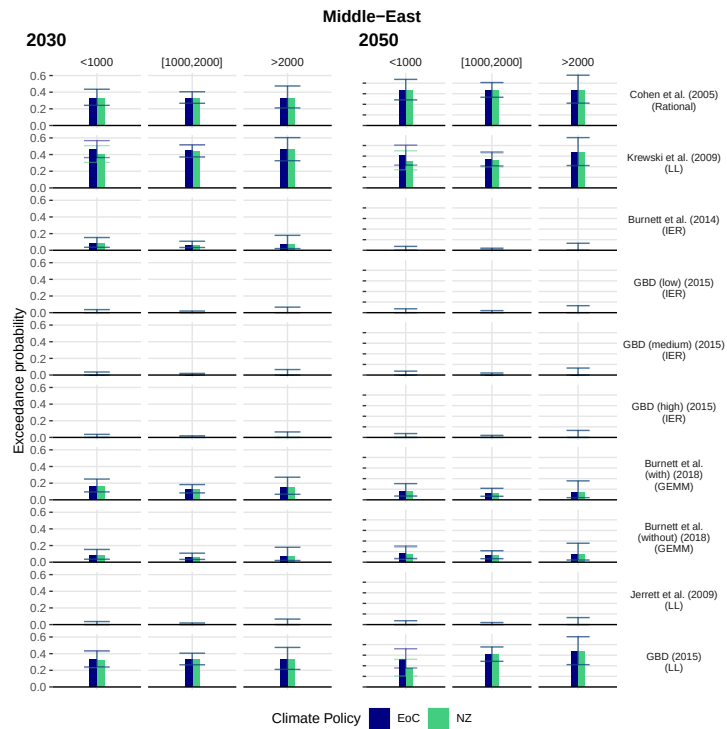
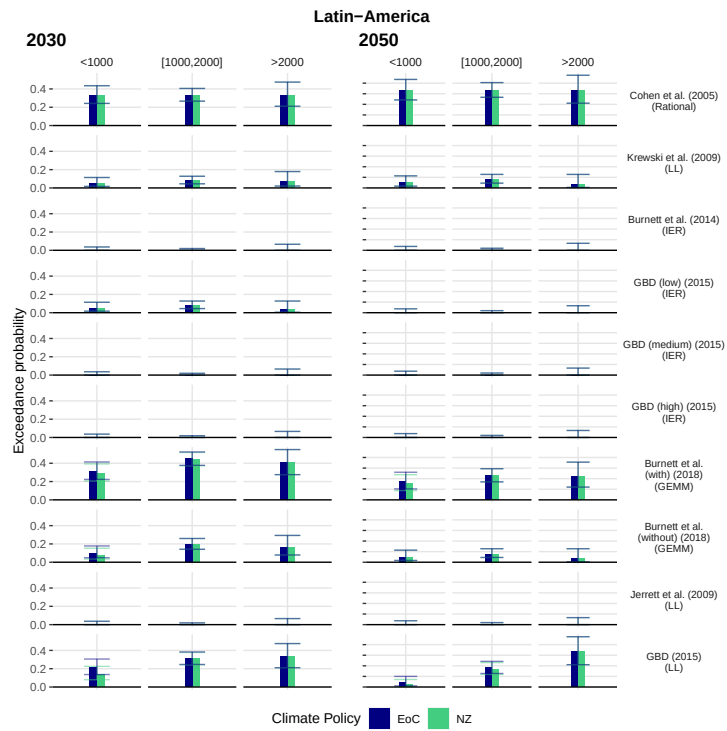
Figure S6: Tail heaviness probability for each R10 region by economic equation. Includes 95% CI. Color indicates the scenario.

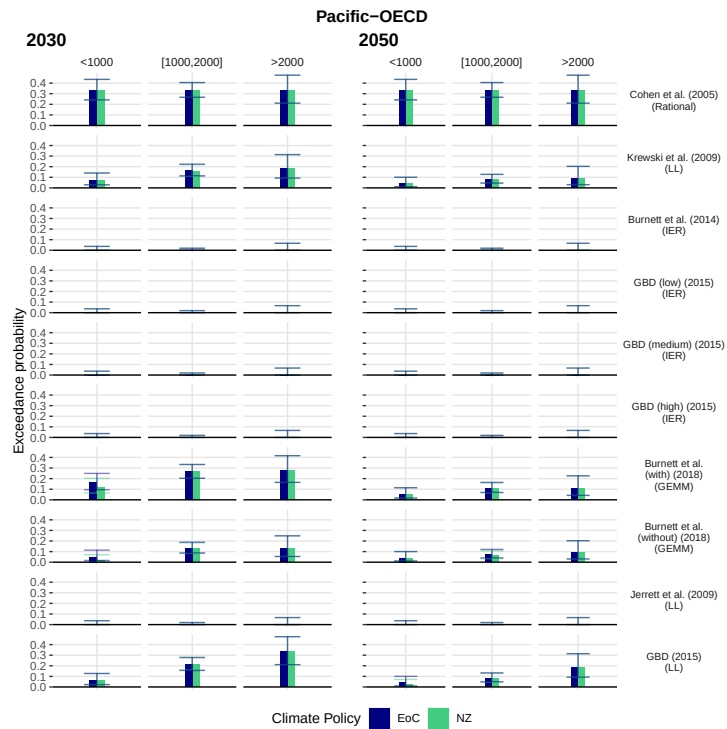
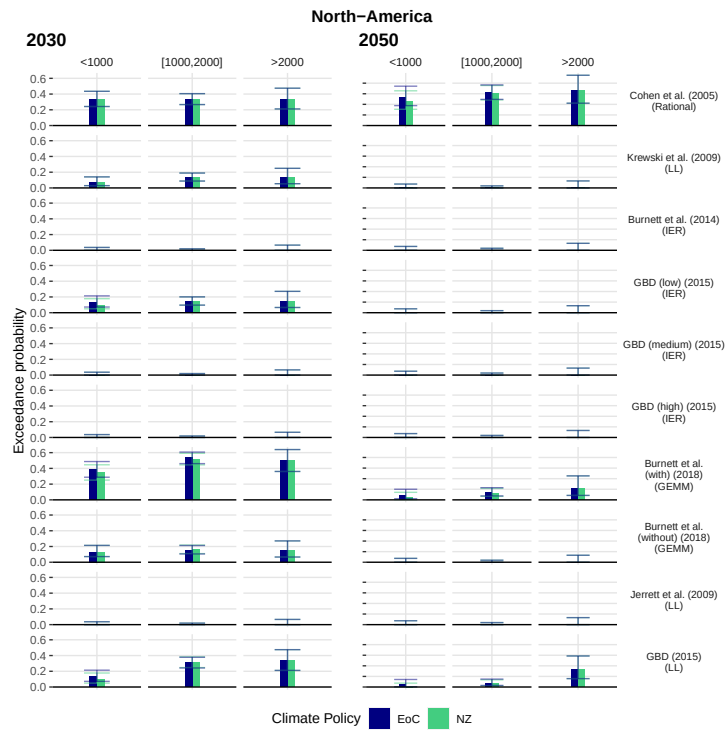
S6.2 Premature deaths sensitivity and uncertainty: tail heaviness probability graphs

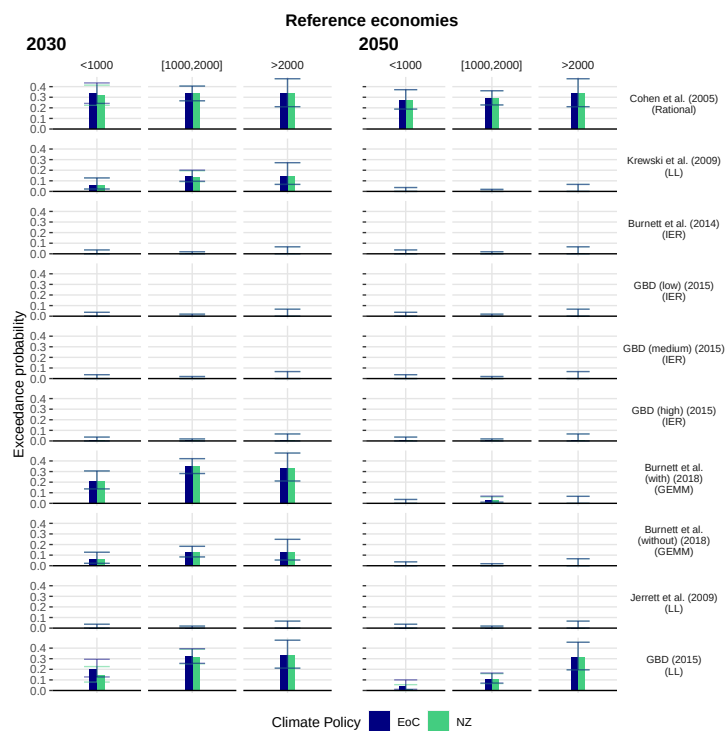












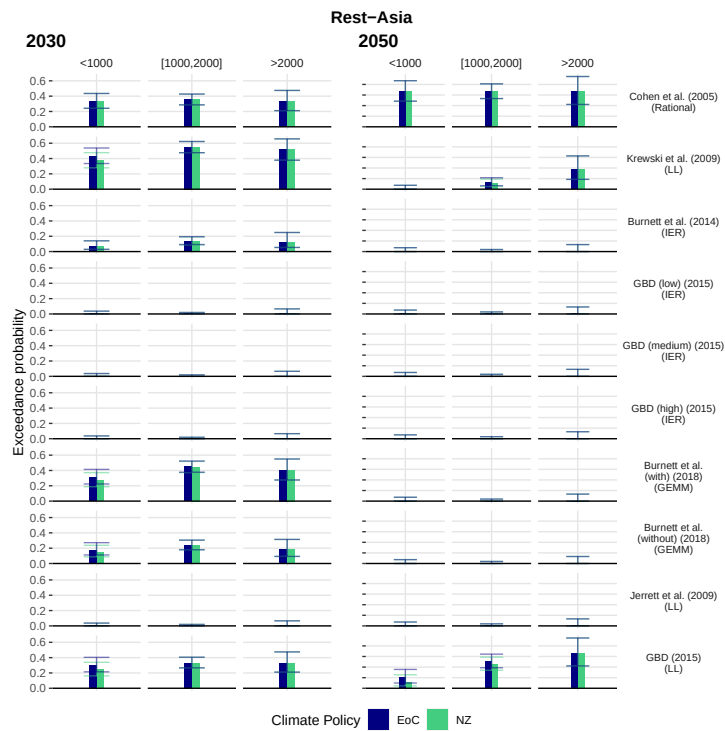
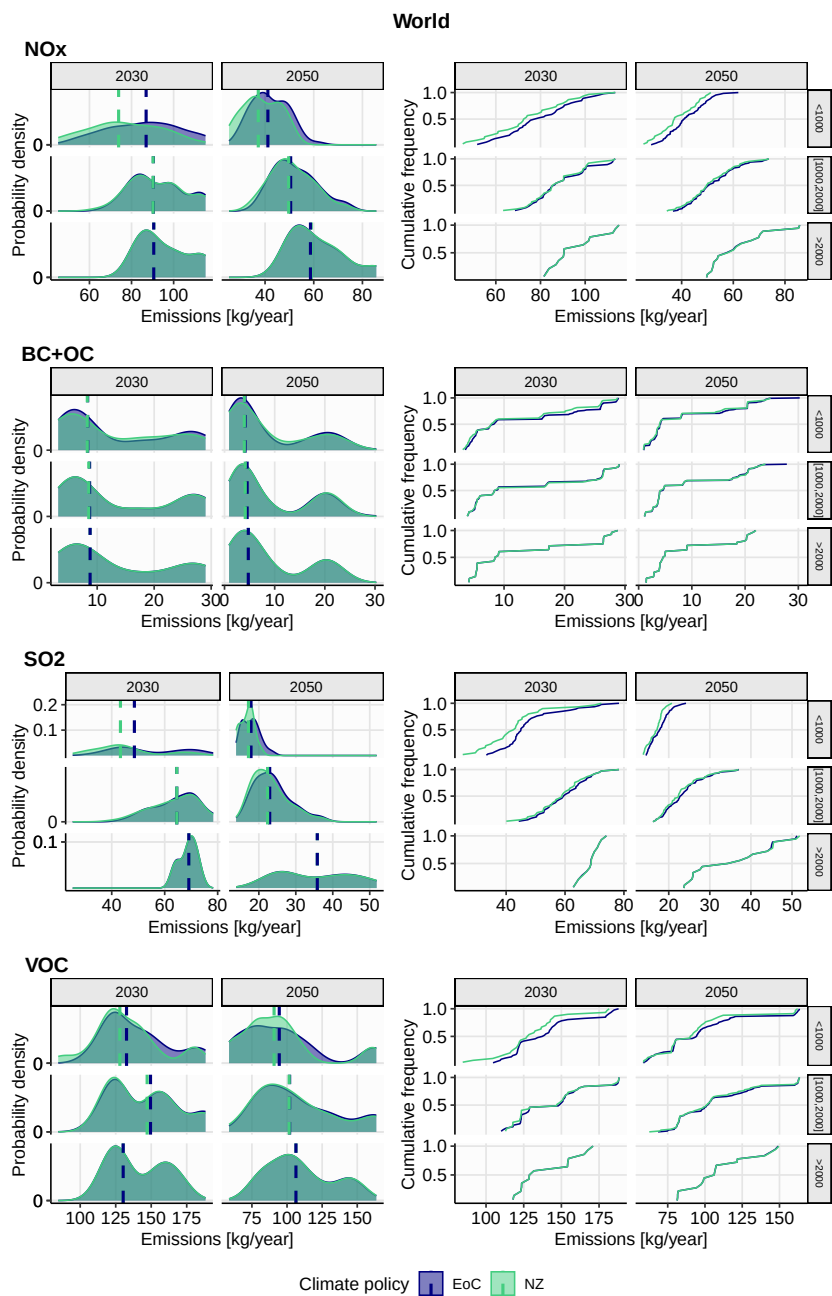
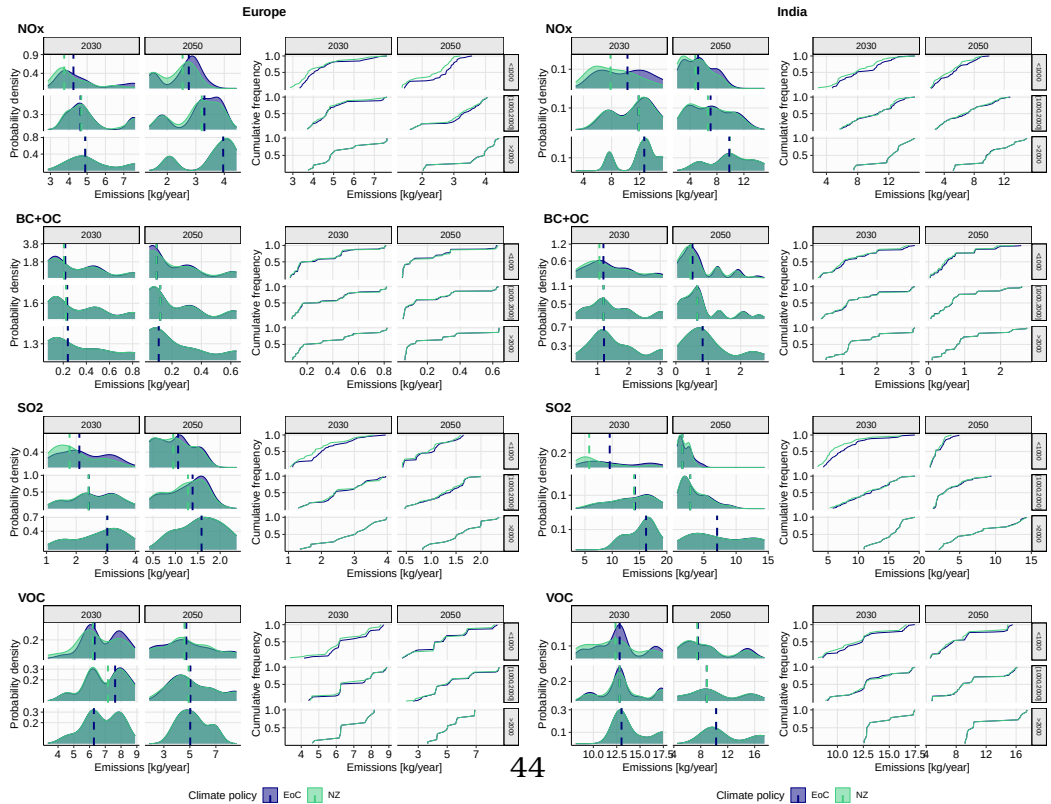
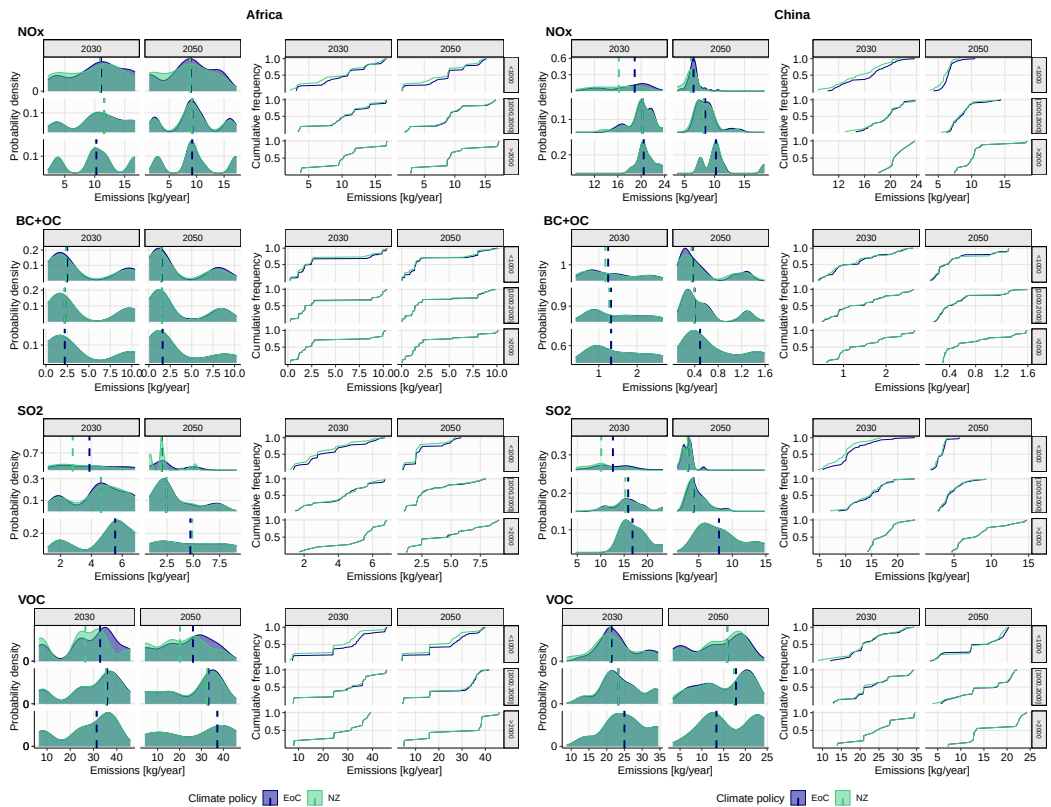
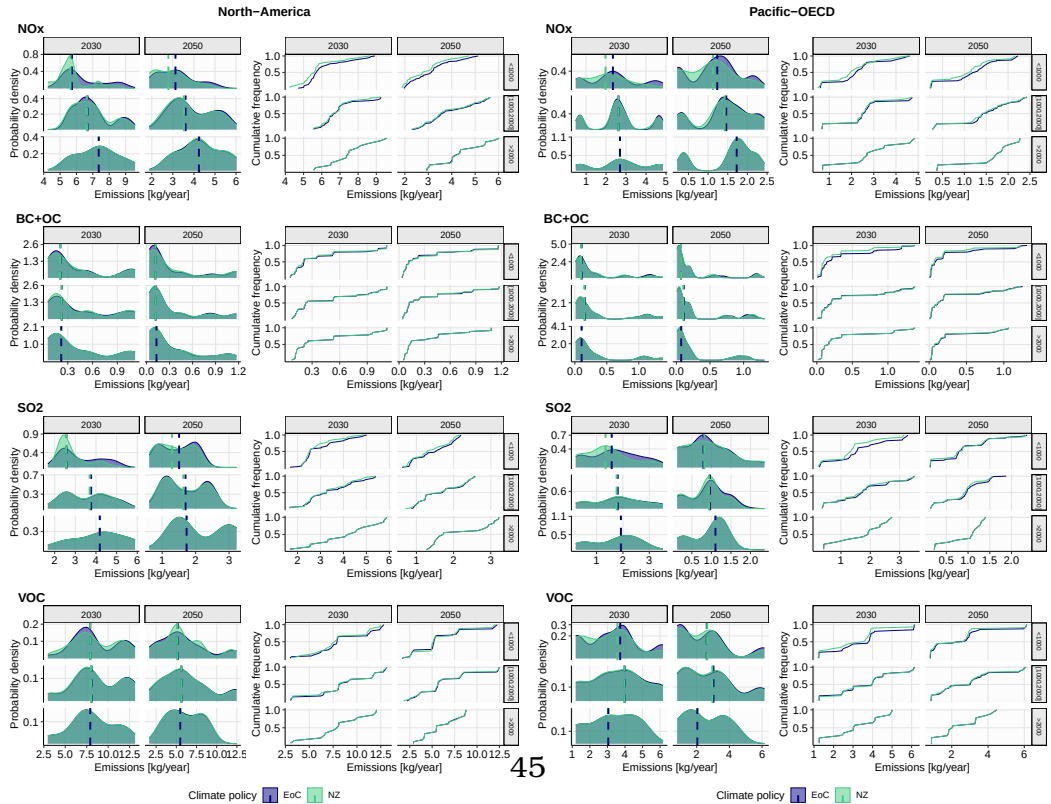
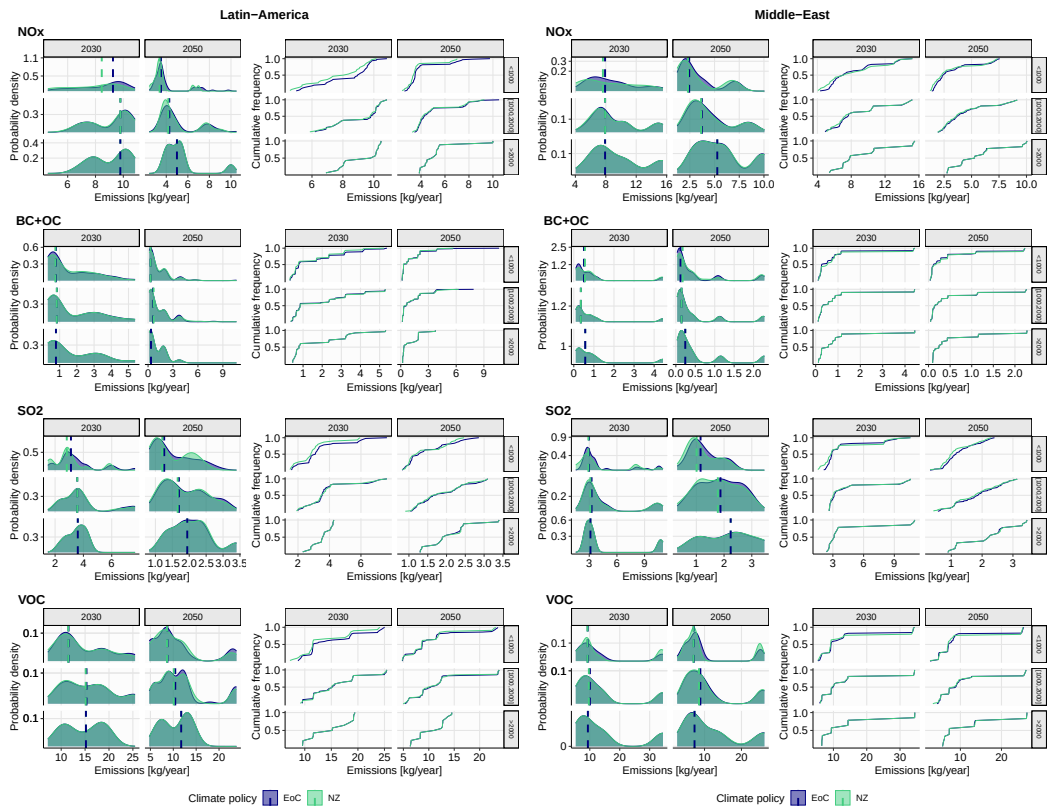


