# Is it possible to predict ENSO frequency changes for the coming century?

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#### Abstract

El Nino Southern Oscillation (ENSO) is one of the most important climate variabilities on an inter-annual time-scale. We aim to find out whether ENSO frequency will change in a changing climate. We analyse two ensembles of General Circulation Models that participated in the Coupled Model Intercomparison Project Phase 6 (CMIP6) and an initial-conditions ensemble of the MPI-ESM-LR model. We identify the uncertainty caused by natural variability by comparing 120-year time-series of the pre-industrial control and the 1-percent CO2 simulations for the CMIP6 ensembles. We found that the multi-member mean for all ensembles predicts almost no change in ENSO frequency, but the uncertainties are large, and that most of the inter-member variability can be attributed to natural variability. This means that the impact of inter-model differences might have been overstated in previous studies. This makes it impossible to make reliable predictions of changes in ENSO frequency based on 120-year simulations.

## Is it possible to predict ENSO frequency changes for the coming century?

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### 5 Key Points:

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6	• Multi-model mean in CMIP6 1pct CO2 simulation as well as in the MPI-ESM-
7	LR 1pct simulation predict almost no future change in ENSO frequency
8	• Most of the inter-model spread can be attributed to the natural variability

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#### 9 Abstract

El Niño Southern Oscillation (ENSO) is one of the most important climate variabilities 10 on an inter-annual time-scale. We aim to find out whether ENSO frequency will change 11 in a changing climate. We analyse two ensembles of General Circulation Models that par-12 ticipated in the Coupled Model Intercomparison Project Phase 6 (CMIP6) and an initial-13 conditions ensemble of the MPI-ESM-LR model. We identify the uncertainty caused by 14 natural variability by comparing 120-year time-series of the pre-industrial control and 15 the 1-percent  $CO_2$  simulations for the CMIP6 ensembles. We found that the multi-member 16 mean for all ensembles predicts almost no change in ENSO frequency, but the uncertain-17 ties are large, and that most of the inter-member variability can be attributed to nat-18 ural variability. This means that the impact of inter-model differences might have been 19 overstated in previous studies. This makes it impossible to make reliable predictions of 20

changes in ENSO frequency based on 120-year simulations.

#### 22 Plain Language Summary

El Niño Southern Oscillation (ENSO) is a coupled atmosphere-ocean circulation 23 in the Pacific and of great interest since it impacts weather worldwide. The question how 24 it will change in a changing climate is important to be able to risks due to extreme weather. 25 Global Circulation Models can help assess this question. This study focuses on the ques-26 tion if ENSO frequency will change in a changing climate. We use two ensembles of 4327 Global Circulation Models that participated in the Coupled Model Intercomparison Project 28 Phase 6. By comparing the pre-industrial control simulation to a future scenario with 29 increasing  $CO_2$  we can identify the part of the variability caused by different behaviours 30 of the models and the part caused by natural variability. We also use one 68-member 31 ensemble of the MPI-ESM-LR model, because a bigger ensemble might yield statistically 32 more reliable results. We found that on average the models predict only a very small change 33 in ENSO frequency but the uncertainty is big. Because most of this uncertainty can be 34 attributed to the natural variability it can be reduced only marginally. Therefore, it is 35 impossible to make reliable predictions of changes in ENSO frequency based on 120 years 36 of model simulations. 37

#### 38 1 Introduction

El Niño Southern Oscillation (ENSO) is one of the most important climate vari-39 abilities on an inter-annual time-scale. Due to teleconnections it impacts weather con-40 ditions worldwide and can lead to extreme weather events. To reduce the social, economic 41 and environmental risk of theses events, accurate forecasting is required. Therefore, un-42 derstanding and predicting ENSO mechanisms is a central question of current research. 43 In particular, the question of how ENSO will react to global warming is of great inter-44 est. Global warming could have different effects on the equatorial Pacific and therefore 45 on ENSO. ENSO frequency can be affected by the strength and depth of the equatorial 46 thermocline, the meridional and zonal sea surface temperature (SST) gradients as well 47 as the strength of the trade winds (Yang et al., 2005; Deng et al., 2010). How these (and 48 other) mechanisms work together and which one(s) will predominate, defines how ENSO 49 will react in future and has yet to be investigated. If and how ENSO behaviour will change 50 under a changing climate has been studied intensely in the past years. 51

