CLIMATE CHANGE PROGRAMME

Climate scenarios in MACSUR2

S. Fronzek [1], T. R. Carter[1], M. Semenov, R. Rötter, F. Ewert, A. Ruane

[1]Finnish Environment Institute (SYKE)

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Outline

- Climate scenario selection and weather-generated climate scenarios for 15 sites across Europe – M. Semenov
- Inventory of gridded observed and climate scenario datasets
- Enhanced delta-change method to construct a gridded European climate scenario dataset

Local-scale climate scenarios for impact assessments in MACSUR2

Mikhail Semenov, Rothamsted Research, UK

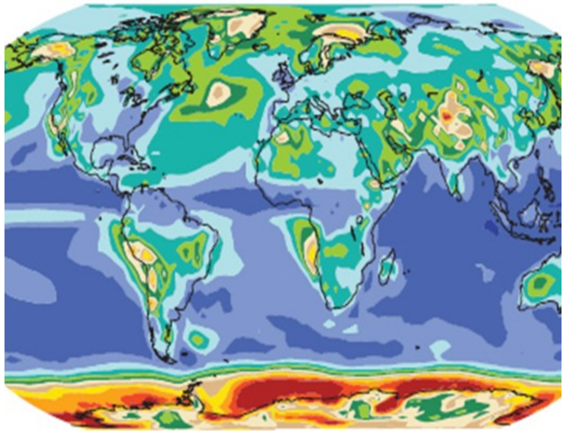
- 100 yrs of daily weather generated by LARS-WG for 15 sites with contrasting climates across Europe representing major crop areas
- 5 GCMs with contrasting climate sensitivity
- Two RCP: RCP4.5 and RCP8.5
- Time periods: baseline (1980-2010), near-term (2021-2040), mid-term (2041-2060) and long-term (2081-2100) future.
- Scenarios available from Mikhail Semenov (mikhail.semenov@rothamsted.ac.uk)

LARS-WG weather generator

- Generates precipitation, min and max temperature, radiation and potential evapotraspiration
- Modelling of precipitation event is based on wet/dry series
- Semi-empirical distributions are used for distribution of climatic variables
- LARS-WG was extensively tested in diverse climates and is used for impact assessments of climate change in more than 70 countries for research and in several Universities as an educational tool
- LARS-WG is available for academic, governmental and nonprofit organizations