Figure S7: Tail heaviness probability of premature mortality for each R10 region by RR function. Includes 95% CI. Color indicates the scenario

S7 Emissions sensitivity and uncertainty: probability distribution and cumulative frequency emissions figures







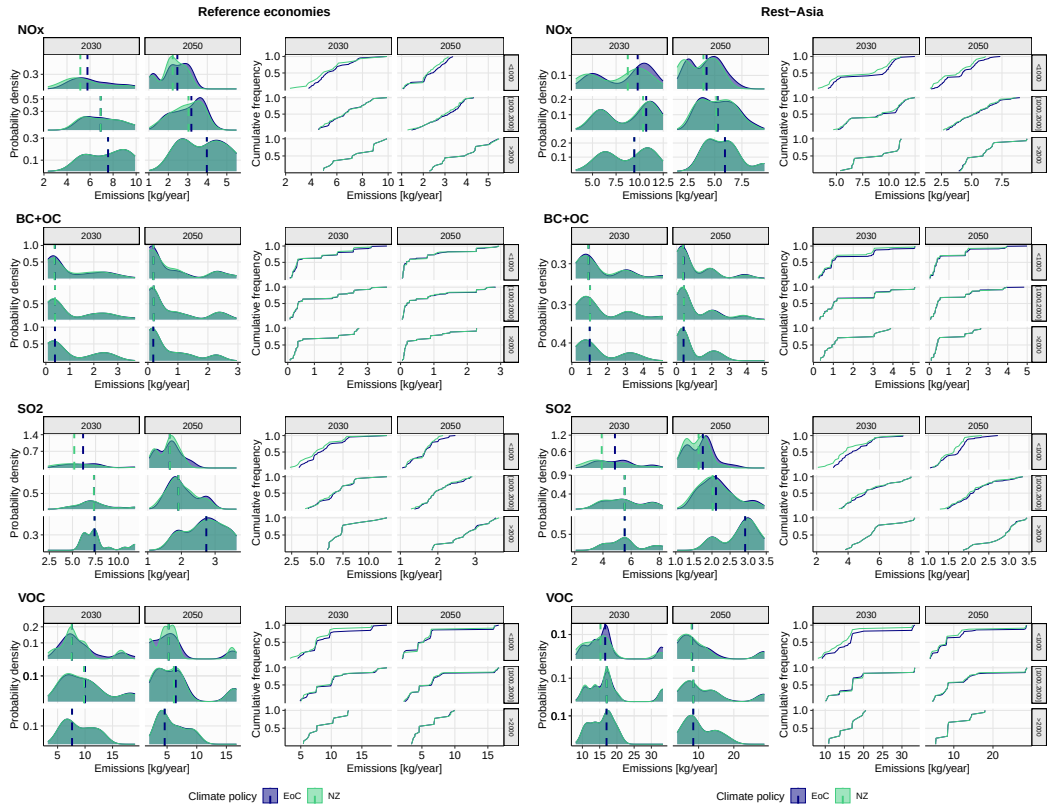
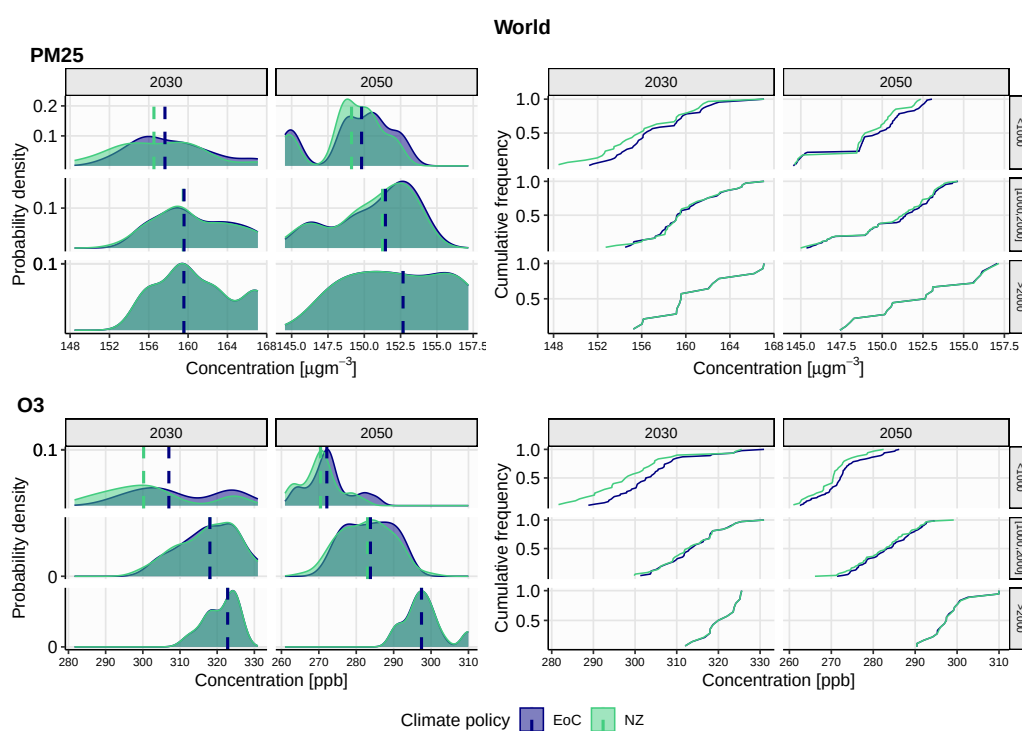
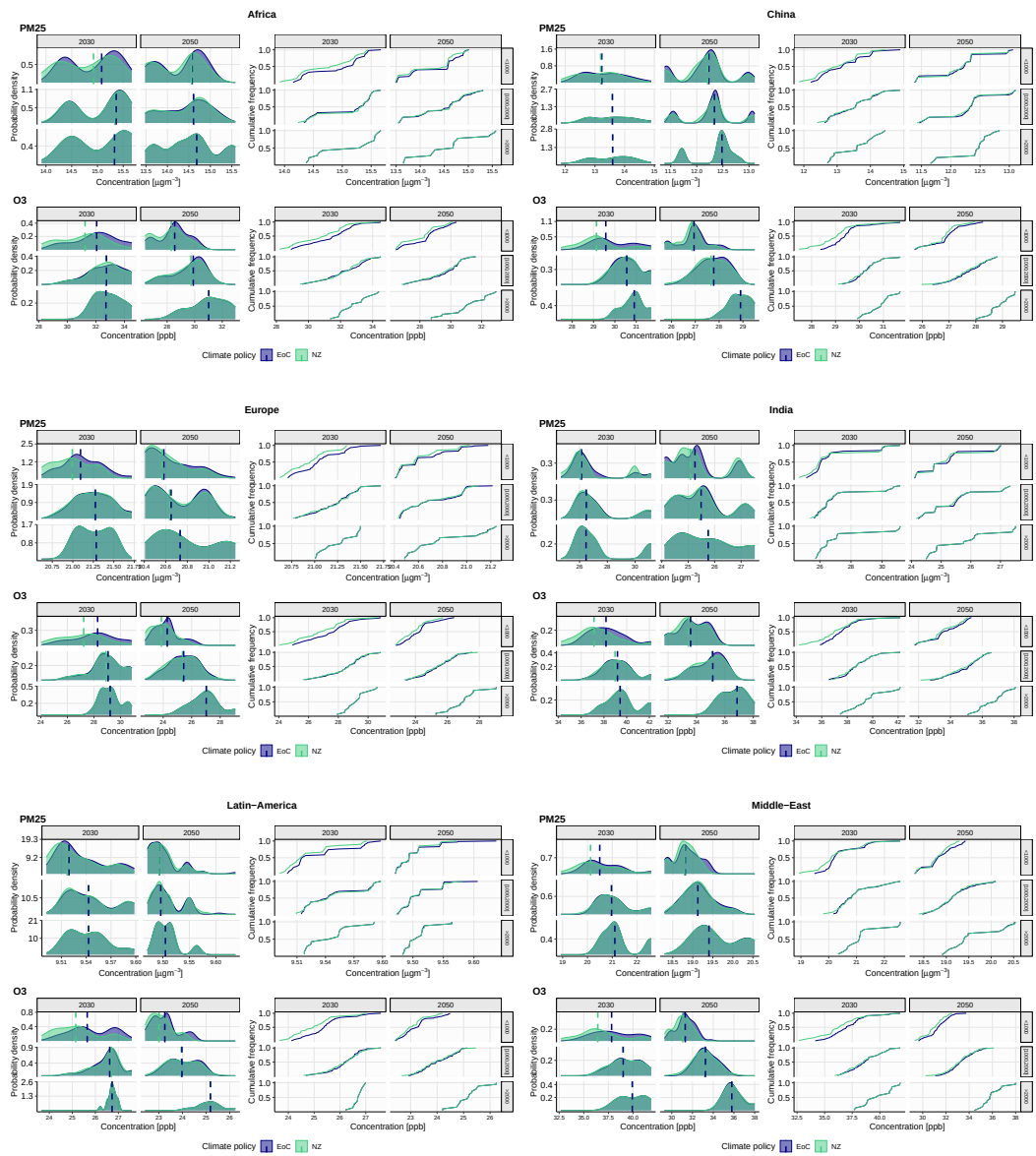


Figure S8: Probability density distribution (left) and cumulative frequency (right) for each R10 region for BC + OC, SO₂, NO_x, and VOC emissions. Includes median line by climate policy. Color indicates the scenario.

S8 Concentrations sensitivity and uncertainty: probability distribution and cumulative frequency average concentrations figures





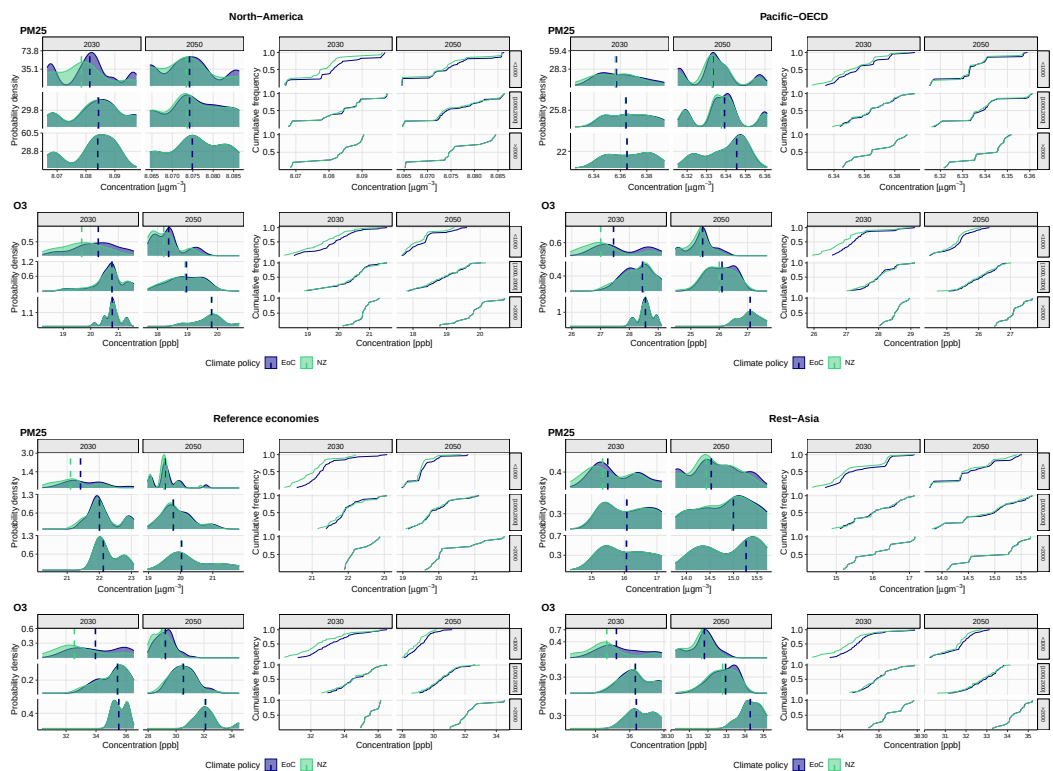
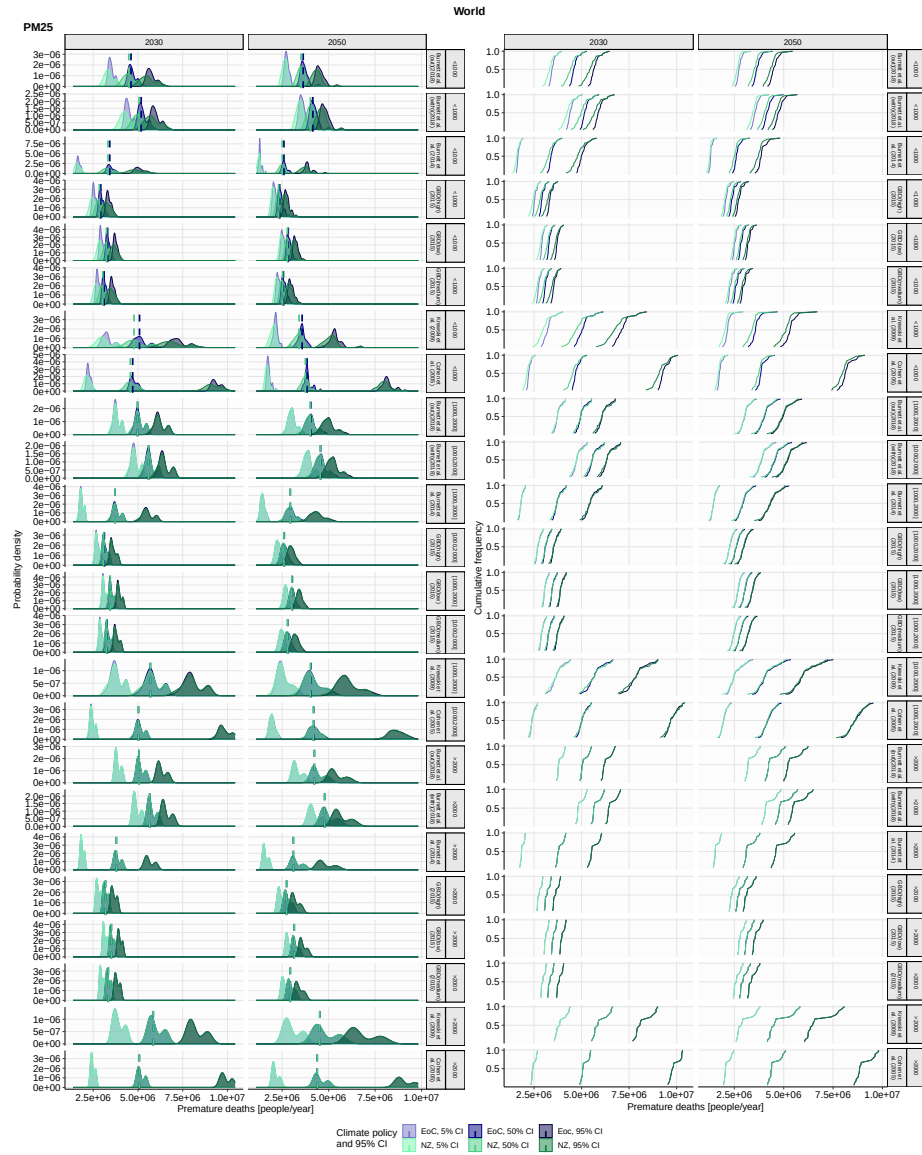
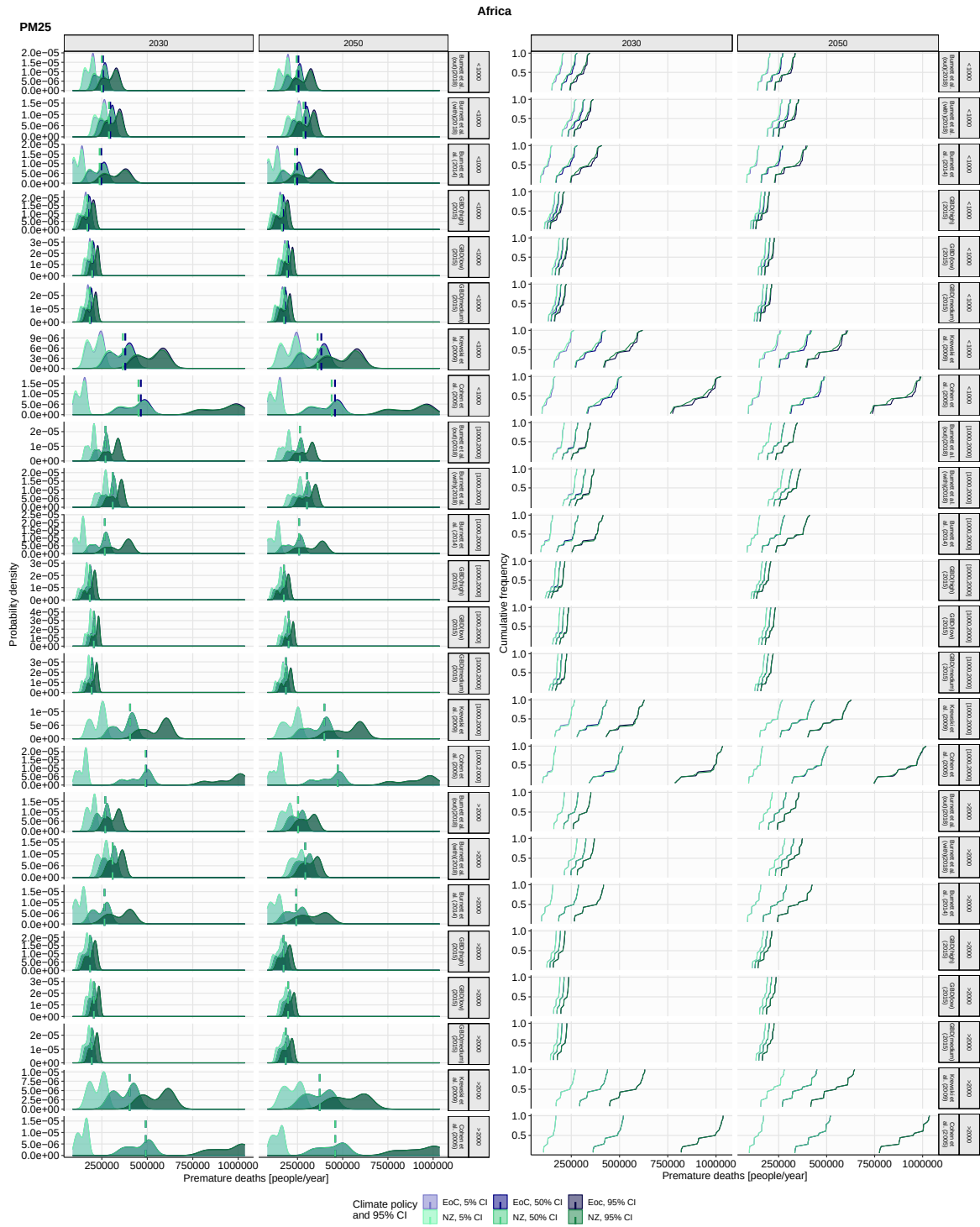
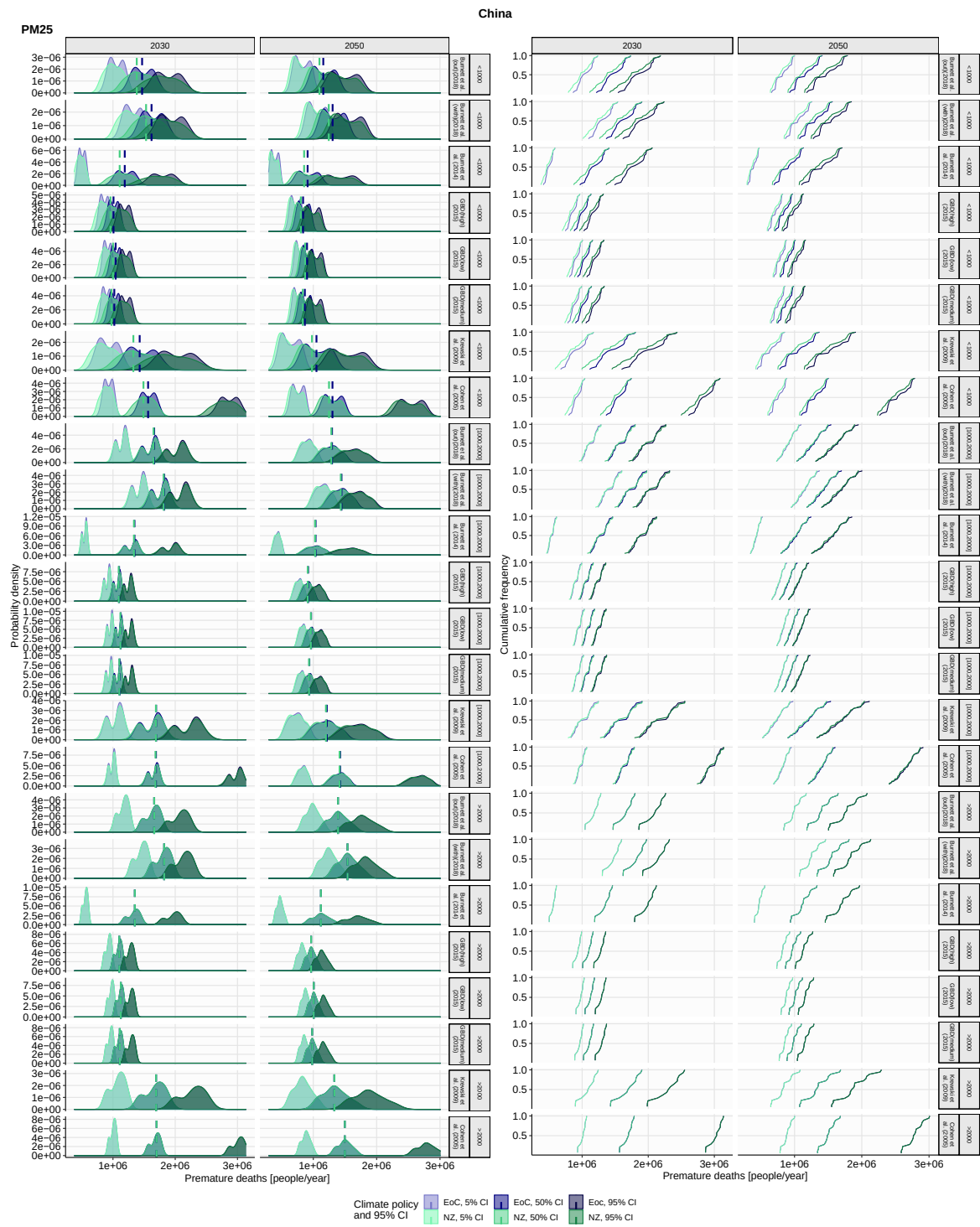