Some studies found an increase in ENSO frequency in the models they examined (Timmermann et al., 1999; Collins, 2000a). Collins (2000a) for example studied ENSO frequency with the second Hadley Centre coupled climate model (HadCM2). The HadCM2 is a coupled climate model which, according to Collins (2000a), represents present day ENSO conditions (amplitude and frequency) well. When running different climate change scenarios he finds that there are only small changes until a quadrupling of CO<sub>2</sub>, when the frequency doubles. On the other hand Yang et al. (2005) investigated ENSO in the

Fast Ocean-Atmosphere Model and find that a reduction of ENSO frequency is very likely 59 as a result of warming climate. Yet other studies argue that ENSO frequency does not 60 react to global warming at all (e.g. Timmermann, 2001; Zelle et al., 2005). Also, Collins 61 (2000b) follows up on his earlier study and finds that in the third Hadley Centre cou-62 pled climate model (HadCM3) there is no change to ENSO frequency under different cli-63 mate change scenarios. Both Zelle et al. (2005) and Collins (2000b) emphasise the ef-64 fect that model specifics can have on the sensitivity of ENSO to climate change. There-65 fore, to increase the robustness multi-model ensembles have been used in many later stud-66 ies. In a study by Merryfield (2006) 12 out of 15 models (prepared for IPCC AR4) agreed 67 on a decrease in ENSO period. Cai et al. (2014): Cai, Santoso, et al. (2015) and Cai, Wang, 68 et al. (2015) analysed models participating in the Coupled Model Intercomparison Project, 69 Phases 3 and 5. They conclude, that there is a high inter model agreement, that extreme 70 El Niño/ La Niña events become more frequent in a warming climate. Wang et al. (2017) 71 also use 13 models participating in Coupled Model Intercomparison Project Phase 5 (CMIP5) 72 and come to the same conclusion. But, many studies that have investigated multi-model 73 ensembles come to the conclusion that the predictions of ENSO frequency are strongly 74 model dependent. Studies by Guilyardi (2006), Deng et al. (2010), Xu et al. (2017) and 75 Chen et al. (2017) suggest that the model consensus is very small on the topic of how 76 ENSO frequency will change in a changing climate. 77

Chen et al. (2017) mention that the difficulty in predicting ENSO properties is not 78 only the inter-model spread but also the significant natural variability and Zheng et al. 79 (2018) support this hypothesis in a study about ENSO amplitude. A similar study by 80 Maher et al. (2018) shows that (depending on the warming scenario) up to 90% of the 81 variability of ENSO amplitude can be attributed to internal variability. In this study we 82 want to quantify the aspect of natural variability of ENSO frequency. Climate forecasts 83 can be improved by using multi-model ensembles (Xu et al., 2017) instead of single sim-84 ulations because parametrisation errors of individual models are expected to be averaged 85 out. The uncertainty due to differences in the model realisation is reducible but it is not 86 the only uncertainty in such ensembles. The chaotic nature of the climate system will 87 cause an internal variability which remains irreducible. We want to identify the signal 88 caused by this internal climate variability. Therefore we make use of the multi-model en-89 semble that is part of the Coupled Model Intercomparison Project Phase 6 (CMIP6). 90 We compare the simulation with increased  $CO_2$  to the pre-industrial control simulation. 91 By doing so we can estimate how much of the variability is caused by the different model 92 responses to the forcing and how much is due to internal variability. 93

Additional to the multi-model ensemble we analyse a bigger ensemble resulting from running the MPI-ESM-LR model with perturbed initial conditions, to increase the statistical confidence of our results. As suggested by Maher et al. (2018), the use of large single-model ensembles can give important insight into changes in ENSO properties.