Local-scale CMIP5-based scenarios:
LARS-WG weather generator

GCMs from CMIP5



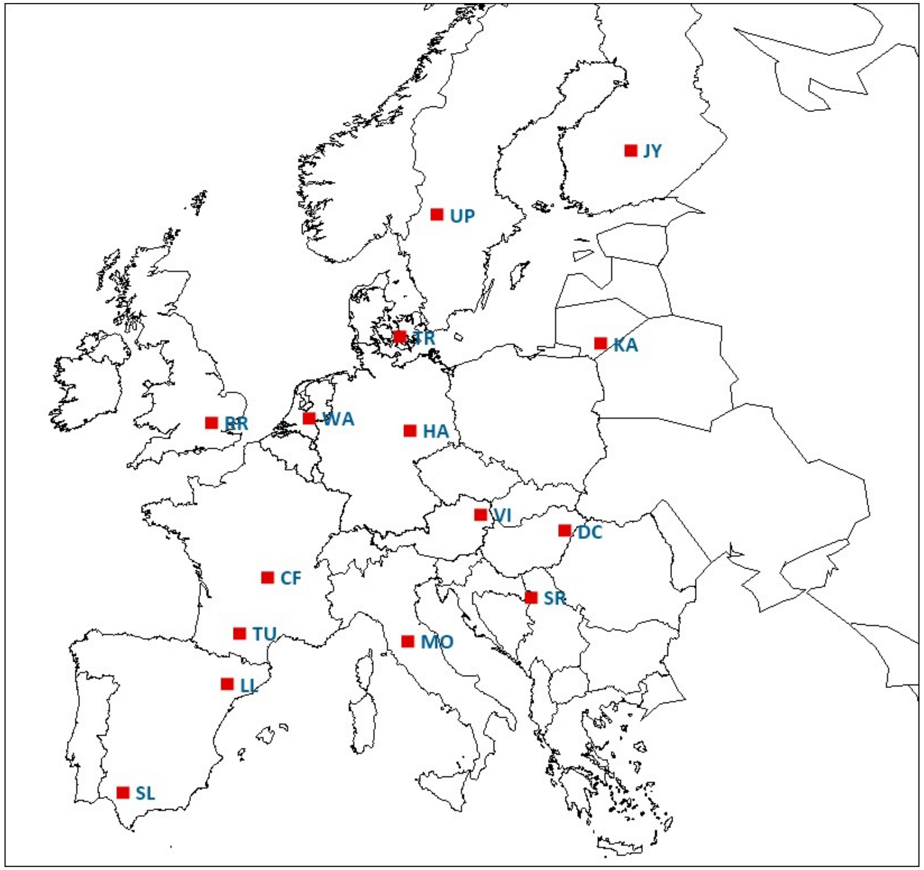
LARS-WG

Site parameters derived from observed weather or ELPIS

Local-scale climate scenarios
for MACSUR2 impact assessments

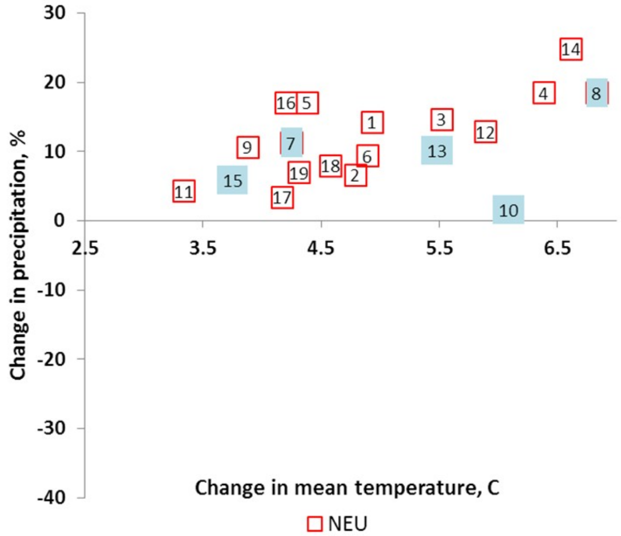
(Semenov & Stratonovitch (2015), Clim Research, 65:123-139)

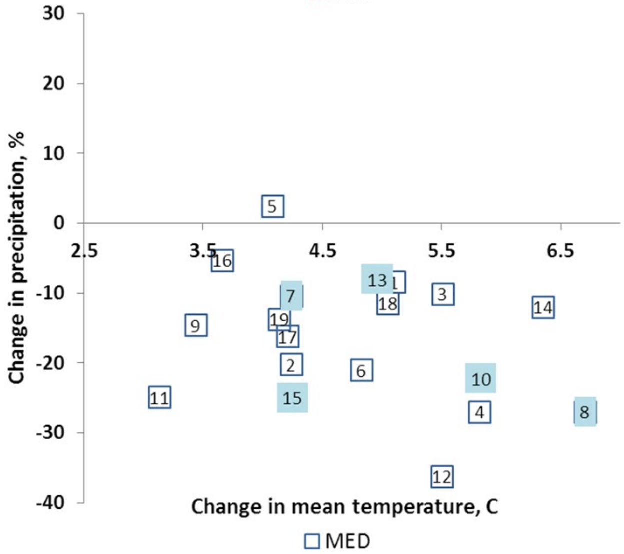
Selection of sites



Site	Nick	Lat	Lon	Alt, m
Jyvaskyla	JY	62.40	25.68	141
Uppsala	UP	59.90	13.60	24
Tylstrup	TR	55.15	11.33	13
Kaunas	KA	54.88	23.83	77
Wageningen	WA	51.97	5.67	7
Rothamsted	RR	51.80	-0.35	128
Halle	HA	51.51	11.95	93
Vienna	VI	48.23	16.35	198
Debrecen	DC	47.60	21.60	114
Clermont-Ferrand	CF	45.80	3.10	329
Sremska	SR	45.00	19.51	84
Toulouse	TU	43.62	1.38	151
Montagnano	MO	43.30	11.80	250
Lleida	LL	41.63	0.60	190
Seville	SL	37.42	-5.88	34

Selection of GCMs





CMIP5.CORDEX	MACSUR	AgMIP	ISI-MIP	Tem.MED	Tem.NEU	Rain.MED	Rain.NEU
ACCESS1-3	1	1	1	5.1	4.9	-8.4	14.3
BCC-CSM1-1	2	2	2	4.2	4.8	-20.2	6.7
CanESM2	3	3	3	5.5	5.5	-10.1	14.7
CMCC-CM	4	4	4	5.8	6.4	-27	18.5
CNRM-CM5	5	5	5	4.1	4.4	2.5	17.1
CSIRO-MK36	6	6	6	4.8	4.9	-21	9.4
EC-EARTH	7	7	7	4.2	4.3	-10.4	11.3
GFDL-CM3	8	8	8*	6.7	6.8	-27	18.5
GISS-E2-R-CC	9	9	9	3.4	3.9	-14.6	10.7
HadGEM2-ES	10	10	10	5.8	6.1	-22.2	1.6
INMCM4	11	11	11	3.1	3.3	-24.9	4.3
IPSL-CM5A-MR	12	12	12	5.5	5.9	-36.2	12.9
MIROC5	13	13	13	5.0	5.5	-8	10.2
MIROC-ESM	14	14	14	6.4	6.6	-12	24.9
MPI-ESM-MR	15	15	15	4.3	3.8	-25	5.9
MRI-CGCM3	16	16	16	3.7	4.2	-5.3	17.1
NCAR-CCSM4	17	17	17	4.2	4.2	-16.2	3.4
NCAR-CESM1-CAM5	18	18	18	5.1	4.6	-11.4	8
NorESM1-M	19	19	19	4.1	4.3	-13.7	7

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Inventory of gridded observed and scenario climate datasets

Different methods to construct scenario data from climate model output

Change factor ("delta change") method: Differences or ratios between simulated baseline and simulated future climate are used to adjust observed data.