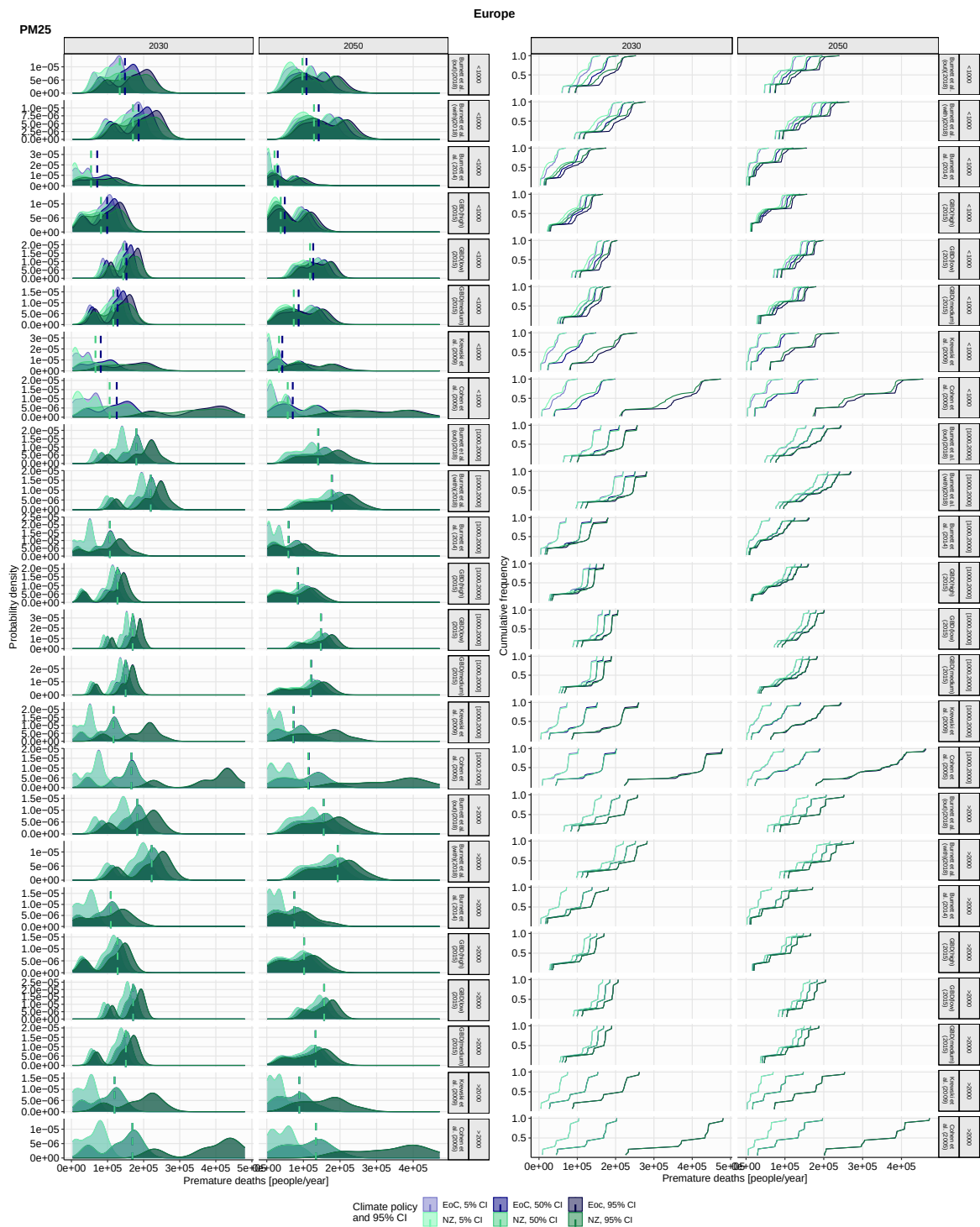
Figure S9: Probability density distribution (left) and cumulative frequency (right) for each R10 region for PM_{2.5} and O₃ concentration. Includes median line by climate policy. Color indicates the scenario.

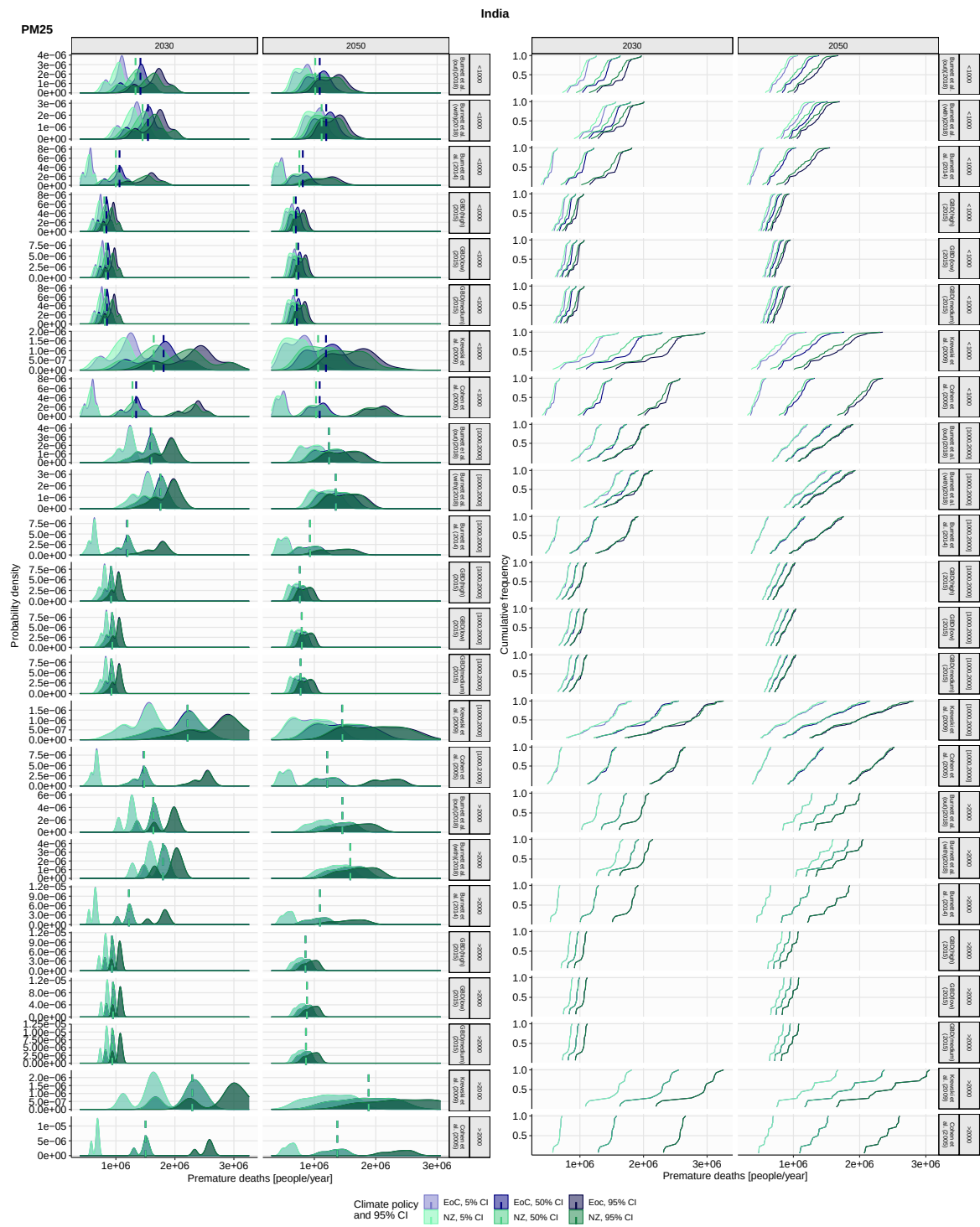
S9 Premature deaths sensitivity and uncertainty: probability distribution and cumulative frequency mortality figures