#### 98 2 Data

In this work we first make use of two multi-model ensembles of CMIP6, which con-99 sist of 43 members (a list with detailed information can be found in table 1). We com-100 pare the simulations for the 1 percent  $CO_2$  (1pct  $CO_2$ ) experiment to the pre-industrial 101 Control (piControl) simulations. In the piControl experiment 1850 is used as a reference 102 year and the simulations are run for at least 500 years (Eyring et al., 2016). The 1pct 103 CO2 simulation is initialised from the control run. A 150-year period is simulated dur-104 ing which the  $CO_2$  concentration is continuously increased by 1% per year. This results 105 in a doubling of  $CO_2$  after 70 and a quadrupling after 140 years, respectively (Giorgetta 106 et al., 2013). To make the two ensembles comparable we only use the last 150 years of 107 the piControl run. For the IPSL model apparently files were added at different times. 108 Because the files' meta-data implied that the later simulations might not actually be from 109 the same model version and the first simulation is already 500 years long, we decided to 110

Table 1.	List of the 43	CMIP6 models	used in this study.
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No.	Model	Variant	Version	<sup>1pct</sup> C	pi Control	Institute	Resolution <sup><math>a</math></sup> because $a$ and $a$ and $a$ because $a$ and $a$ and $a$ because $a$ and $a$ a	Reference
1	ACCESS-CSM2	r1i1p1f1	v20191109	x	v	CSIRO	300x360	Dix et al. (2019)
2	ACCESS-ESM1-5	r1i1p1f1	v20191112 v201911115	x	~	CSIRO	300x360	Ziehn et al. $(2019)$
3	AWI_CM_1_1_MB	r1i1p1f1	v20191214 v20181218	v	x	Δ₩Τ	83030 <sup>c</sup>	Semmler et al. $(2018)$
4	BCC-CSM2-MB	r1i1p1f1	v20181015	x	x	BCC	232x360	Xin et al. $(2018)$
5	BCC-ESM1	r1i1p1f1	v20190611	x		BCC	232x360	Zhang et al. $(2018)$
		<i>P</i>	v20181218		x			8 ++ ++ (_+++)
6	CAMS-CSM1-0	r1i1p1f1	$v20190708^{b}$	x		CAMS	200x360	Rong (2019)
		r	$v20190729^{b}$		x			8 8 ( 4 4 7 )
7	CESM-FV2	r1i1p1f1	$v20200310^{b}$	x		NCAB	384x320	Danabasoglu (2019a)
.	01011112		$v20191120^{b}$		v		00 11020	Danababogra (2010a)
8	CESM-WACCM-EV2	r1i1p1f1	v20101120 $v20200226^{b}$	v	A	NCAR	384+320	Danabasoglu (2019c)
	CLOM-WICCM-I V2	mpm	v20200220 $v20191120^{b}$	л	v	nomi	0041020	Danabasogiu (2010C)
9	CESM2-WACCM	r1i1p1f1	v20101120 $v20100425^{b}$	v	A	NCAR	384+320	Danabasoglu (2019d)
9	OESM2-WACOM	impin	$v_{20190420}^{v_{20190420}}$	л	v	NOAR	364x320	Dallabasogiu (20150)
10	CESMO	n1;1n1f1	$v_{20190320}$		л	NCAR	284-220	Danabagarly (2010b)
10	CESM2	riiipiii	v20190425	x		NOAN	384x320	Danabasogiu (2019b)
11	CIERM		v20190320		x	TIII	294220	$H_{max} = (2010)$
11	CIESM CNDM CMG 1 HD	r111p111	v20200220	x	x		384x320	Huang $(2019)$
12	CNRM-CM6-I-HR	rlilplf2	v20191021°	x	x	CNRM-CERFACS	1050x1442	Voldoire (2019)
13	CNRM-CM6-1	r1i1p1f2	v20180626°	x		CNRM-CERFACS	294x362	Voldoire (2018)
			v20180814 <sup>6</sup>		x			
14	CNRM-ESM2-1	r1i1p1f2	v20181018 <sup>b</sup>	x		CNRM-CERFACS	294x362	Seferian (2018)
			v29181115 <sup>o</sup>		x			
15	CanESM5	r1i1p1f1	v20190429	x	x	CCCma	291x360	Swart et al. $(2019)$
16	CanESM5	rlilp2fl	v20190429	x	x	CCCma	291x360	Swart et al. $(2019)$
17	E3SM-1-0	rmpfff	v20191008	х		E3SM-Project	180x360	Bader et al. $(2019)$
			v20200129°		x	EC E. di		
18	EC-Earth3	r3i1p1f1	$v20200727^{b}$	x		EC-Earth-	292x362	EC-Earth Consortium (2019)
						Consortium		
10	FIO FSM 2.0	r211p111	v20200420 v20200206		x	FIO OI NM	284-220	Song et al. $(2010)$
19	F10-E5W1-2-0	mpm	v20200300	х	v	FIO-QLINI	364x320	50lig et al. (2019)
20	GFDL-CM4	r1i1p1f1	v20191012 v20180701	v	л	NOAA-GEDL	$1080 \times 1440$	Guo et al $(2018)$
20	GI DE OMI	impin	v20190201	А	x	NOILL OF DE	1000/1110	Guo et al. (2010)
21	GISS-E2-1-G	r102i1p1f1	v20190815	x	x	NASA-GISS	90x144	NASA/GISS (2018a)
22	GISS-E2-1-G	r1i1p1f1	v20190824	x	x	NASA-GISS	90x144	NASA/GISS (2018a)
23	GISS-E2-1-G	r1i1p5f1	v20190905	x		NASA-GISS	90x144	NASA/GISS (2018a)
			v20190710		x			
24	GISS-E2-1-H	r1i1p1f1	$v20190403^{b}$	x		NASA-GISS	90x144	NASA/GISS (2018b)
			$v20190410^{b}$		x			
25	GISS-E2-2-G	r1i1p1f1	$v20191120^{b}$	x	x	NASA-GISS	90x144	NASA/GISS (2019)
26	HadGEM3-GC31-LL	r1i1p1f3	$v20190620^{b}$	x		MOHC	330x360	Ridley et al. (2018)
		r1i1p1f1	$v20190628^{b}$		x			
27	INM-CM4-8	r1i1p1f1	v20190530	x		INM	180x360	Volodin et al. (2019a)
			$v20190605^{b}$		x			
28	INM-CM5-0	r1i1p1f1	v20200226	x		INM	$180 \times 360$	Volodin et al. (2019b)
			v20190619		x			
29	IPSL-CM6A-LR	r1i1p1f1	v20180727	x		IPSL	332x362	Boucher et al. $(2018)$
20	MCM IIA 1.0	n1;1-1£1	v20200326		x	TTA	80,109	Stouffor $(2010)$
21	MIDOC FS91	r111p111	v20190731	x	x	MIROC	256x260	Hajima at al. $(2019)$
32	MIROC-E52L MIROC6	r1i1p112	v20190823	x	x	MIROC	256x360	Tatebe and Watanabe $(2018)$
1.52	MIIICOOU	impin	V20101212	л	л	HAMMOZ-	200,000	Tatebe and Watanabe (2018)
33	MPI-ESM-1-2-HAM	r1i1p1f1	v20190628	x		Consortium	220x256	Neubauer et al. $(2019)$
			v20190627		x	Comportrain		
34	MPI-ESM1-2-HR	r1i1p1f1	v20190710	x	x	MPI-M	404x802	Jungclaus et al. (2019)
35	MPI-ESM1-2-LR	r1i1p1f1	v20190710	x	x	MPI-M	220x256	Wieners et al. (2019)
36	MRI-ESM2-0	r1i1p1f1	$v20190904^{b}$	x	x	MRI	363x360	Yukimoto et al. (2019)
37	MRI-ESM2-0	r1i2p1f1	v20200303 $^{b}$	x		MRI	363x360	Yukimoto et al. (2019)
			$v20200222^b$		x			、 /
38	NESM3	r1i1p1f1	v20190703	x		NUIST	292x362	Cao and Wang (2019)
			v20190704		x			- ` `
39	NorCPM1	r1i1p1f1	v20190914	x	x	NCC	384x320	Bethke et al. $(2019)$
40	NorESM2-LM	r1i1p1f1	v20190815	x		NCC	385x360	Seland et al. $(2019)$
			$v20210118^{b}$		х			
41	NorESM2-MM	r1i1p1f1	v20191108	x	x	NCC	385x360	Bentsen et al. (2019)
42	SAM0-UNICON	r111p1f1	v20190323	х		SNU	384x320	Park and Shin $(2019)$
19	IIKESM1 O I I	r1;1r1f9	v20190910 v20100701	37	х	моче	3302360	Tang at al. $(2010)$
43	OVE2MIT-0-FF	1111p112	v20190701 v20190701	х	v	MORU	006X066	rang et al. (2019)
1	I		v20200020		~			