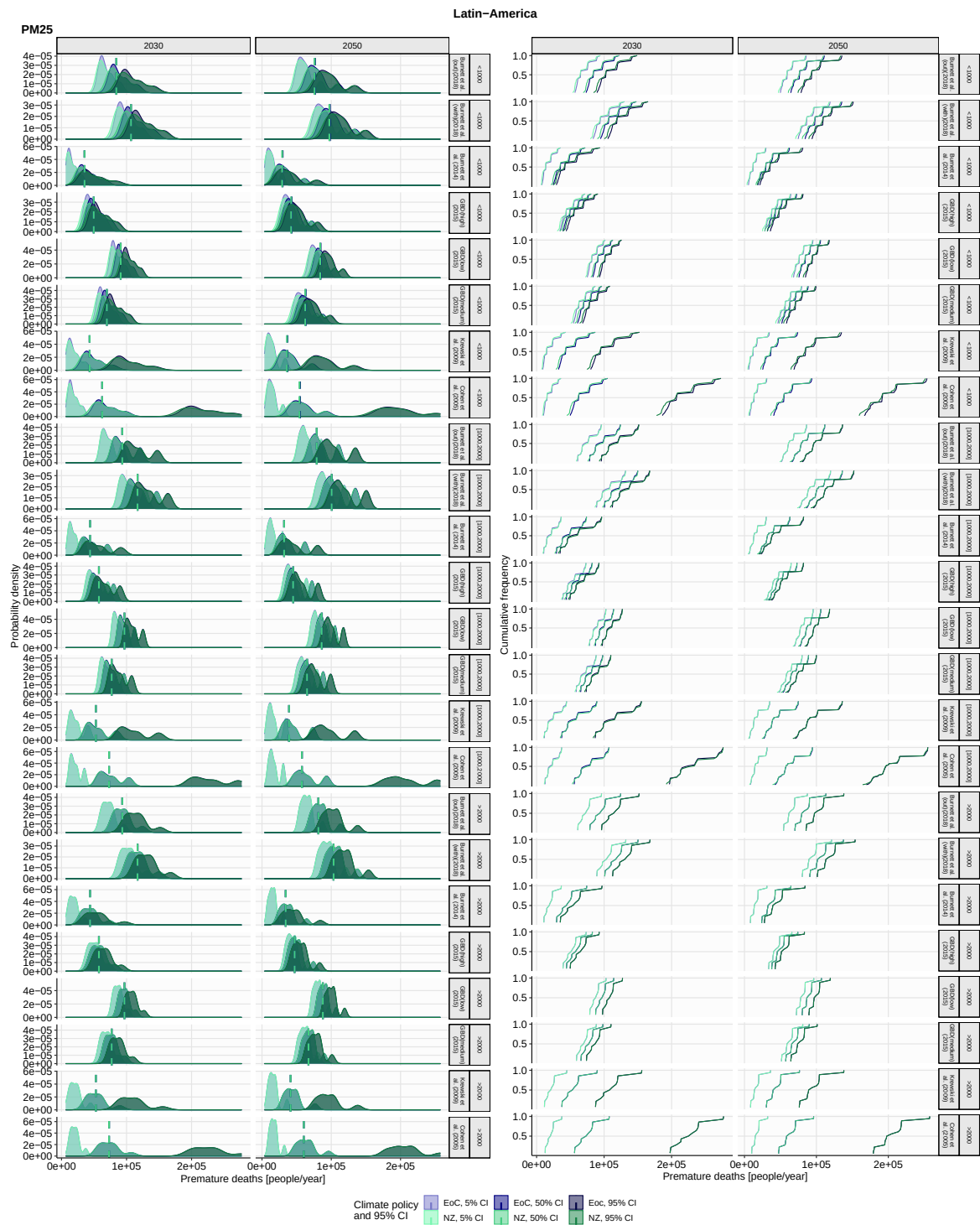


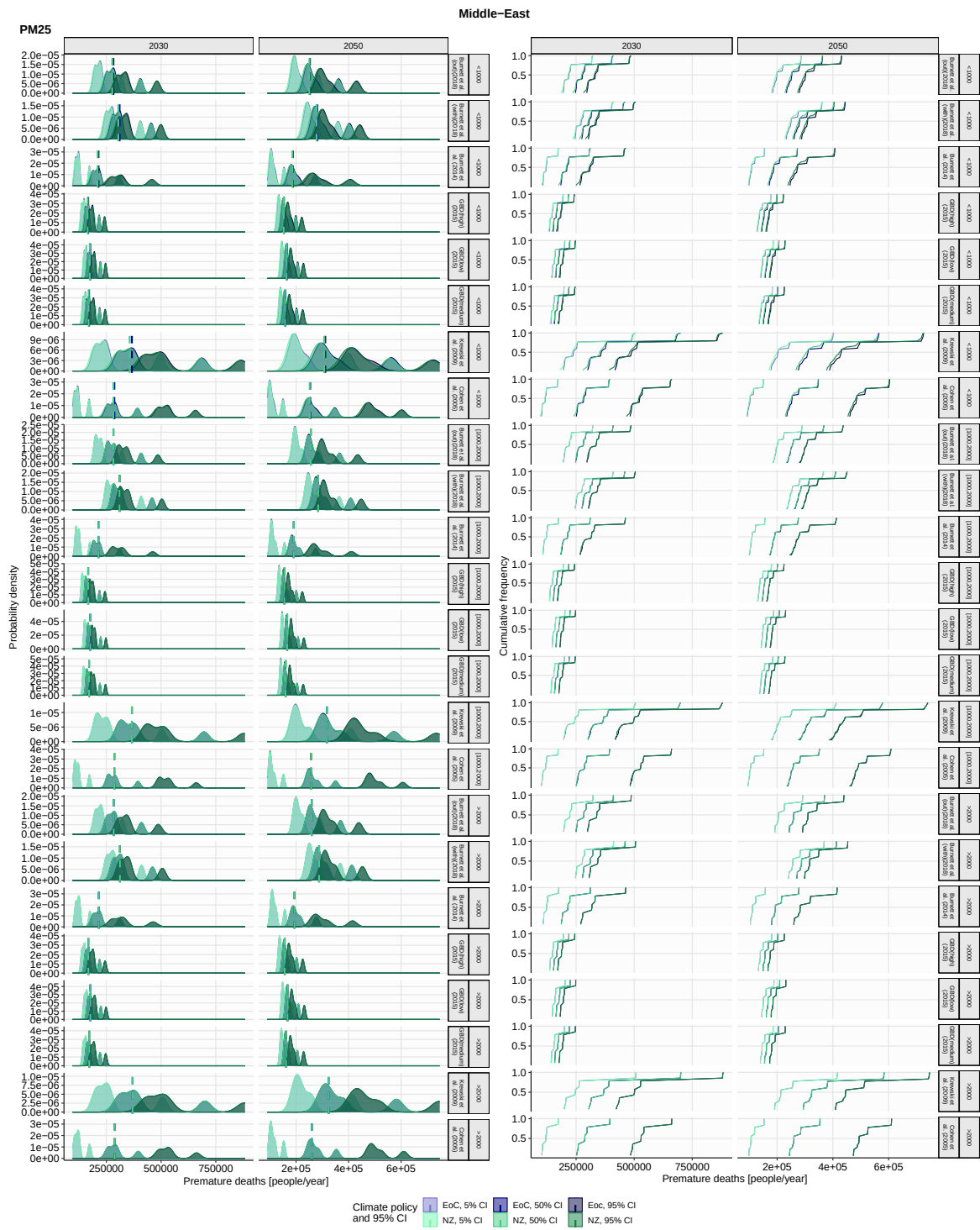


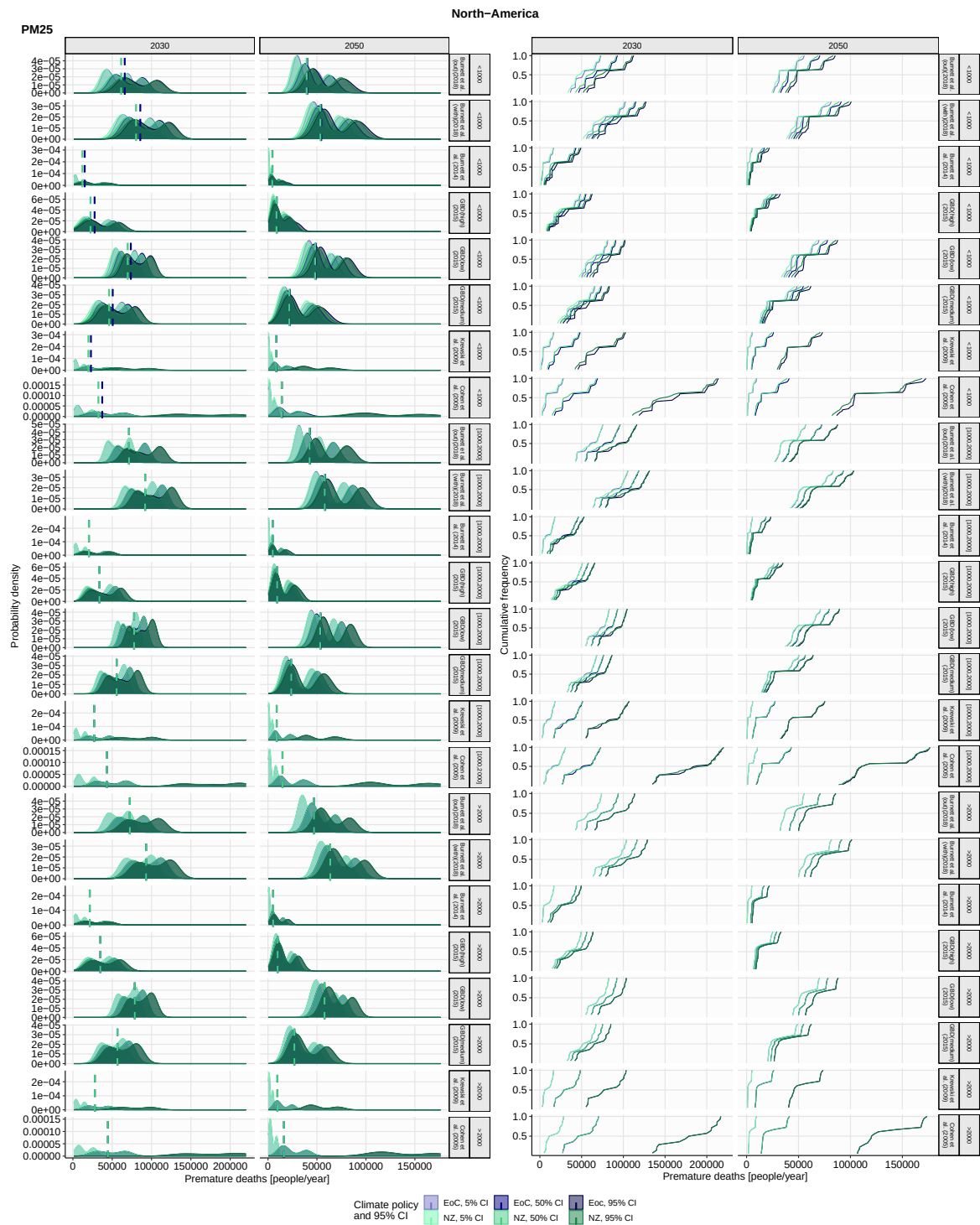


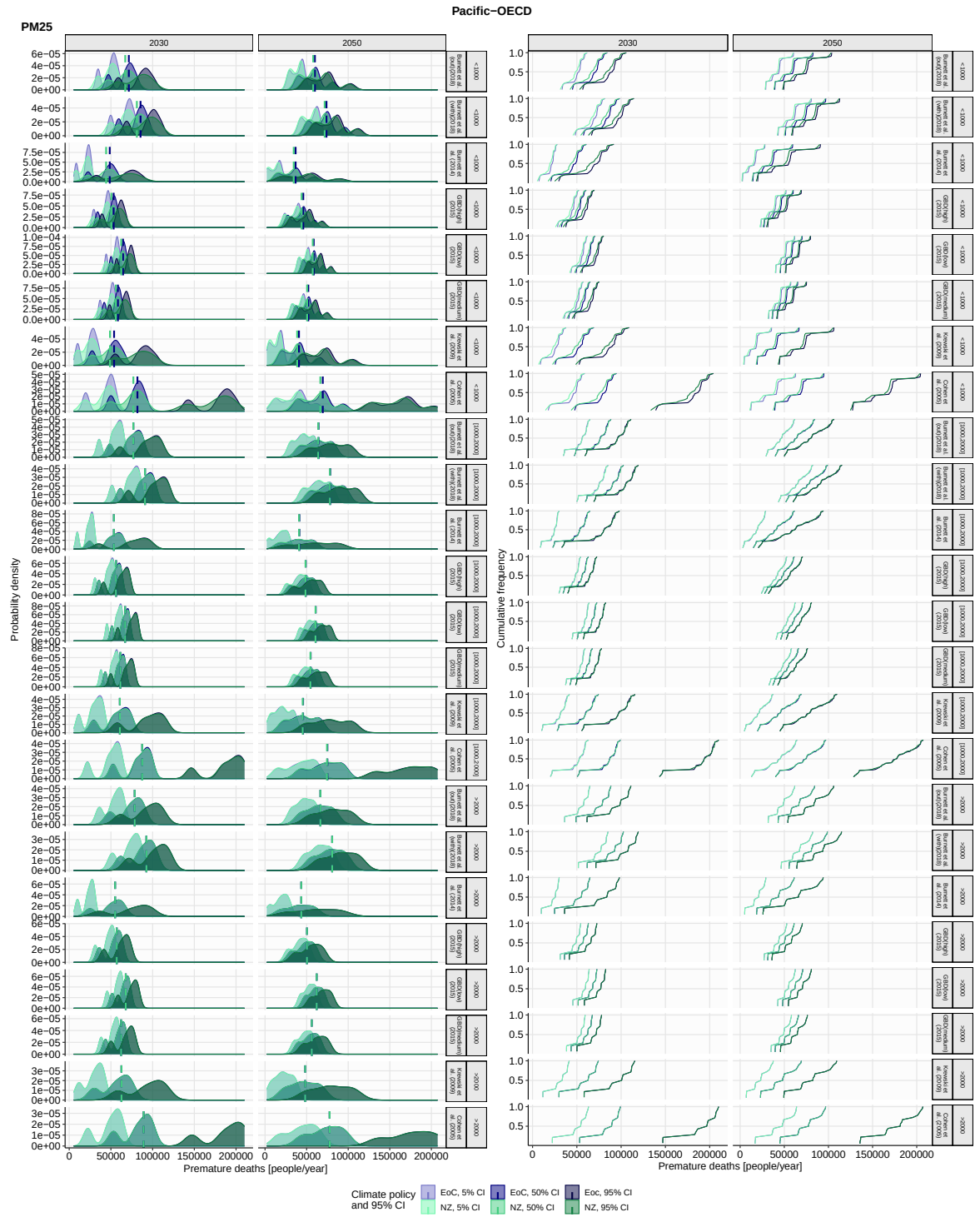


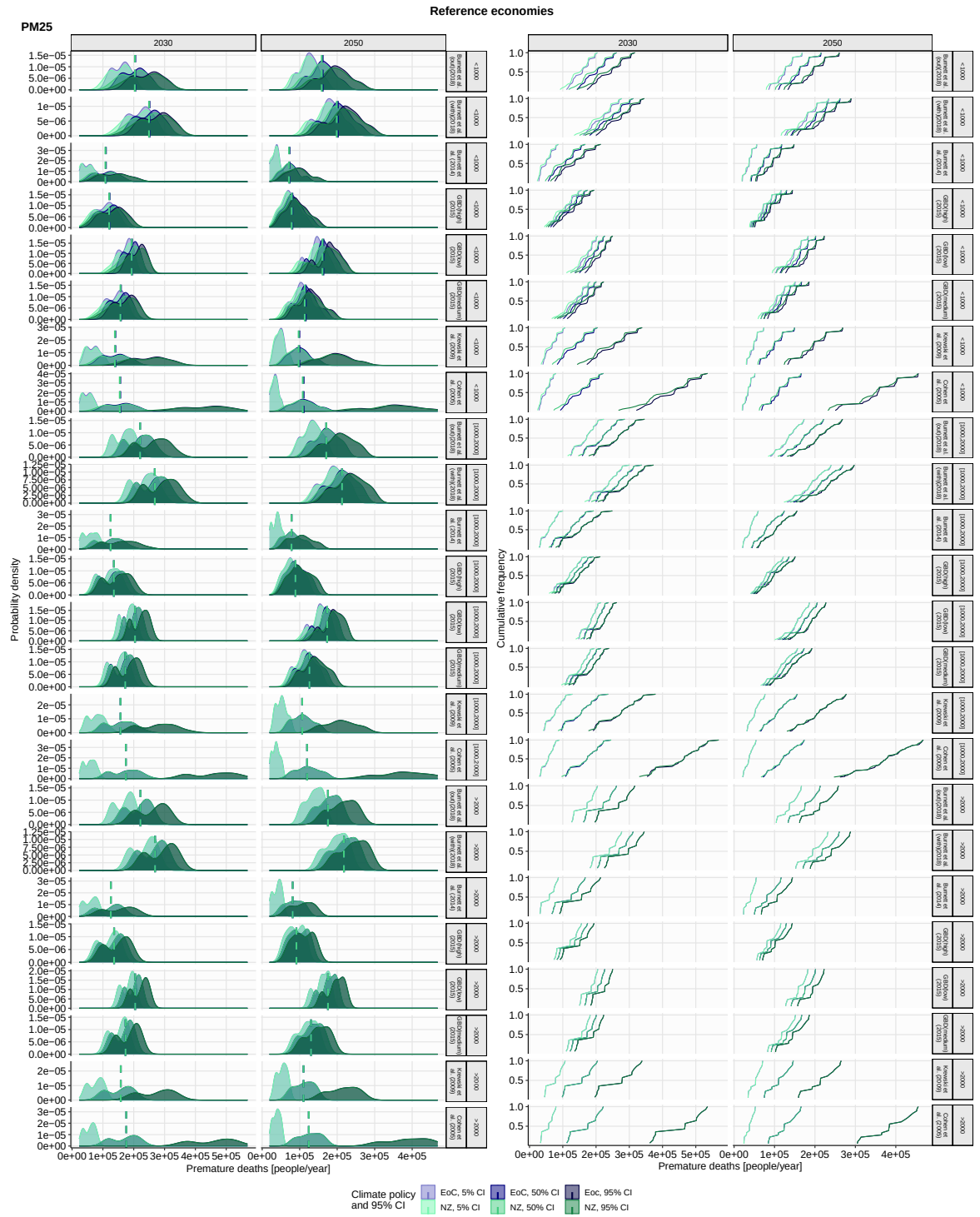












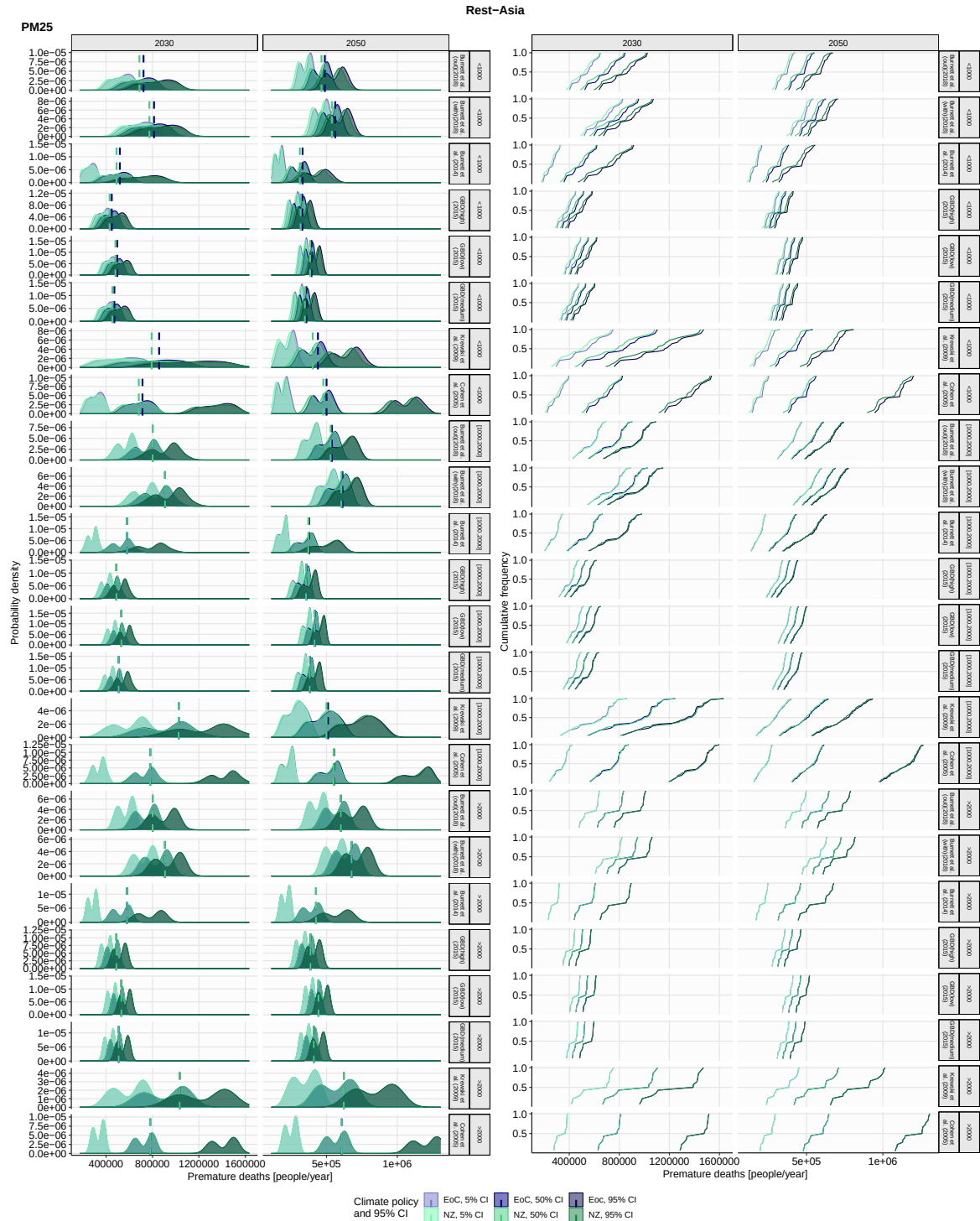
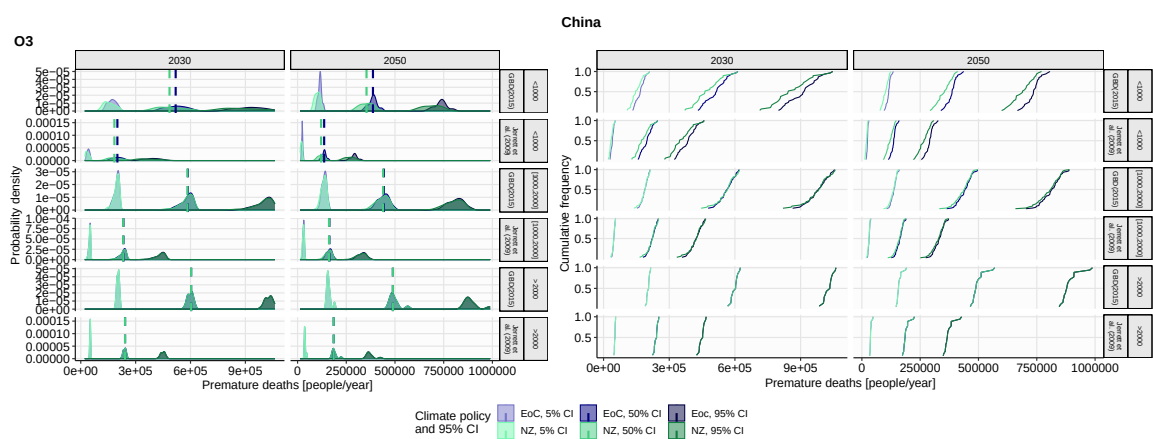
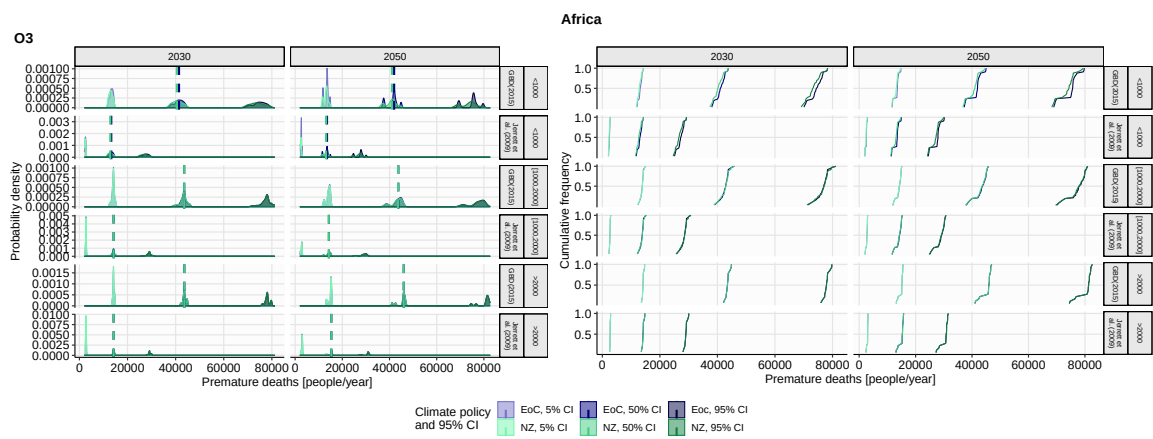
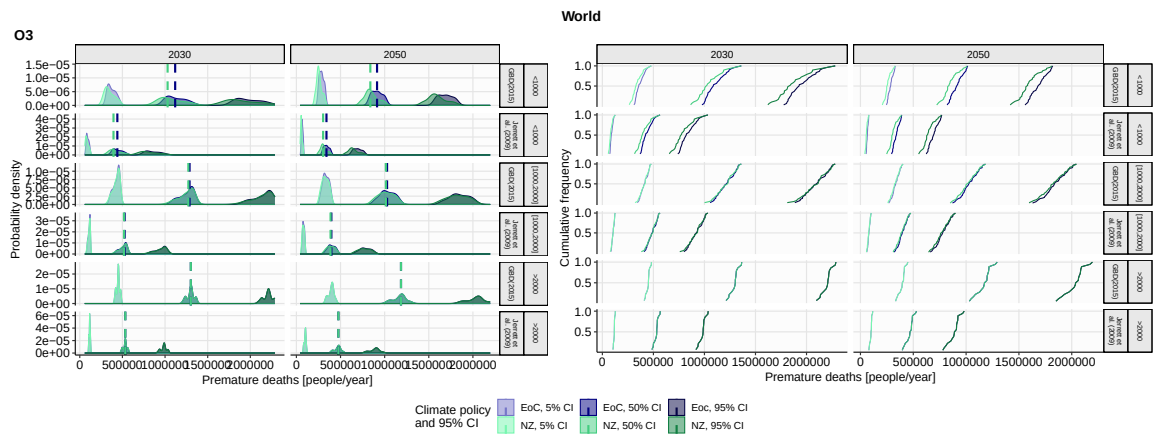
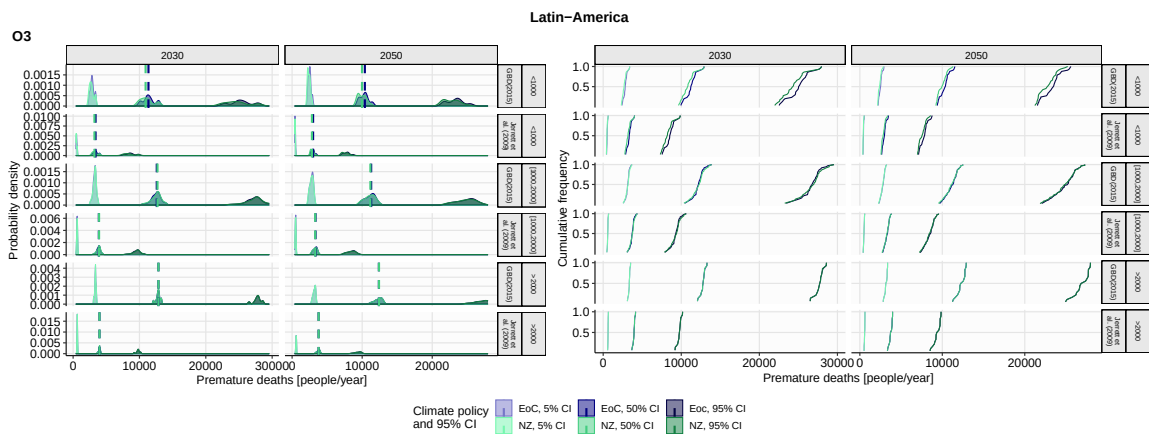
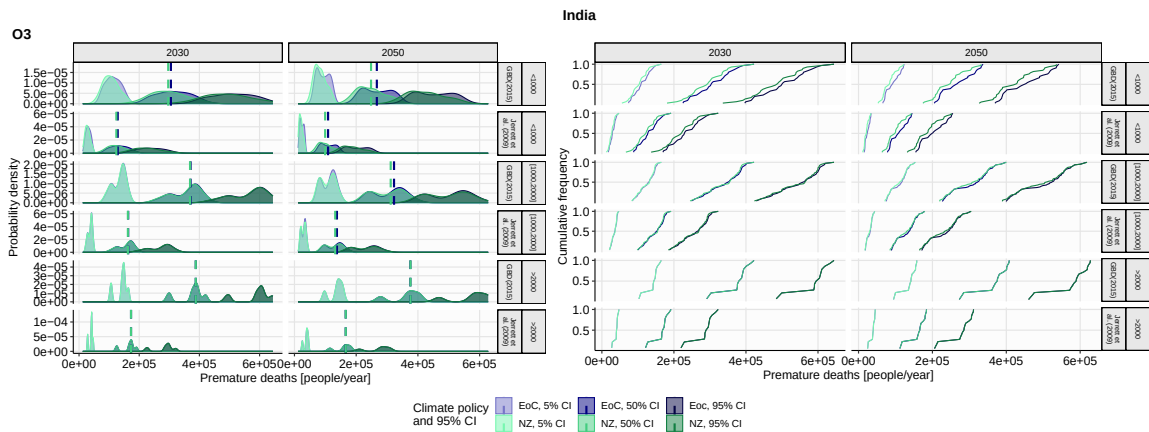
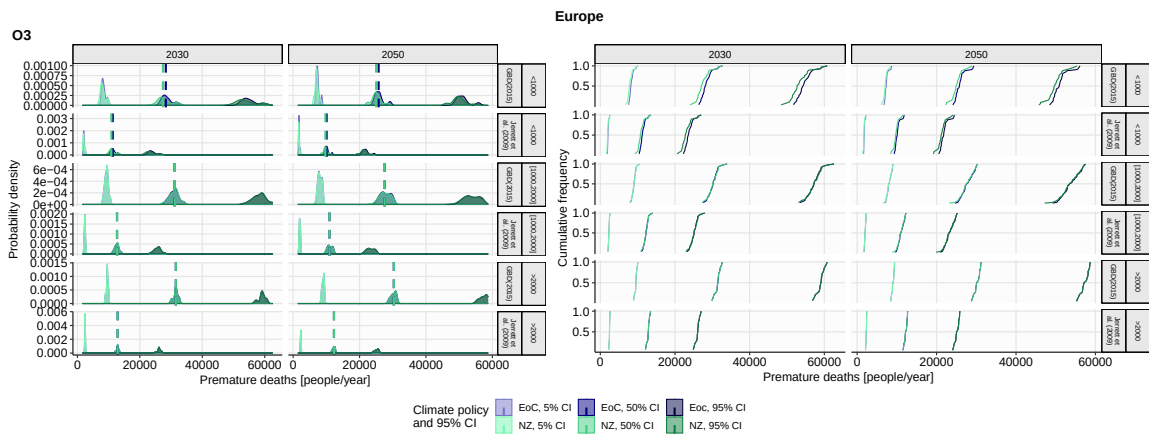
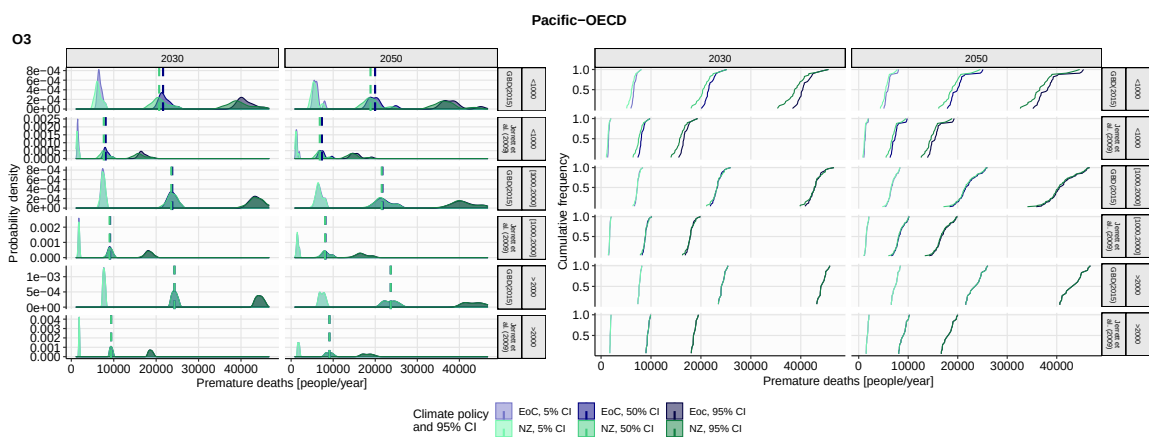
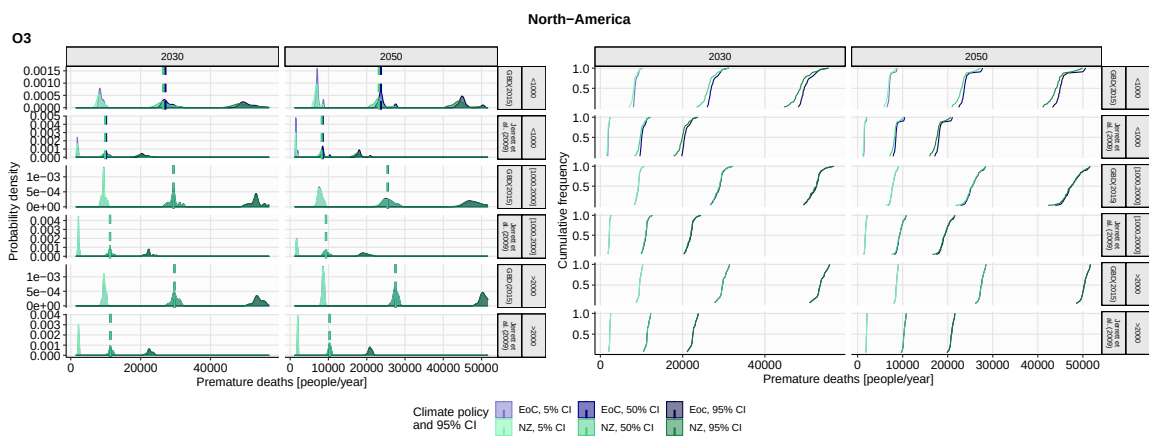
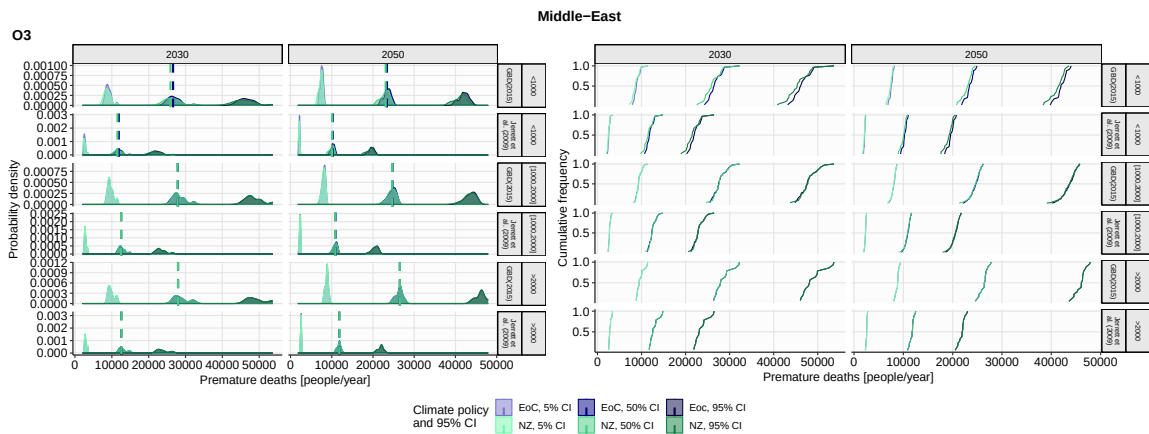