<sup>a</sup> Some files have different resolution information in the meta-data .
 We use the resolution that can be determined from the size of the variable-array
 <sup>b</sup> For these files the creation date precedes the date according to the version number.
 We nevertheless assume that the version number date is correct.
 <sup>c</sup> Irregular grid, number of grid points

use the last 150 years of this first simulation instead of the later ones. The ensembles
 will be referred to as 1pct- and Control-ensemble, respectively.

Another ensemble used in this study is an initial-conditions ensemble. The MPI-ESM-LR model has been run for the 1pctCO2 experiment with slightly different initial conditions which results in a 68-member ensemble (Plesca et al., 2018; Giorgetta et al., 2013; Stevens et al., 2013). This ensemble will from now on be referred to as MPI-ensemble. It should be mentioned that this ensemble is older than the CMIP6 ones, since it was run for the CMIP5. The reason for using an older ensemble for this work was the availability of this dataset.

#### 3 Methods

There are many indices to measure ENSO activity, which all have their advantages 121 and disadvantages. Depending on the available data and the question posed, different 122 indices prove to be helpful. In this work we make use of an index based on the first em-123 pirical orthogonal function (EOF) of SST data from the tropical Pacific (120°E-60°W, 124 30°N-30°S). The pattern of the first EOF explains most of the variability in the tropi-125 cal Pacific, particularly in the Nino3.4 region (Dommenget et al., 2013). Therefore, the 126 principle component (PC) of the first EOF can be used as an ENSO-index (a very sim-127 ilar approach was used in other studies (e.g. Merryfield, 2006; Berner et al., 2020)). In 128 fact, it can be shown that this index is highly correlated with the Ocean Nino Index (ONI) 129 defined by NOAA Climate Prediction Center, National Weather Service (2020a) (Berner 130 et al., 2020; Penland & Sardeshmukh, 1995). This means that they indeed describe the 131 same ENSO variations. We calculated the correlation between these two indices for the 132 43-member ensemble of the CMIP6 piControl experiment and obtained a mean value of 133 0.971 (min: 0.883, max: 0.991 ).134

In order to calculate this index the climate trend and annual cycle have to be elim-135 inated. This is done as described by NOAA Climate Prediction Center, National Weather 136 Service (2020a) for the ONI. Anomalies are calculated for each grid-point with respect 137 to a centred base-period. This base-period is updated every 5 years to account for the 138 warming trend in the region. The base-period corresponding to the years x to x+5 is the 139 period x-15 to x+15 (NOAA Climate Prediction Center, National Weather Service, 2020b). 140 Subsequently, the anomalies are smoothed by a 3-month-running mean. From these smoothed 141 anomalies EOFs can be calculated, which also yields the time series of the PCs. The first 142 PC is used as the ENSO-index in this study and will be referred to as the PC-index. The 143 base-period-method creates artificial trends at the beginning and end of a dataset, because for the first and last 15 years there is no centred base-period available. Therefore, 145 the first base-period has to be used for the first 20 years and the last base-period for the 146 last 20 years. This creates an unwanted effect, which can't be corrected. Therefore the 147 first and last 15 years of data can not be correctly evaluated and will not be taken into 148 account for further analysis. We therefore effectively analyse time series with a length 149 of 120 years. 150

According to the NOAA Climate Prediction Center, National Weather Service (2020a) conditions are considered "El Niño-like" when the ONI exceeds +0.5 K and "La Niñalike" when the index goes below -0.5 K. Whenever conditions are met for 5 consecutive months, it is called an "El Niño event" or a "La Niña event". We use the same definition for the PC-index as well.