Figure S10: Probability density distribution (left) and cumulative frequency (right) of PM_{2.5} premature deaths for each R10 region by RR function and carbon budget. Includes median line by climate policy. Color indicates the scenario.







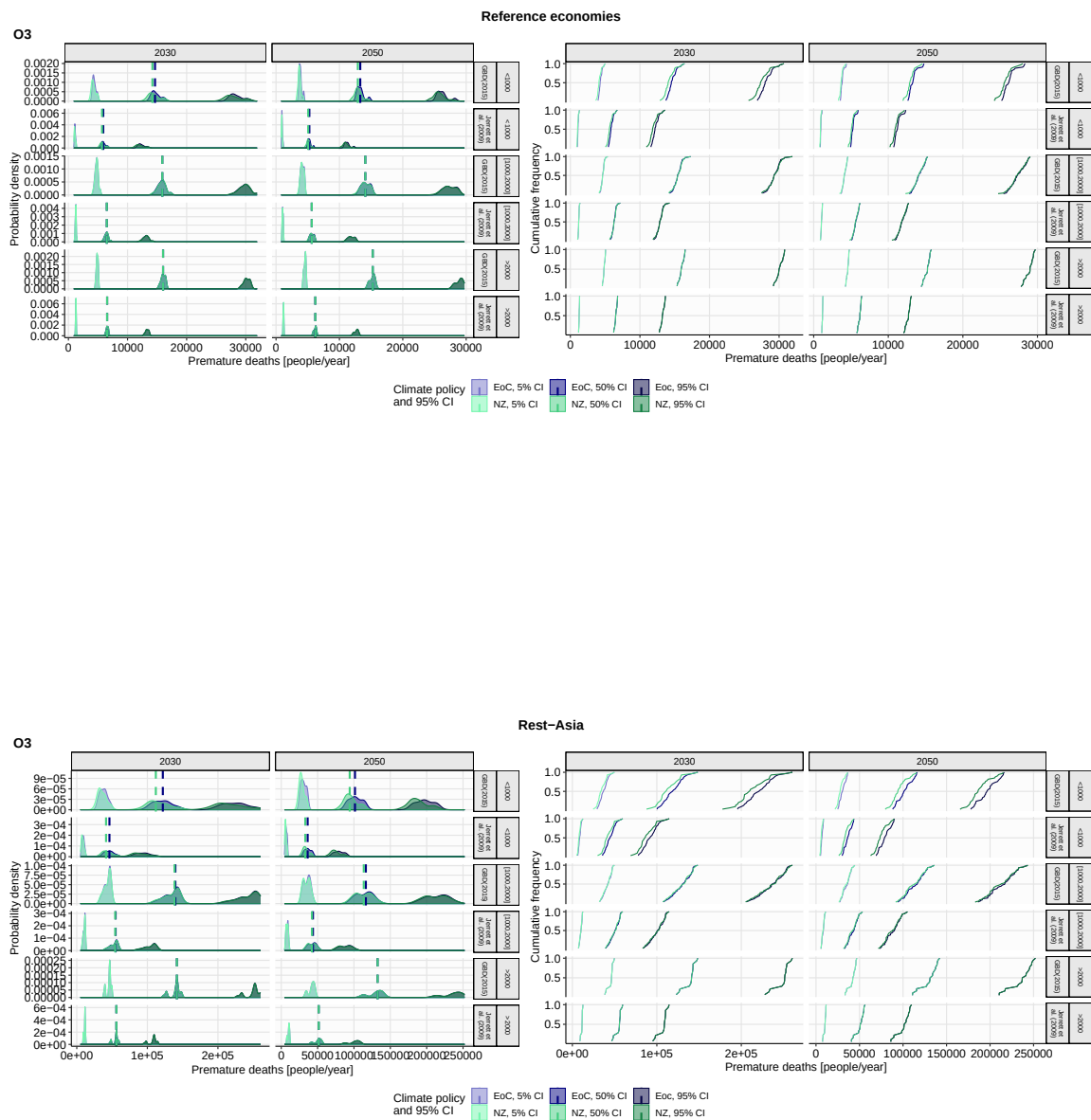
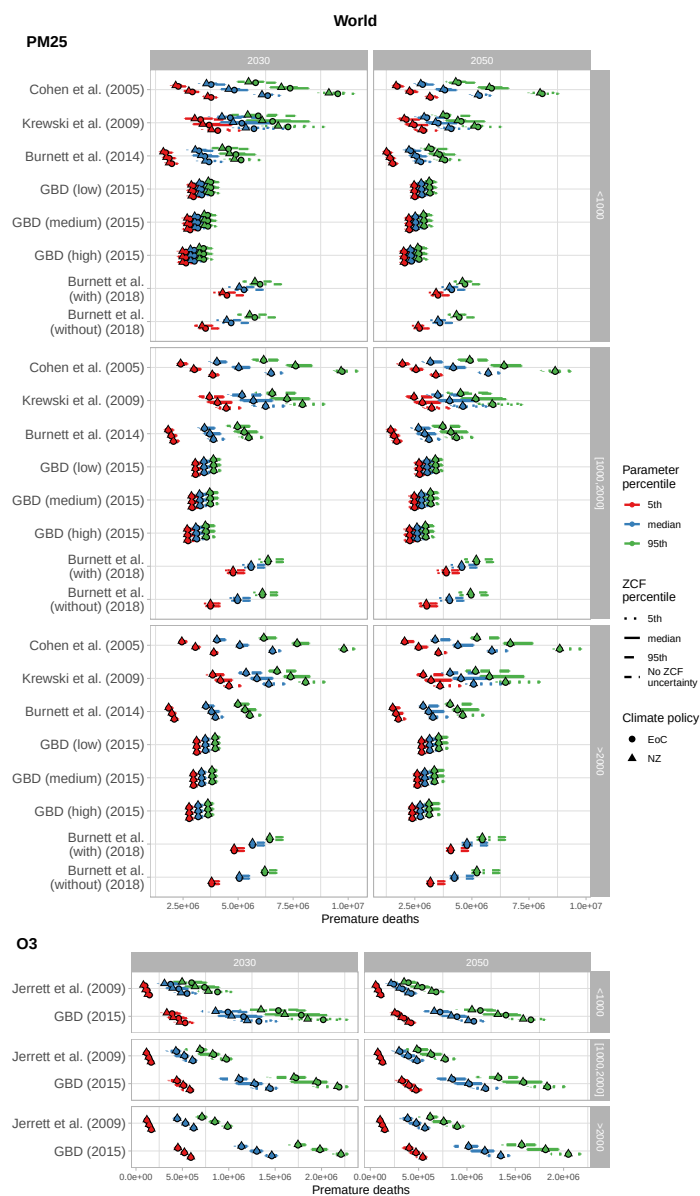


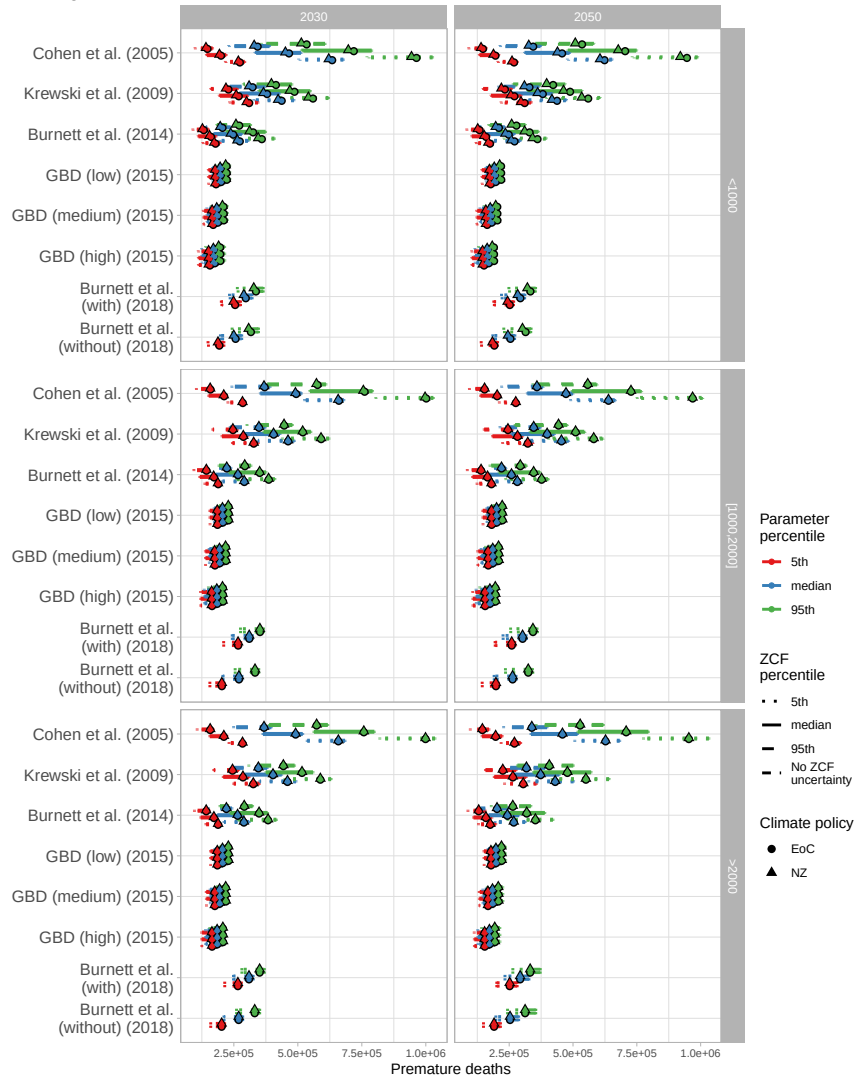
Figure S11: Probability density distribution (left) and cumulative frequency (right) of O_3 premature deaths for each R10 region by RR function and carbon budget. Includes median line by climate policy. Color indicates the scenario.

S10 Premature deaths sensitivity and uncertainty: impact function's parameters and counterfactual value sensitivity figures

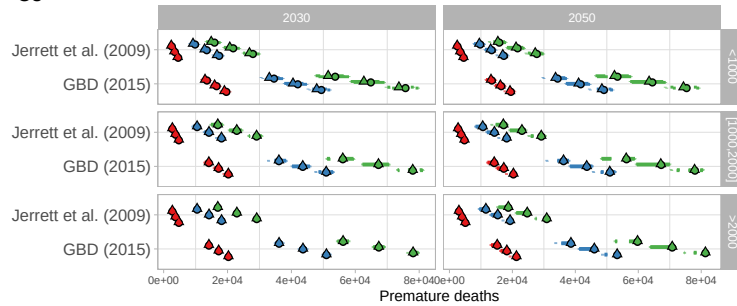


Africa

PM25

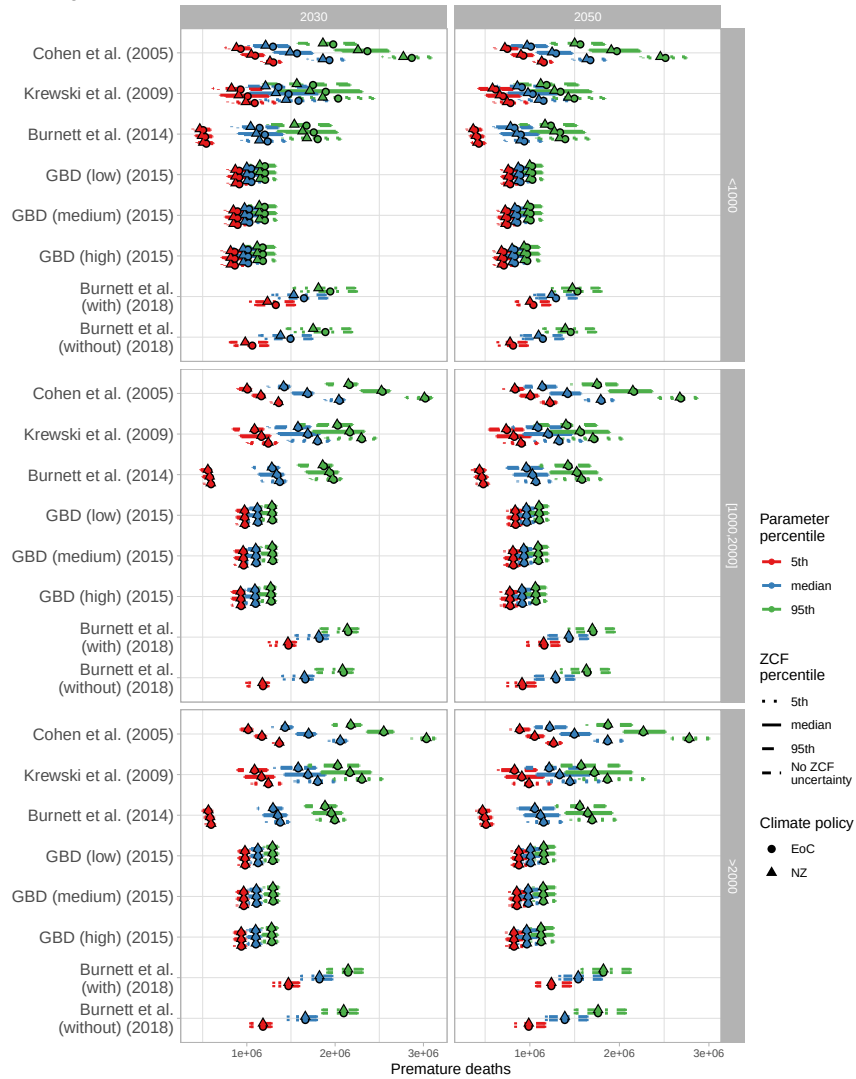


O3

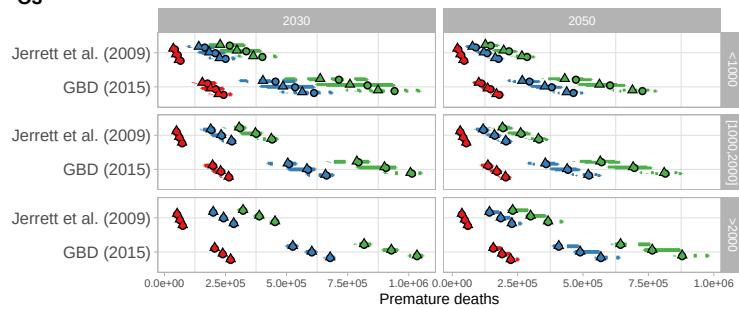


China

PM25

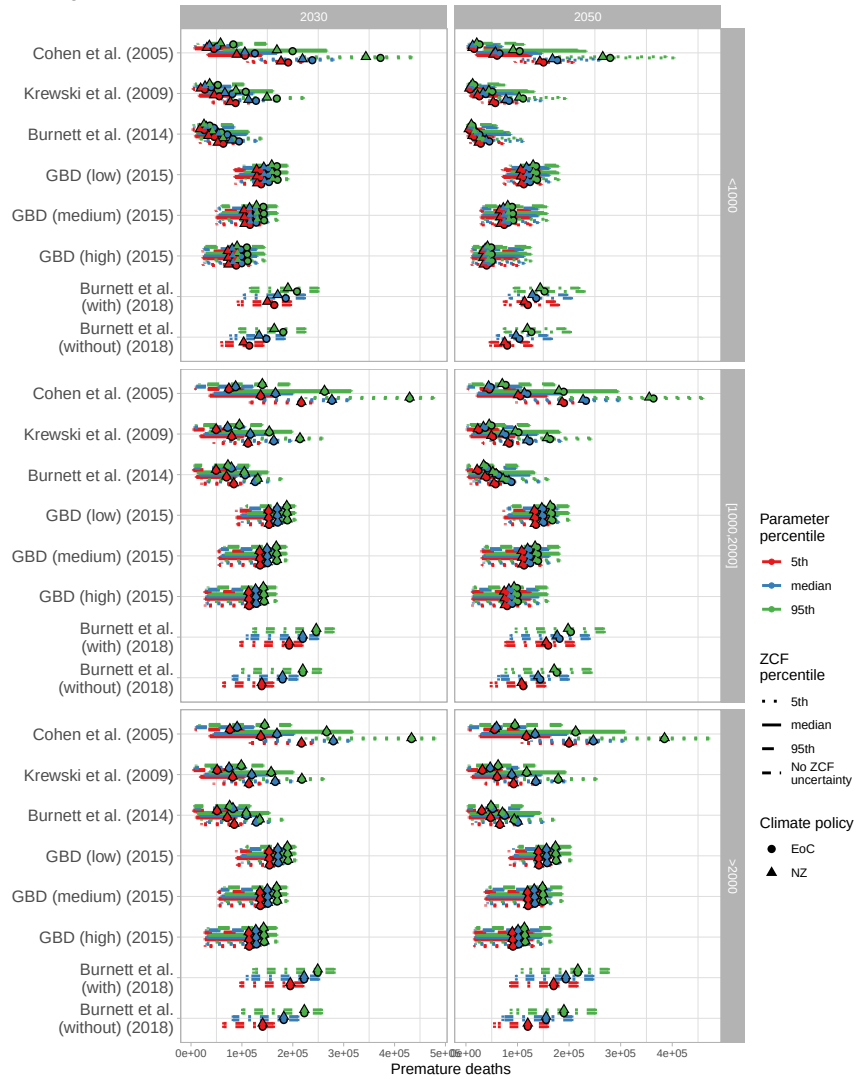


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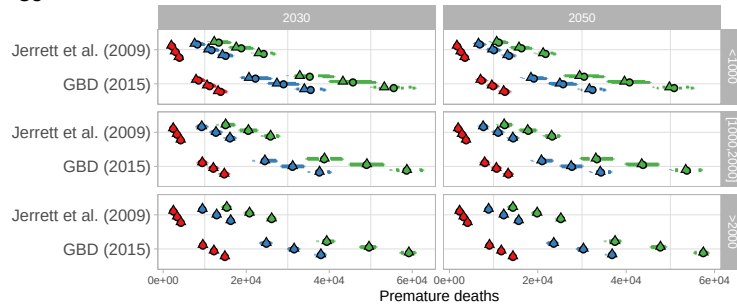