Similarly to Deng et al. (2010) we count El Niño and La Niña events to estimate 156 changes in ENSO frequency. In this study we use a 30-year moving window. The num-157 ber of months within a 30-year period that were "El Niño-" or "La Niña-like" were counted 158 as well as the number of actual El Niño or La Niña events within this period. This re-159 sults in a time series of occurrences, of which a linear regression can be calculated. The 160 slope of this regression line defines the linear trend in the amount of "El Niño-" and "La 161 Niña-like" months and -events. It provides insight into how the number of El Niño/La 162 Niña events will increase or decrease over the years. We have computed the linear trend 163

	EN		LN	"EN-like"		"	LN-like"	
ensemble	mean	σ	mean	$\sigma$	mean	σ	mean	σ
1pct	$0.038\pm0.038$	0.2506	$0.108 \pm 0.030$	0.1987	$0.094 \pm 0.441$	2.8919	$0.622 \pm 0.444$	2.9101
Control	$-0.040 \pm 0.032$	0.2085	$0.022 \pm 0.040$	0.2615	$-0.290 \pm 0.386$	2.5319	$0.179 \pm 0.412$	2.7047
MPI	$0.070 \pm 0.030$	0.2514	$0.020 \pm 0.029$	0.2364	$-0.169 \pm 0.374$	3.0849	$-0.320 \pm 0.390$	3.2138

**Table 2.** Means and standard deviations  $\sigma$  of predicted changes in occurrences of El Niño (EN) and La Niña (LN) events and "EN/LN-like" conditions for all three ensembles<sup>*a*</sup>.

 $^{a}$ All numbers are unitless, they represent changes in occurences during one decade.

for every member of each of the three ensembles. For convenience, the gradient in months<sup>-1</sup> can be converted into a more intuitive measure for the change in ENSO frequency by multiplying it by 120 months, which then gives the change in the number of occurrences during a decade.

#### 4 Results

Figures 1 and 2 show the linear trend of El Niño and La Niña -events and -like months. On average the 1pct-ensemble predicts an increase of  $0.038 \pm 0.038$  El Niño events and an increase of  $0.108 \pm 0.030$  La Niña events per decade (the  $\pm$  values are the standard errors,  $\sigma/\sqrt{N}$ ). The standard deviations ( $\sigma$ ) are 0.2506 and 0.1987 events per decade for El Niño and La Niña events, respectively. Hence, the inter-model spread appears to be larger than the mean change itself, which makes it difficult to detect changes in ENSO frequency (see Tab. 2).

An interesting question is whether this uncertainty can be reduced at all. Therefore we compare the 1pct-ensemble to the Control-ensemble. It can be expected that the 177 performed problem in the term of the different reactions of the differ-178 ent models to the forcing ( $\sigma_{\text{ModelDiff}}$ ) as well as uncertainties due to the natural variabil-180 ity ( $\sigma_{\text{NaturalVariability}}$ ). Under the assumption that the errors are uncorrelated this re-181 sults in

$$\sigma_{1
m pct}^2 = \sigma_{
m ModelDiff}^2 + \sigma_{
m NaturalVariability}^2$$

(1)

(2)

Therefore its standard deviation should be greater than the standard deviation of the Control-ensemble, which only contains the uncertainty due to natural variability:

$$\sigma_{\rm Control}^2 = \sigma_{\rm Natural Variability}^2$$

Still under the assumption of uncorrelated errors, the difference in the variances  $\sigma^2$  of the two ensembles should be a measure for the uncertainty caused by model differences, ie.

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$$\sigma_{\text{ModelDiff}}^2 = \sigma_{1\text{pct}}^2 - \sigma_{\text{Control}}^2 \tag{3}$$

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This uncertainty can be reduced, while the rest, the natural variability, will remain.

For El Niño events the standard deviation due to model differences is therefore 0.1369 events per decade, which is one order of magnitude less than the standard deviation due to natural variability. For La Niña events the difference in variances is even negative with -0.0281.

This means that the biggest part of the uncertainty in the 1pct-ensemble prediction stems from the natural variability and is therefore irreducible, since the real world



Figure 1. Linear Trend in El Niño/La Niña events for each member of the three ensembles: a) the 1pct-ensemble, b) the Control-ensemble, c) the MPI-ensemble. Values towards the top of the plot indicate increasing number of La Niña (LN) events, values toward the right of the plot indicate an increasing number of El Niño (EN) events. Numbers in panels a) and b) correspond to models as in table 1.