Europe

PM25

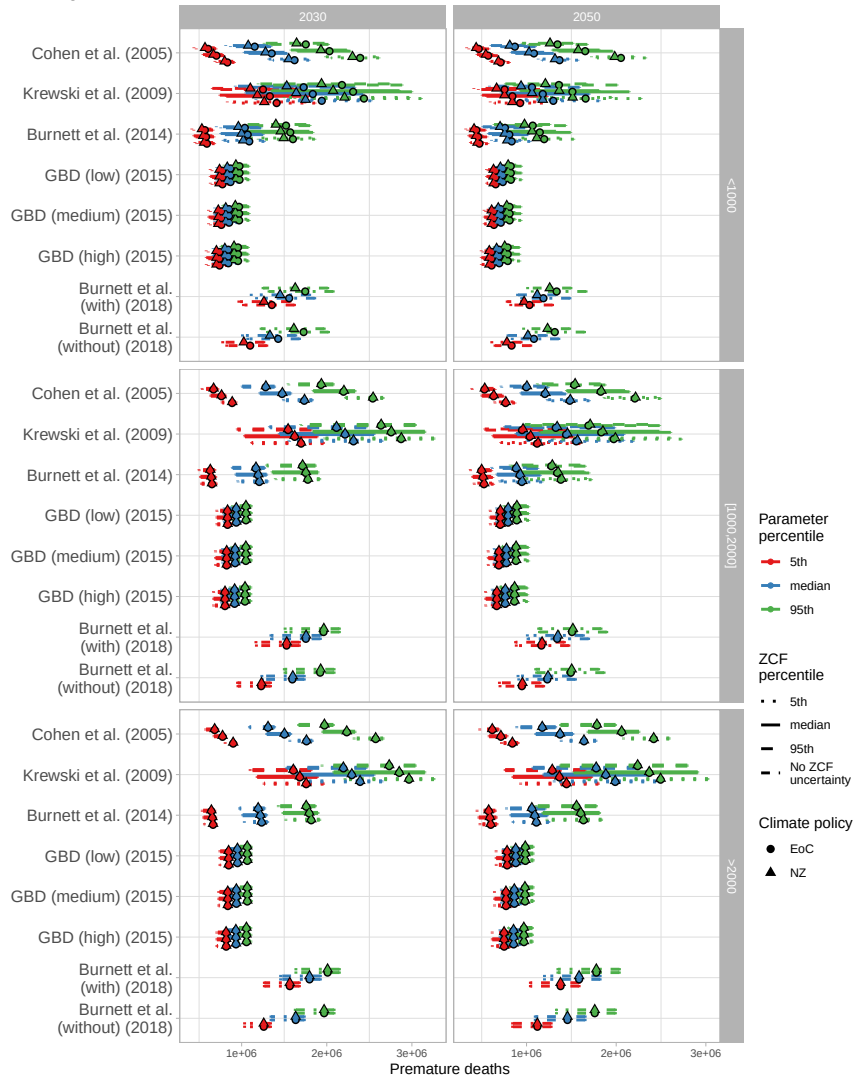


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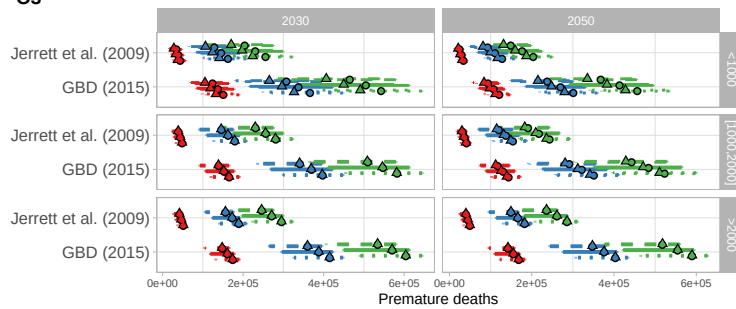


India

PM25

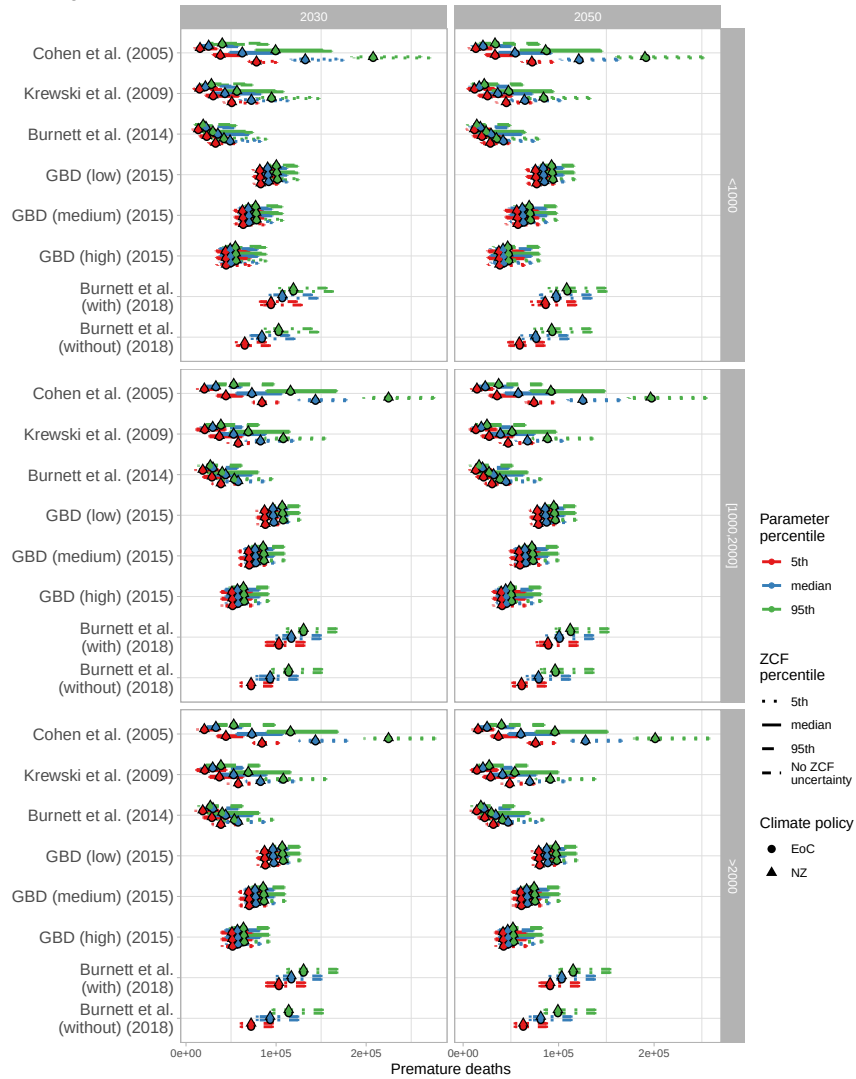


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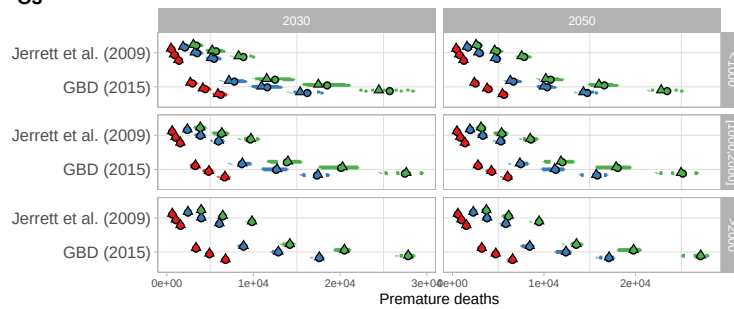


Latin-America

PM25

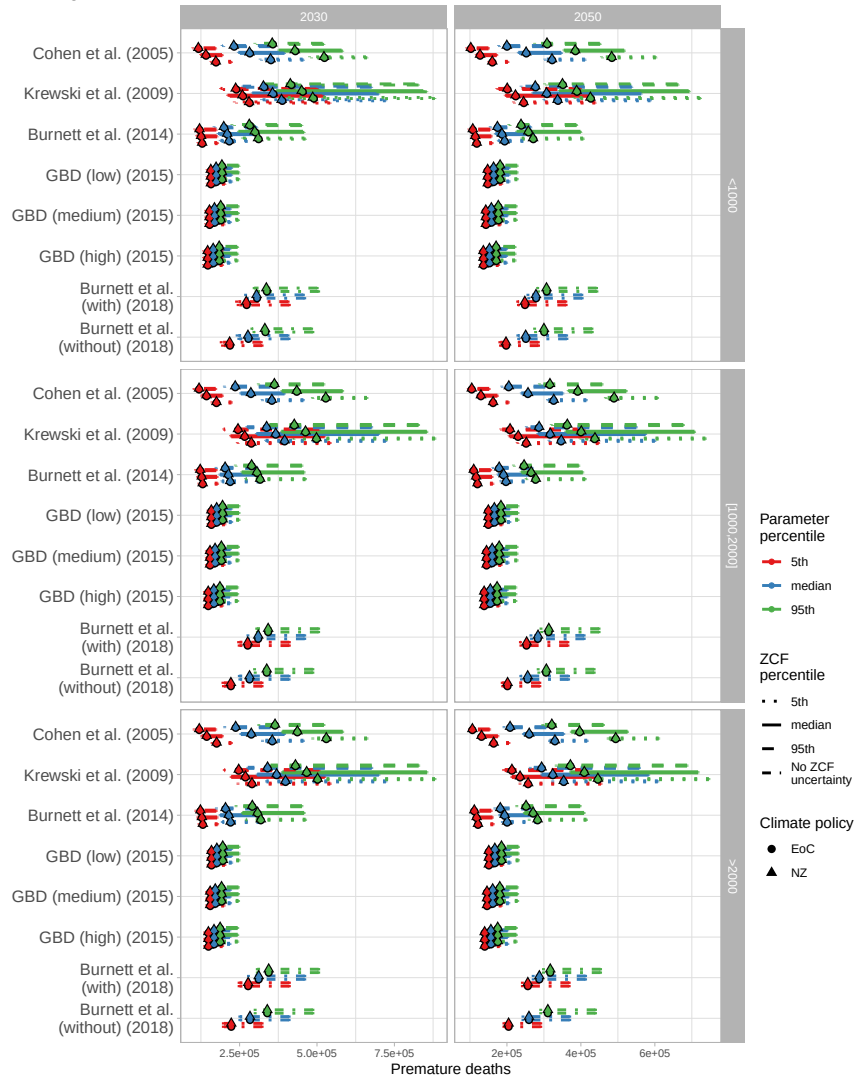


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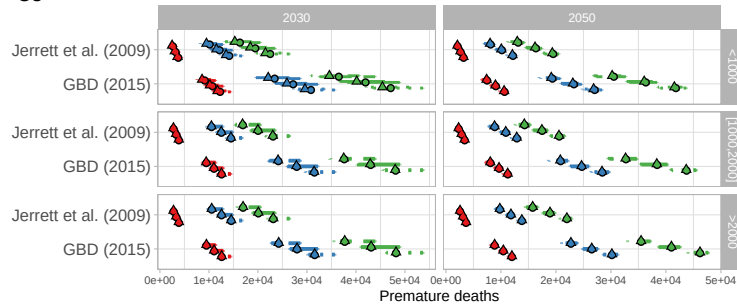


Middle-East

PM25

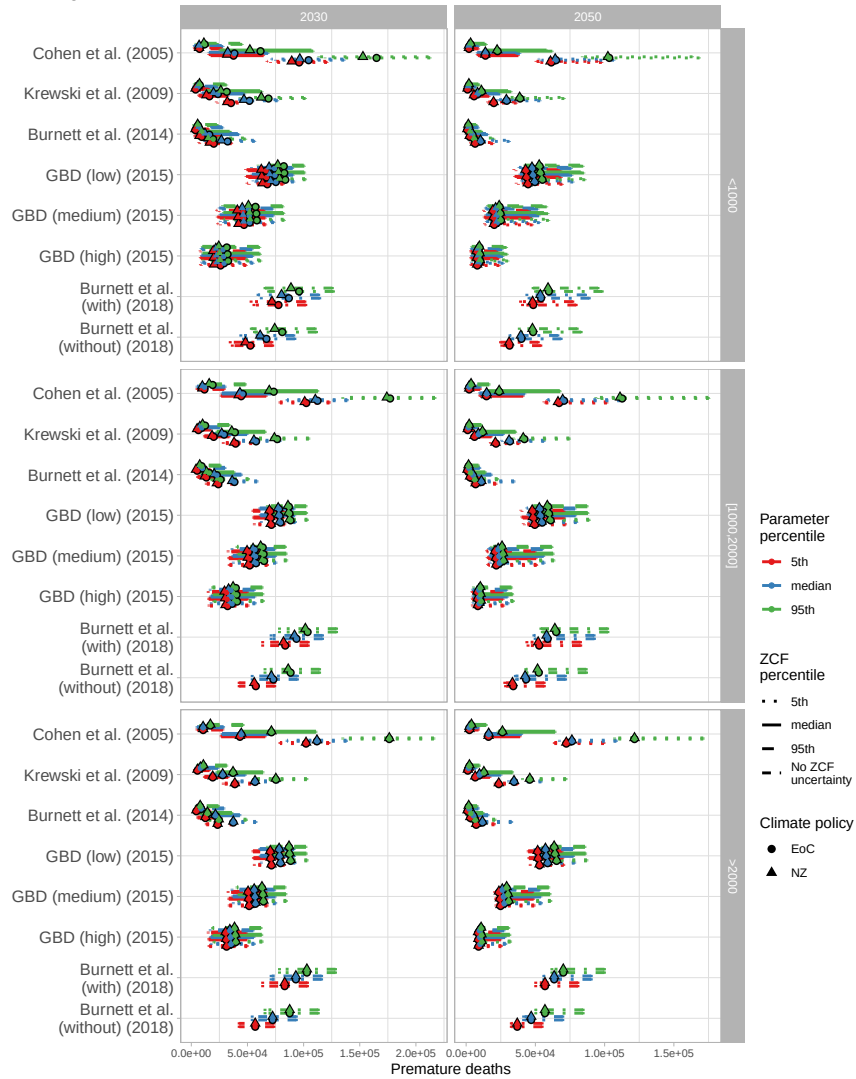


O3

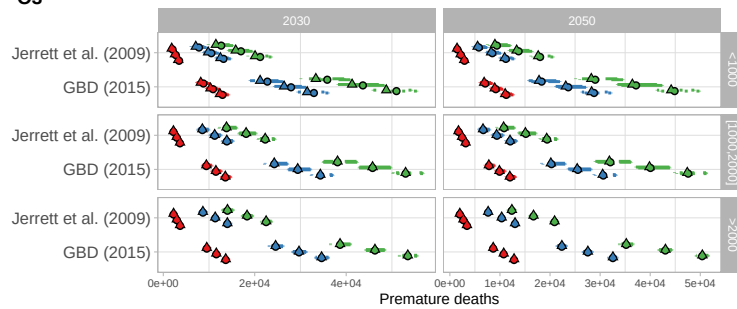


North-America

PM25

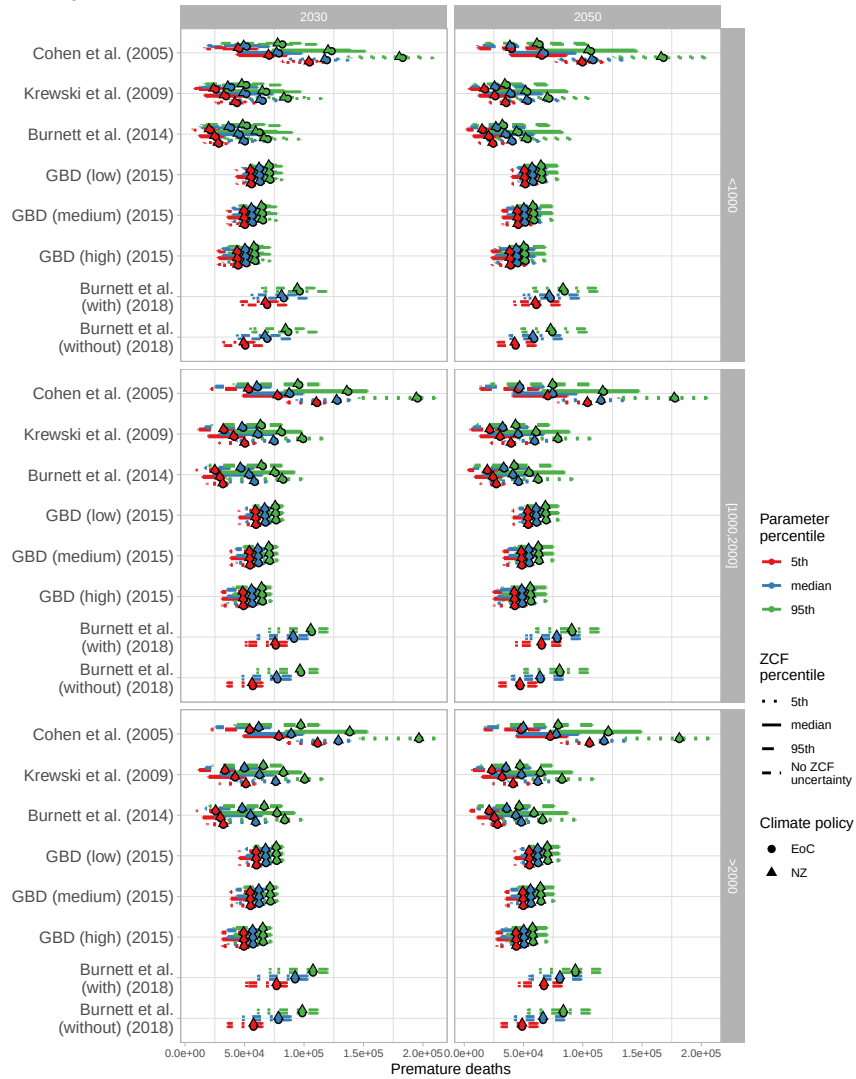


O3

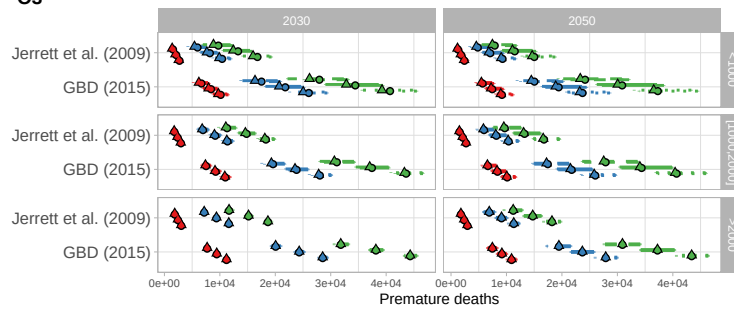


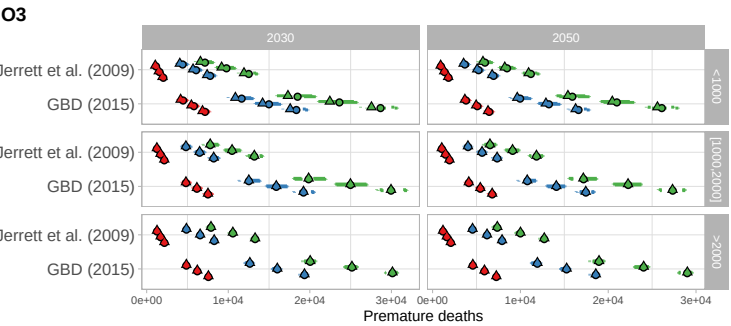
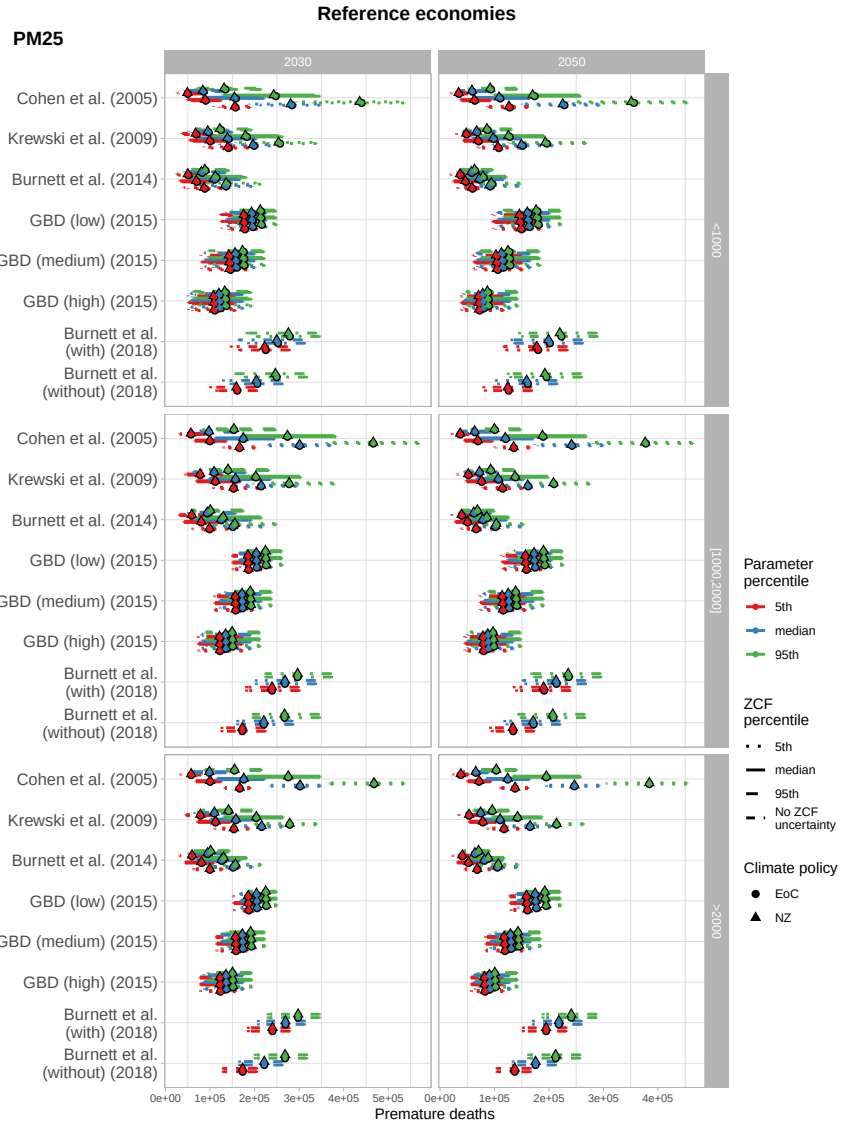
Pacific-OECD