Figure 2. Same as figure 1 but for "El Niño-" and "La Niña-like" conditions.

will evolve like one ensemble member, not like the ensemble mean. Since the uncertainty
is in the range of the predicted mean changes or even exceeds them, no reliable forecast
can be made on the time-scale of 120 years. The result is qualitatively the same for the
"El Niño-" and "La Niña-like" conditions (see Tab. 2 and Fig. 2)

A statistically more reliable result might be achieved by analysing a bigger ensem-201 ble. Therefore we conducted the same analysis for the MPI-ensemble, which consists of 202 68 members. The MPI-ESM-LR model was run with perturbed initial conditions for the 203 1pct CO2 experiment in CMIP5. Since it is an initial-conditions ensemble it only con-204 tains the uncertainty due to natural variability. For the change in El Niño events the big-205 ger ensemble predicts a change of  $0.069 \pm 0.030$  events per decade. The uncertainty seems 206 to be slightly less compared to the earlier analysis. But for the La Niña events and the 207 "El Niño-" and "La Niña-like" conditions the uncertainty is of the same order of mag-208 nitude or bigger than the expected change itself again. This supports the assumption 209 that a reliable prediction of ENSO-frequency on a time-scale of 120 years cannot be made. 210

#### **5** Discussion and Conclusions

The multi-model mean frequency change of El Niño and La Niña events is less than 212  $\pm$  0.2 events per decade in all three ensembles and in all cases the uncertainties are large. 213 Our analysis of the two CMIP6 ensembles showed that the natural variability dominates 214 the results. This suggests that the stronger trends found in individual models like in the 215 studies by Timmermann et al. (1999) or Yang et al. (2005) may be mostly due to nat-216 ural variability. Also the results from Timmermann (2001) and Zelle et al. (2005) who 217 found no trend in the respective models therefore have to be treated carefully. In con-218 219 trast to the studies by Merryfield (2006), Cai et al. (2014), Cai, Wang, et al. (2015), Cai, Santoso, et al. (2015) and Wang et al. (2017) we could not find an inter-model consen-220 sus on a significant trend in ENSO frequency in the ensembles. It should be mentioned 221 though, that we did not distinguish between normal and extreme El Niño and La Niña 222 events like some of the mentioned authors did. 223

Zelle et al. (2005) and Collins (2000b) suggested that prediction of ENSO frequency 224 is strongly model dependent and the studies by Guilyardi (2006), Deng et al. (2010), Xu 225 et al. (2017) and Chen et al. (2017) indeed found a poor inter-model consensus. Our study 226 implies though that it is actually not the model differences that are responsible for the 227 biggest part of the inter-model spread but rather the natural variability. This does not 228 mean that model differences do not play a role, only that their importance relative to 229 natural variability likely has been overstated. We therefore complement the findings of 230 Chen et al. (2017), who found that for changes in for example ENSO asymmetry in am-231 plitude, duration, and transition from the 20th to the 21st century the model agreement 232 is poor, trends are not significant and the variations mostly lie within the range of nat-233 ural variability. Our findings also support the results from the studies by Zheng et al. 234 (2018) and Maher et al. (2018) who did similar analyses but for ENSO amplitude and 235 also attribute most inter-member variability to natural variability. 236

Our results suggest that the uncertainties might only be marginally reducible, since 237 only the uncertainties due to model differences can be minimised but not the natural vari-238 ability. This means that it is impossible to make reliable predictions of changes in ENSO 239 frequency based on 120 years of model simulations. Although we used only a particu-240 lar type of model (coupled climate models as represented in CMIP) we think that this 241 result is general, since the main finding is that the natural variability is so large, and this 242 is unlikely to change for more sophisticated models. Therefore, even if models that rep-243 resent ENSO dynamics more faithfully may exhibit larger and/or more robust ENSO fre-244 quency trends, natural variability is still likely to dominate. 245

#### 246 Acronyms

- <sup>247</sup> CMIP5 Coupled Model Intercomparison Project Phase 5
- <sup>248</sup> **CMIP6** Coupled Model Intercomparison Project Phase 6
- 249 **ENSO** El Niño Southern Oscillation
- **EOF** empirical orthogonal function
- <sup>251</sup> **PC** principle component
- <sup>252</sup> **SST** sea surface temperature

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