PM25

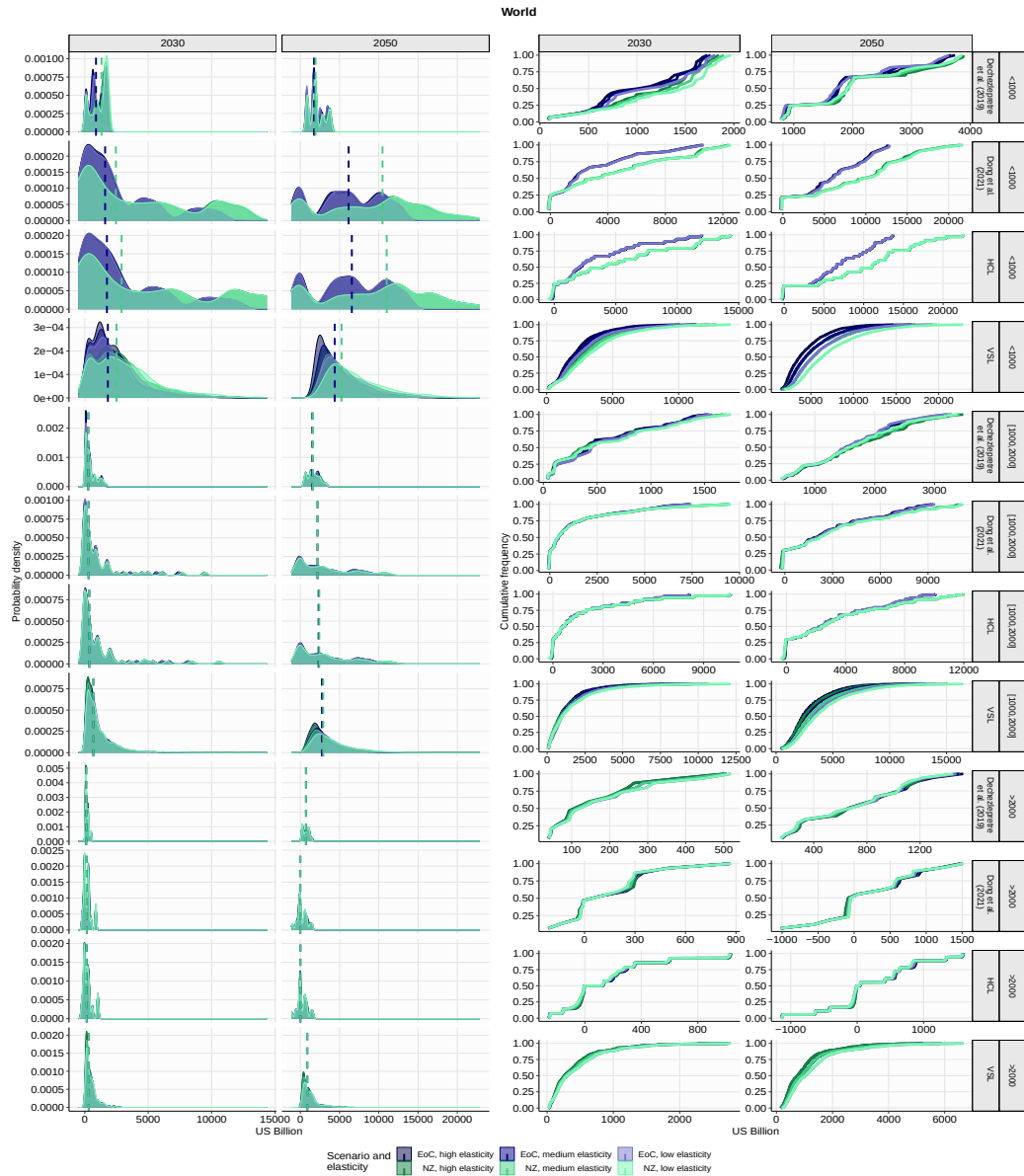


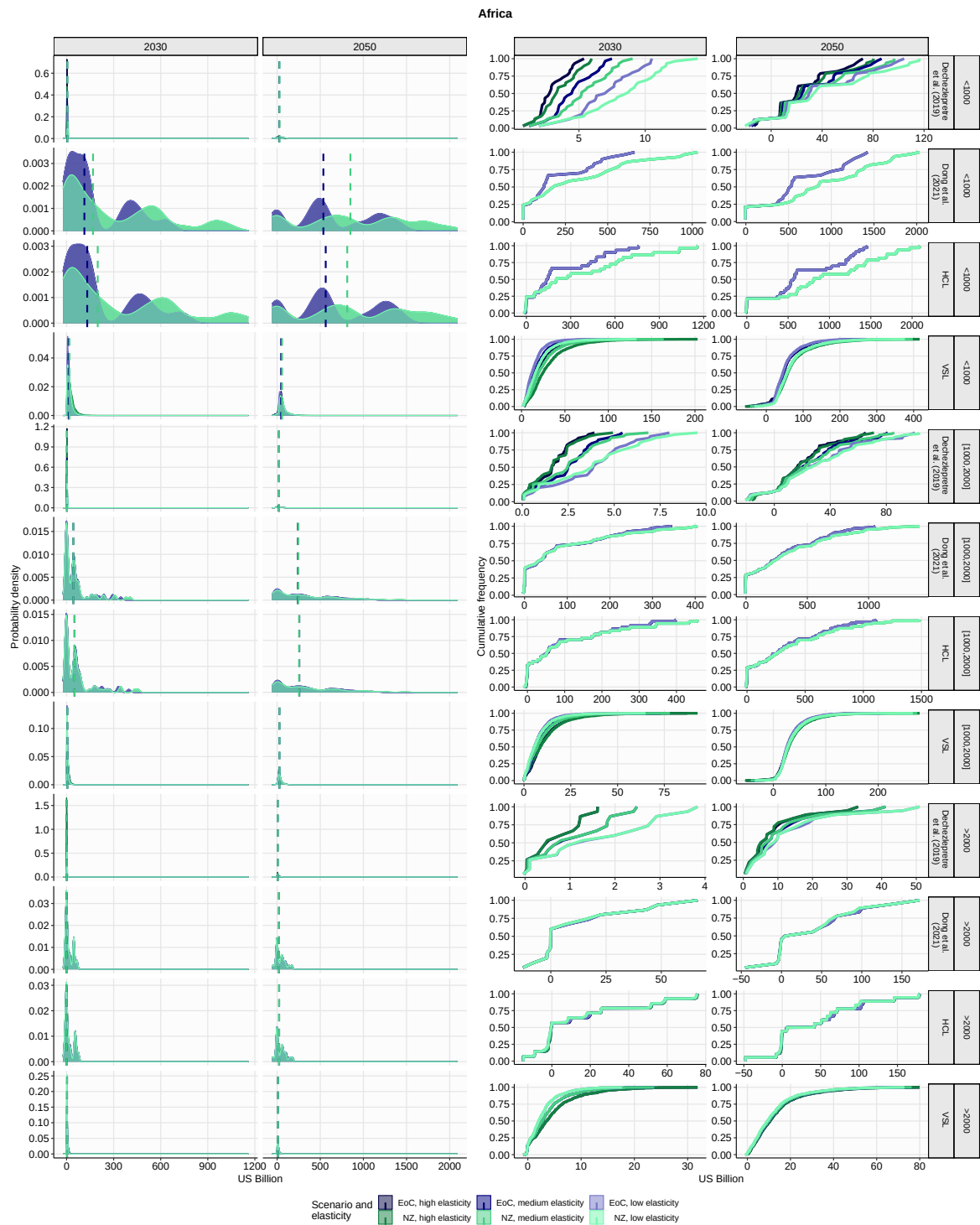
O3

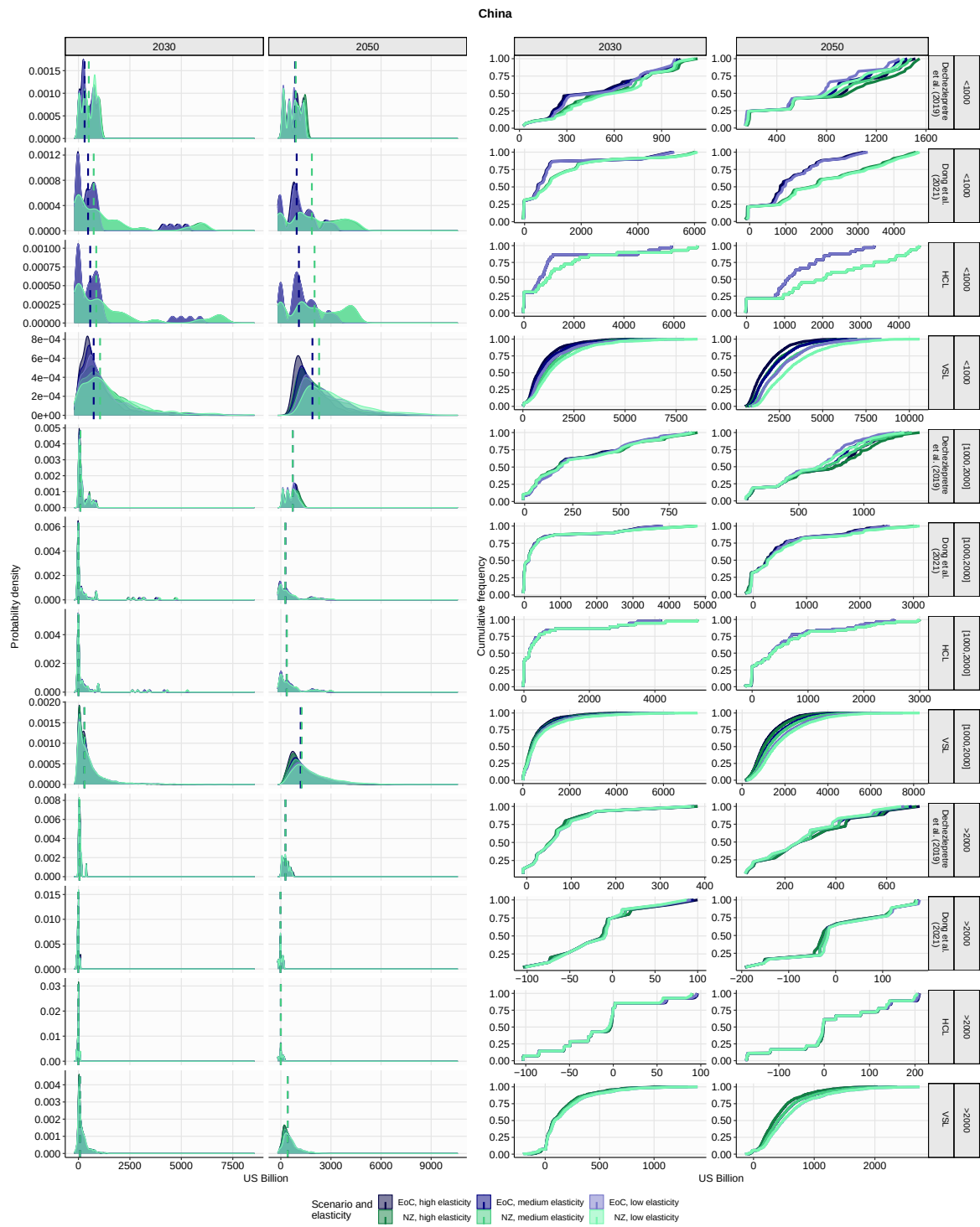




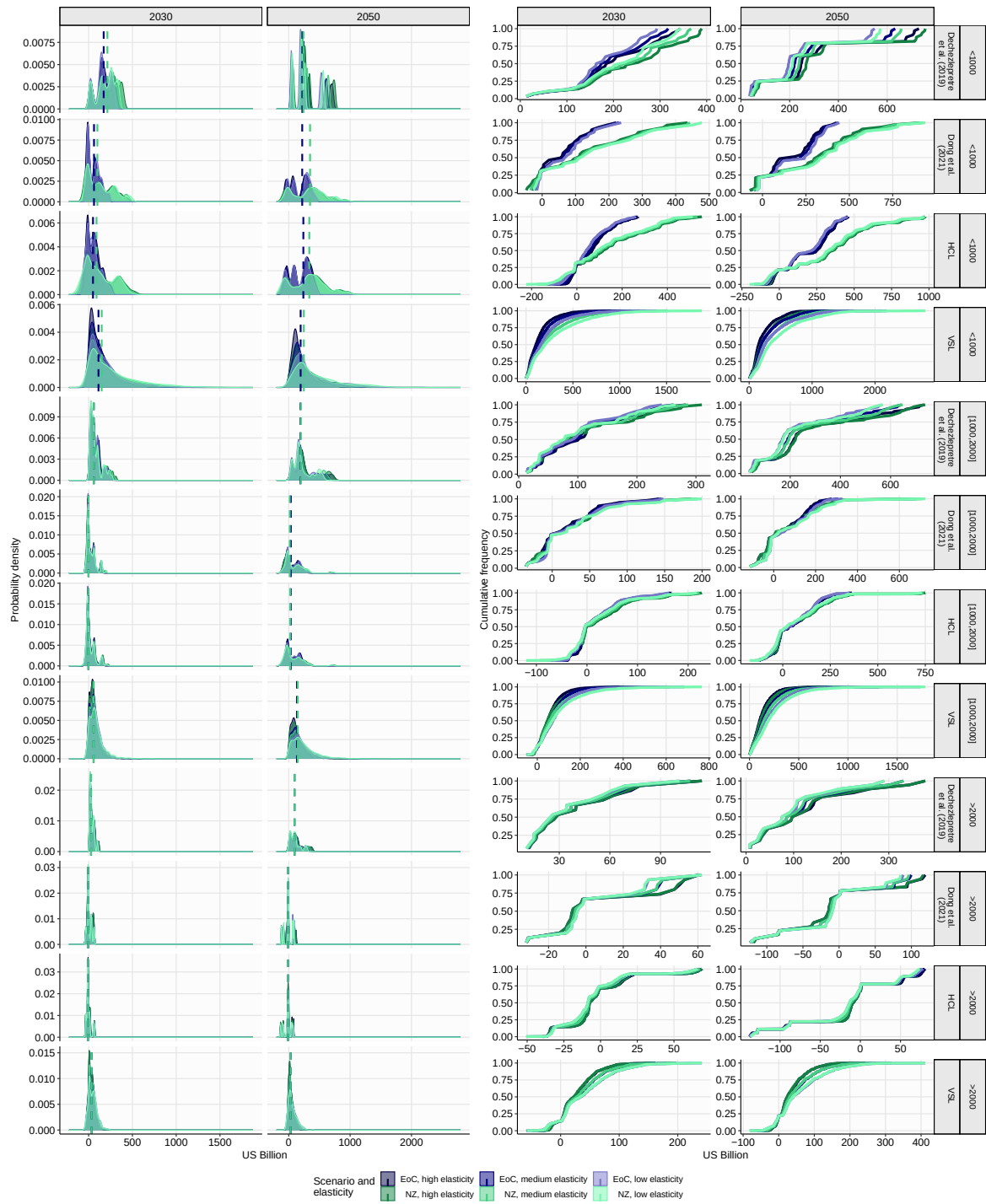
S11 Economical co-benefits sensitivity and uncertainty: probability distribution and cumulative frequency economical co-benefit graphs

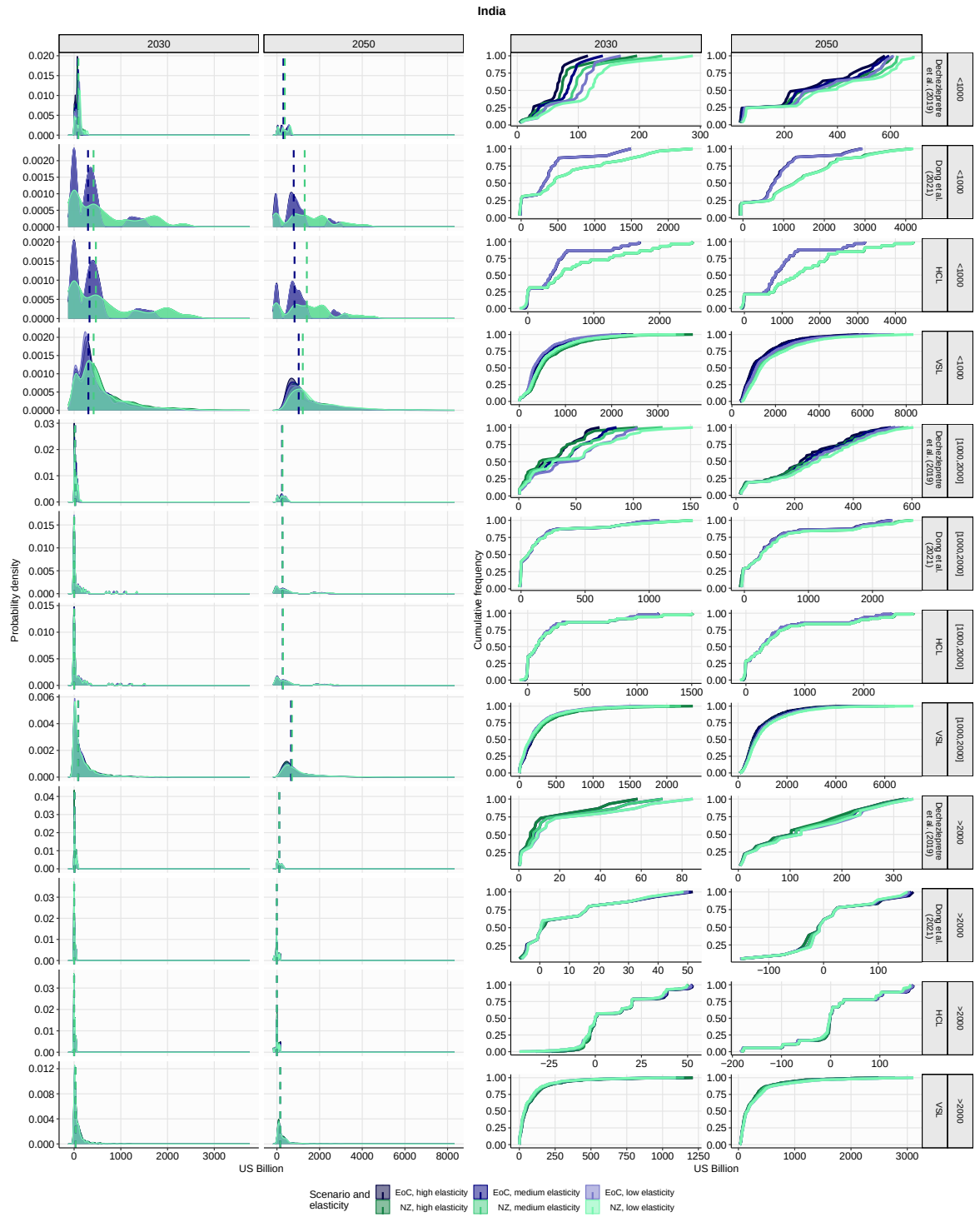




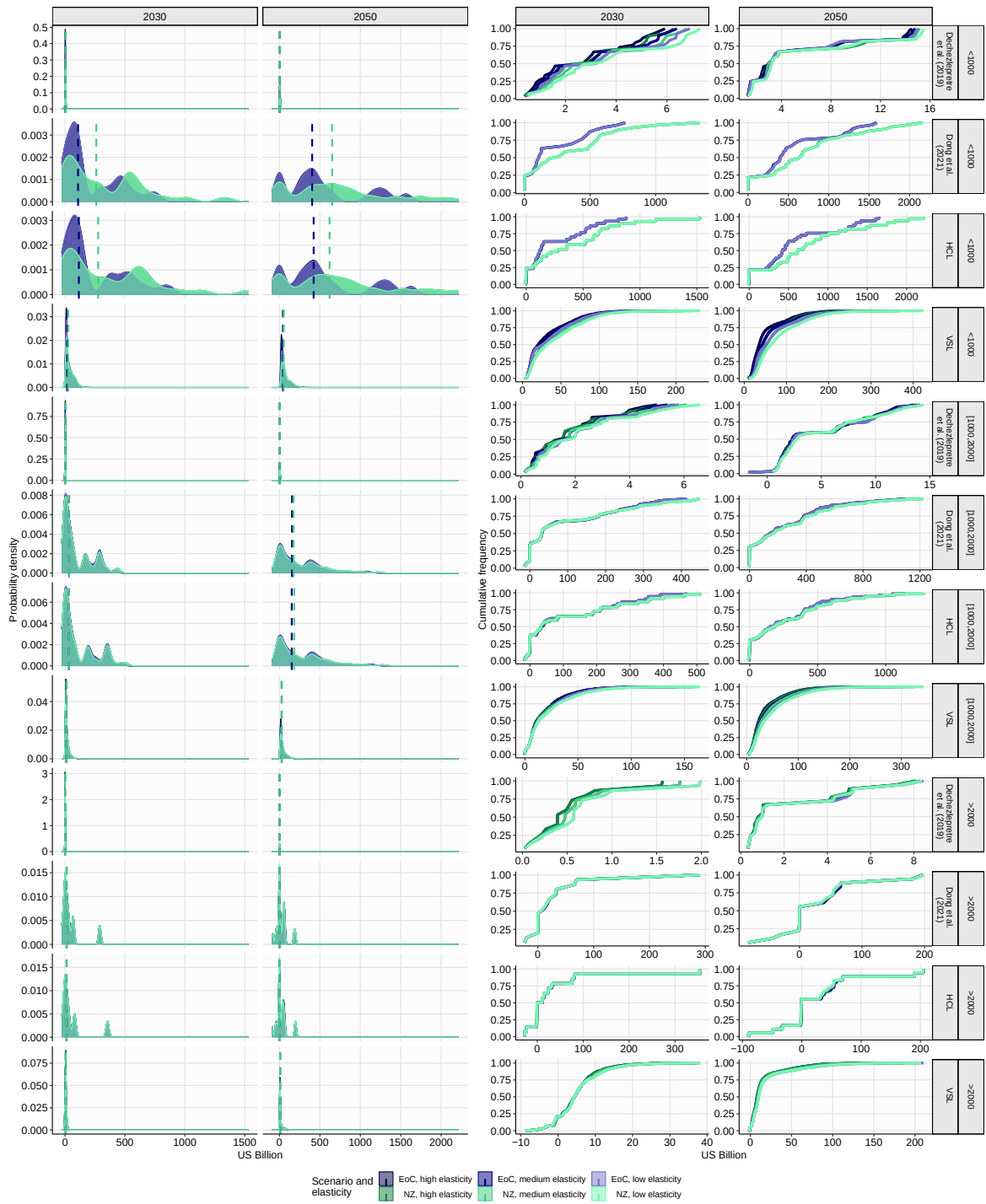


Europe

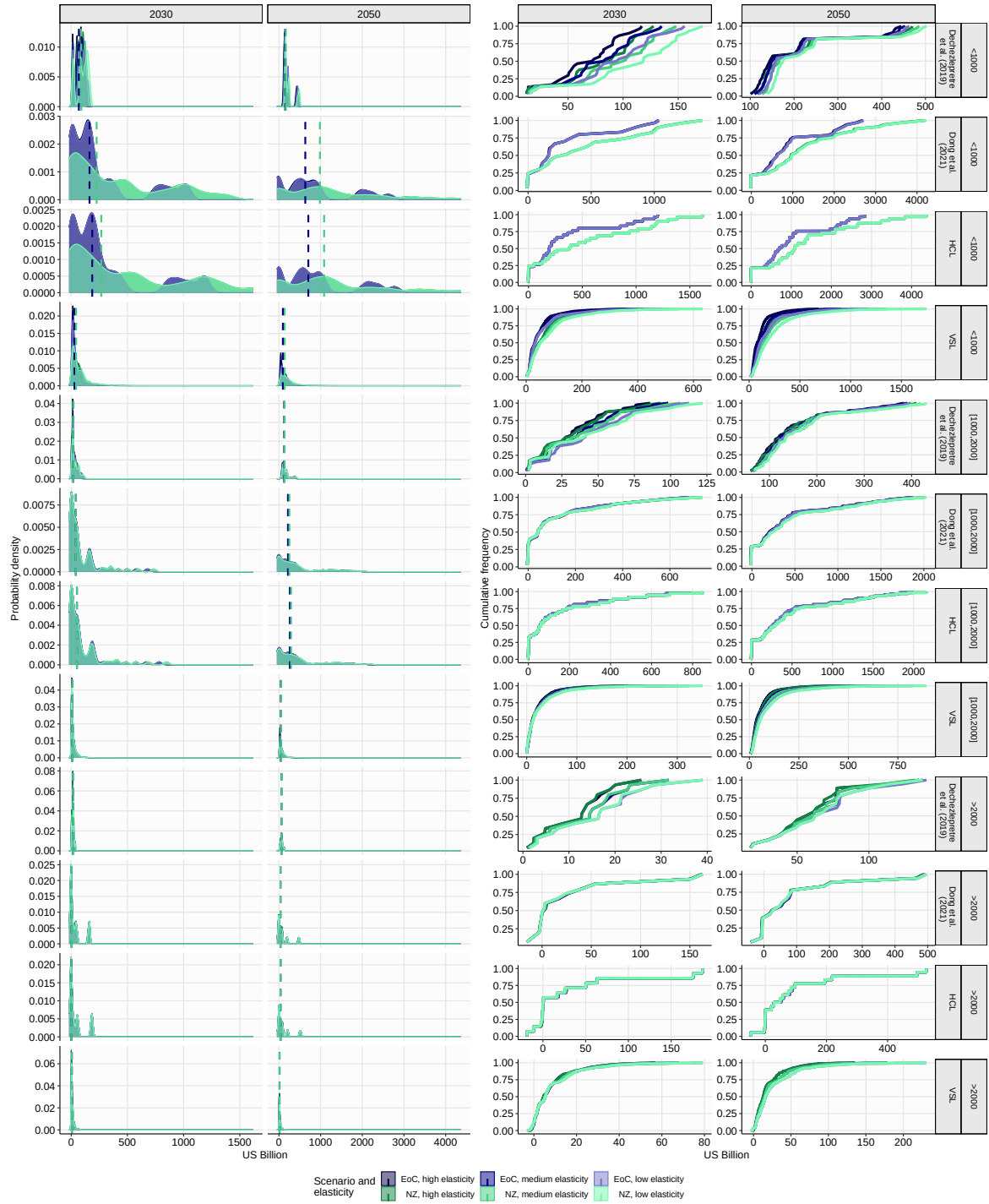




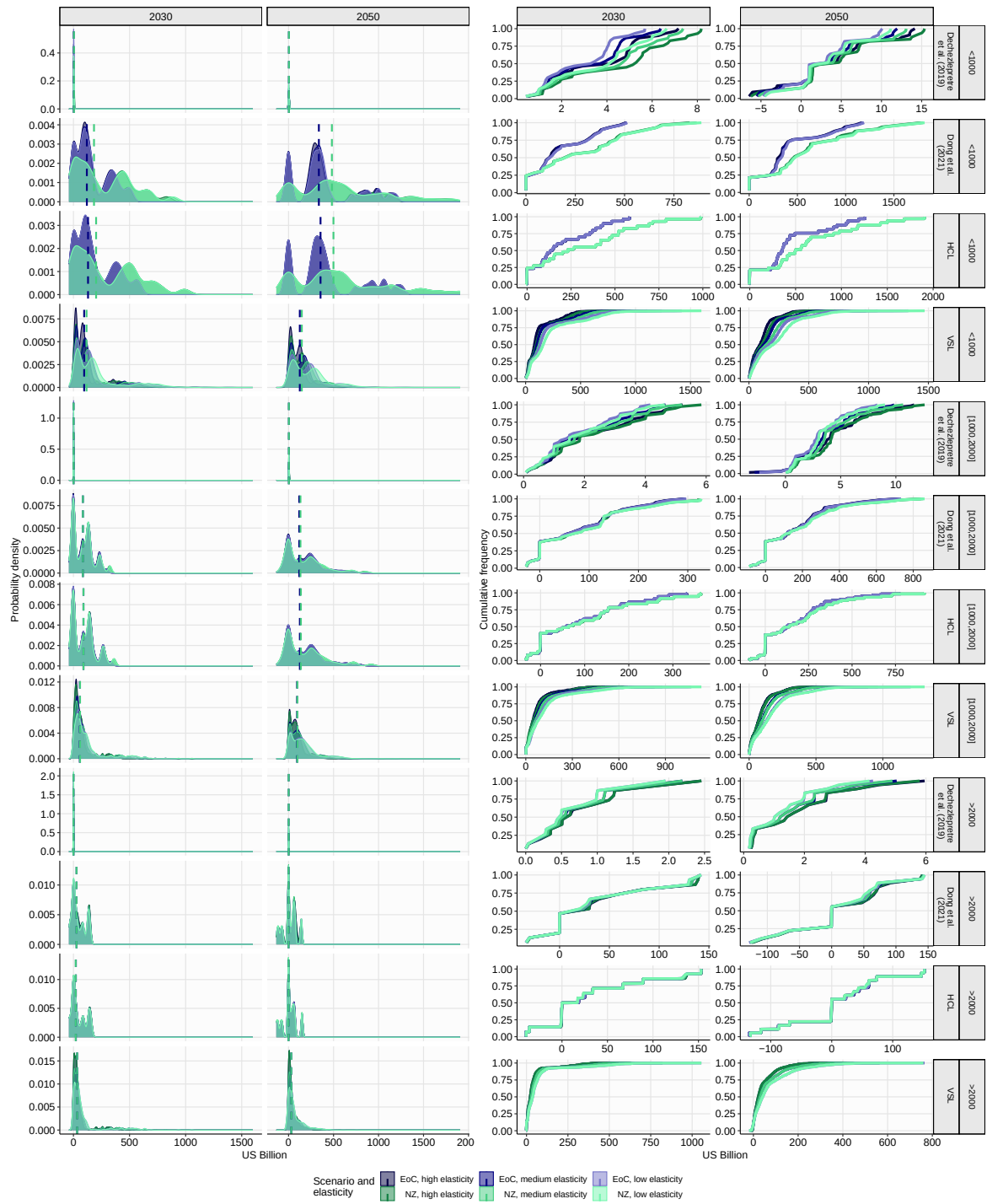
Latin-America



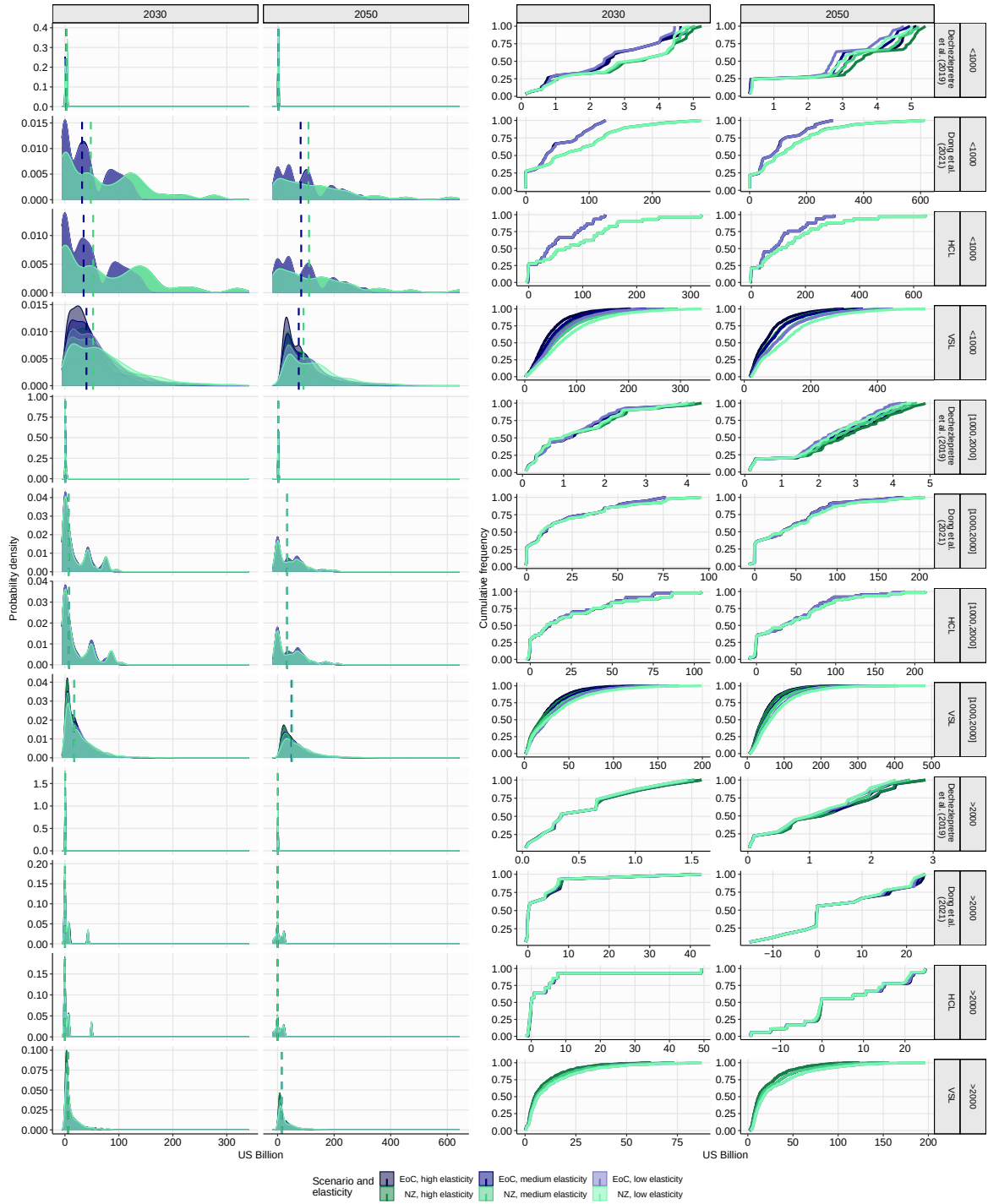
Middle-East



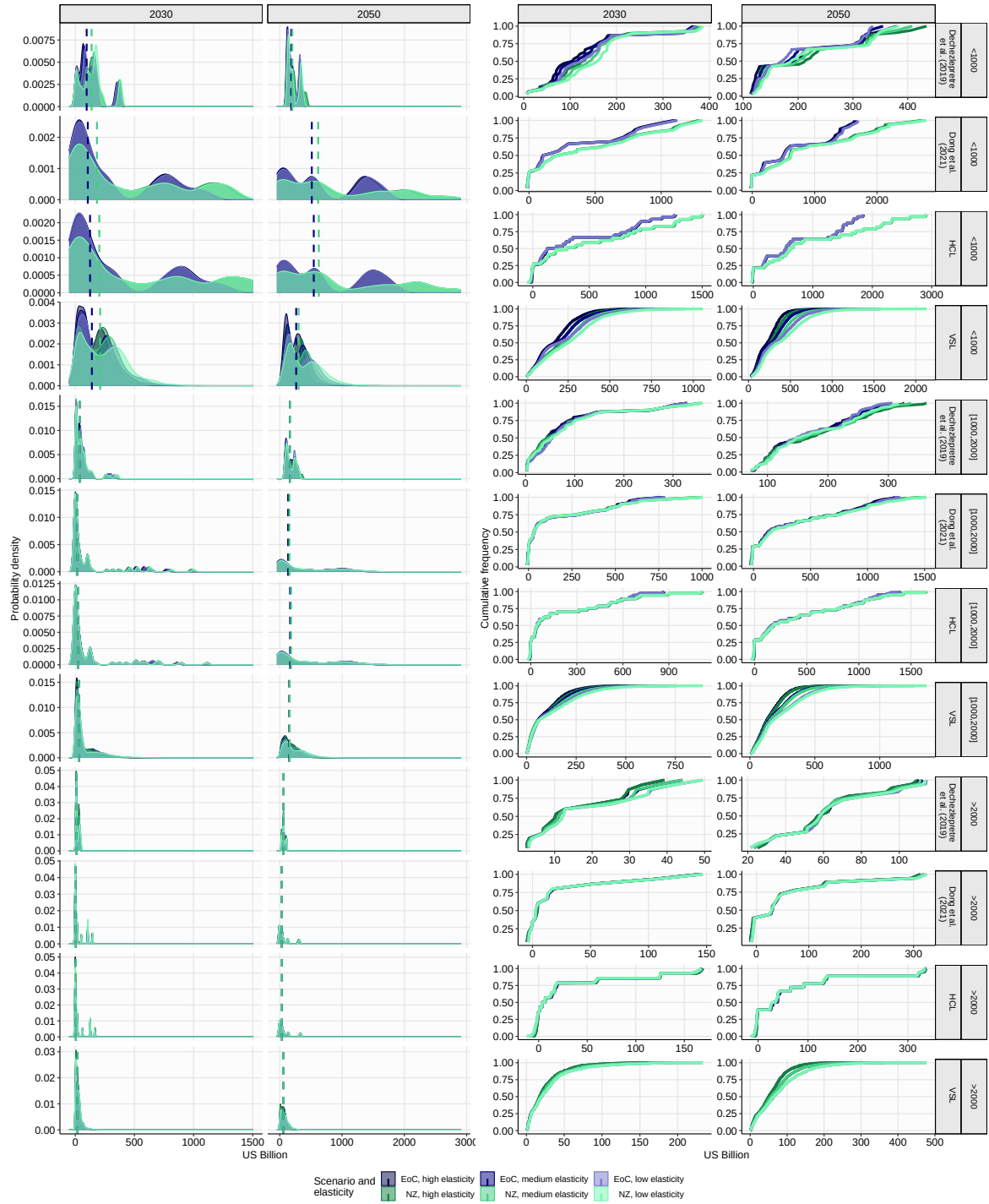
North-America



Pacific-OECD



Reference economies



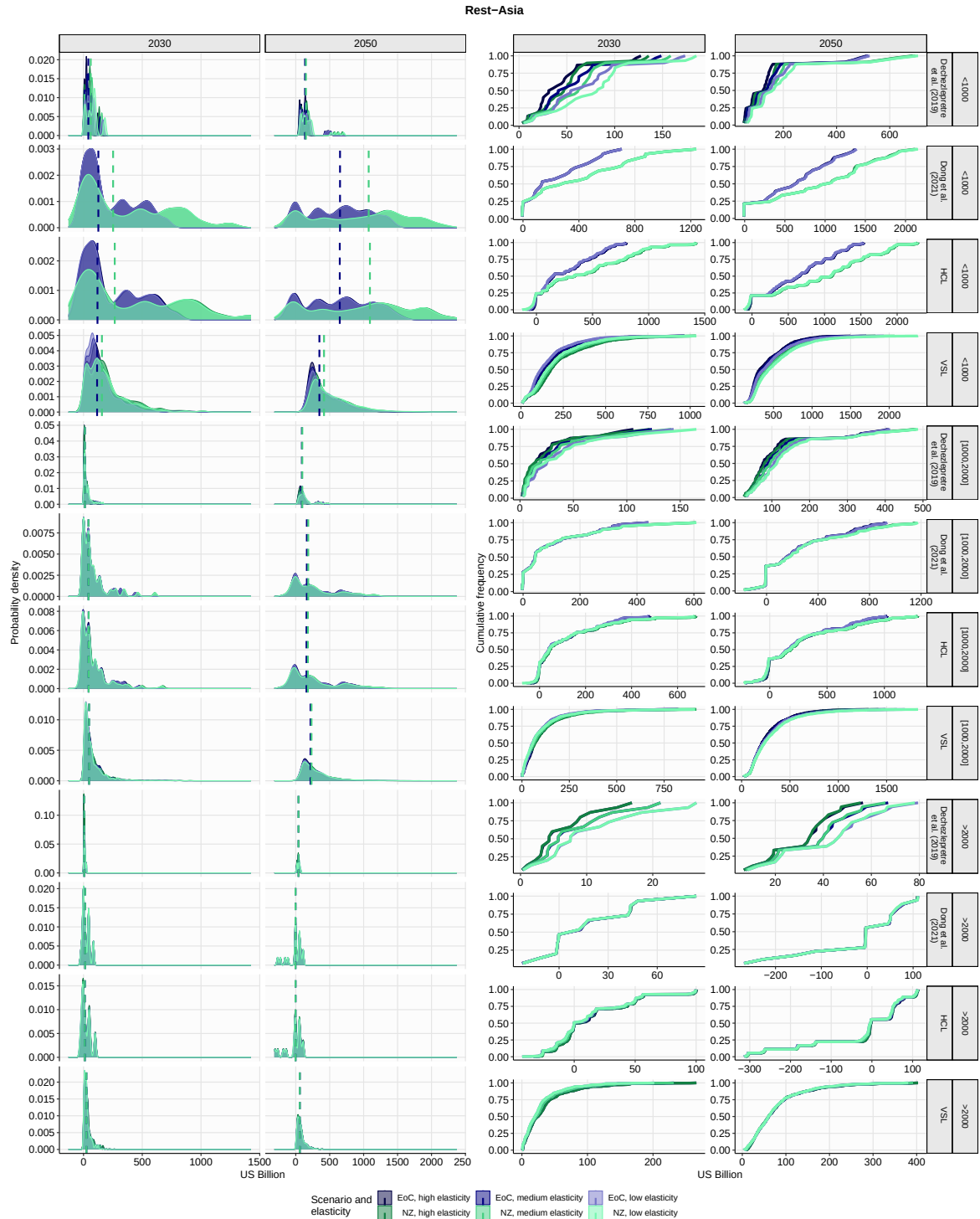


Figure S13: Probability density distribution (left) and cumulative frequency (right) of PM_{2.5} economic co-benefits for each R10 region by economic function. Includes median line by climate policy. Color represents the scenario.

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