Bias-correction (or bias-adjustment) of GCM or RCM simulations: the simulated time-series is adjusted such that statistical properties are close to an observed dataset; several alternative approaches have been developed.

Statistical downscaling: Statistical relationships between from observations of large-scale variables and a local weather variable are used to predict a future time-series of the local variables from equivalent predictors of GCM output.

Weather generators (WG): Statistical properties of observed weather time-series are used to generate synthetic time-series. By modifying the statistical properties based on projections with climate models, future synthetic time-series can be constructed.

➔ All rely on observed climate datasets

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Gridded observed climate datasets

Preliminary – do no cite

Name	Spatial extend +resol.	Period	Temp. resol.	Variables[1]	Method	Reference, web link
E-OBS	Europe, 0.25°	1950-2014	Daily	TG, TN, TX RR, PP	Interpolated from station data	(Haylock et al. 2008), http://eca.knmi.nl/download/ensembles/download.php
JRC/MARS/Agri4Cast	Europe, 25 km	1975-2014	Daily	TG, TN, TX, RR, WS, GR, RH, PE, SN	Interpolated from station data	http://mars.jrc.ec.europa.eu/mars/About-us/AGRI4CAST/Data-distribution/AGRI4CAST-Interpolated-Meteorological-Data
WATCH-WFDEI	Global, 0.5°	1979-2012	Daily and 3-hourly	TG, RR, PP, WS, GR, SH, SN	Combining ERA-interim re-analysis with monthly CRU data (earlier WATCH version used ERA-40)	(Weedon et al. 2011), http://www.eu-watch.org/data_availability
AgMERRA (AgMIP)	Global, 0.25°	1980-2010	Daily	TG, TN, TX, RR, WS, GR, RH	Combining MERRA re-analysis with monthly CRU data and other observations	(Ruane et al. 2015), http://data.giss.nasa.gov/impacts/agmipcf
EURO4M	Europe, 5 km	1989-2010	Daily	TG, TN, TX, RR	Downscaling ERA-interim with the MESAN weather model	http://www.euro4m.eu

[1]) variable abbreviations: mean temperature (TG), minimum temperature (TN), maximum temperature (TX), precipitation sum (RR), sea level pressure (PP), wind speed at 10 m (WS), specific humidity (SH), relative humidity (RH), Penman potential evaporation (PE), global radiation (GR), snowfall rate or depth (SN)

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Gridded climate scenario datasets

Preliminary – do no cite

Name	Spatial extend + res.	Scenarios	Temp. resol.	Variables	Method	Reference, web link
ISI-MIP	Global, 0.5°	5 GCMs x 4 RCPs	Daily	TG, TN, TX RR, PP, SW, GR, SN	Bias-correction using WATCH	(Hempel et al. 2013) https://www.pik-potsdam.de/research/climate-impacts-and-vulnerabilities/research/rd2-cross-cutting-activities/isi-mip
AgMIP Climate Scenario Generation Tool	Global	CMIP5	Daily	All typically needed for crop modelling	R scripts and accompanied data files	Hudson & Ruane 2013
Bias-corrected CORDEX-RCMs	Europe		Daily		Selected RCMs have been bias-corrected using WATCH or EURO4M data	Currently developed in several projects e.g. by SMHI, DMI
LARS-WG	Europe		Daily		Applying LARS-WG with CMIP5-based changes	http://www.rothamsted.ac.uk/mas-models/larswg.php
AgriAdapt	Europe, sub-regions	SRES, several GCMs	Daily	All typically needed for crop modelling	Delta change using MARS observations	(Angulo et al. 2013)
JRC-MARS-Agri4Cast	Europe, 25 km	SRES RCMs	Daily	All typically needed for crop modelling	ClimGen WG	Duveller et al. 2015 http://agri4cast.jrc.ec.europa.eu/DataPortal

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Some (personal) recommendations for MACSUR

- When focusing on (e.g. 30-year) **mean changes** in climate, the change factor method would be sufficient
- **Changes in (inter-annual and day-to-day) variability** as projected by climate models are included in bias-corrected climate scenario datasets, although one cannot differentiate between the impacts of mean changes vs. impacts of variability changes. WG and statistical downscaling usually also includes changes in IA variability (restricted to the statistical properties of the WG).
- The **spatial coherence** of weather time-series on a grid (e.g. a dry year in one grid cell is also dry in the neighbouring grid cell) is not given for weather generator datasets, although there might be exceptions.
- As the delta method uses **observations for the baseline**, crop model simulations can be directly compared to observed yields or field validation data on a year-by-year (or day-by-day) basis. This is not the case for any of the other methods, which use modelled or synthetic climate data for the baseline.
- Availability of scenario datasets

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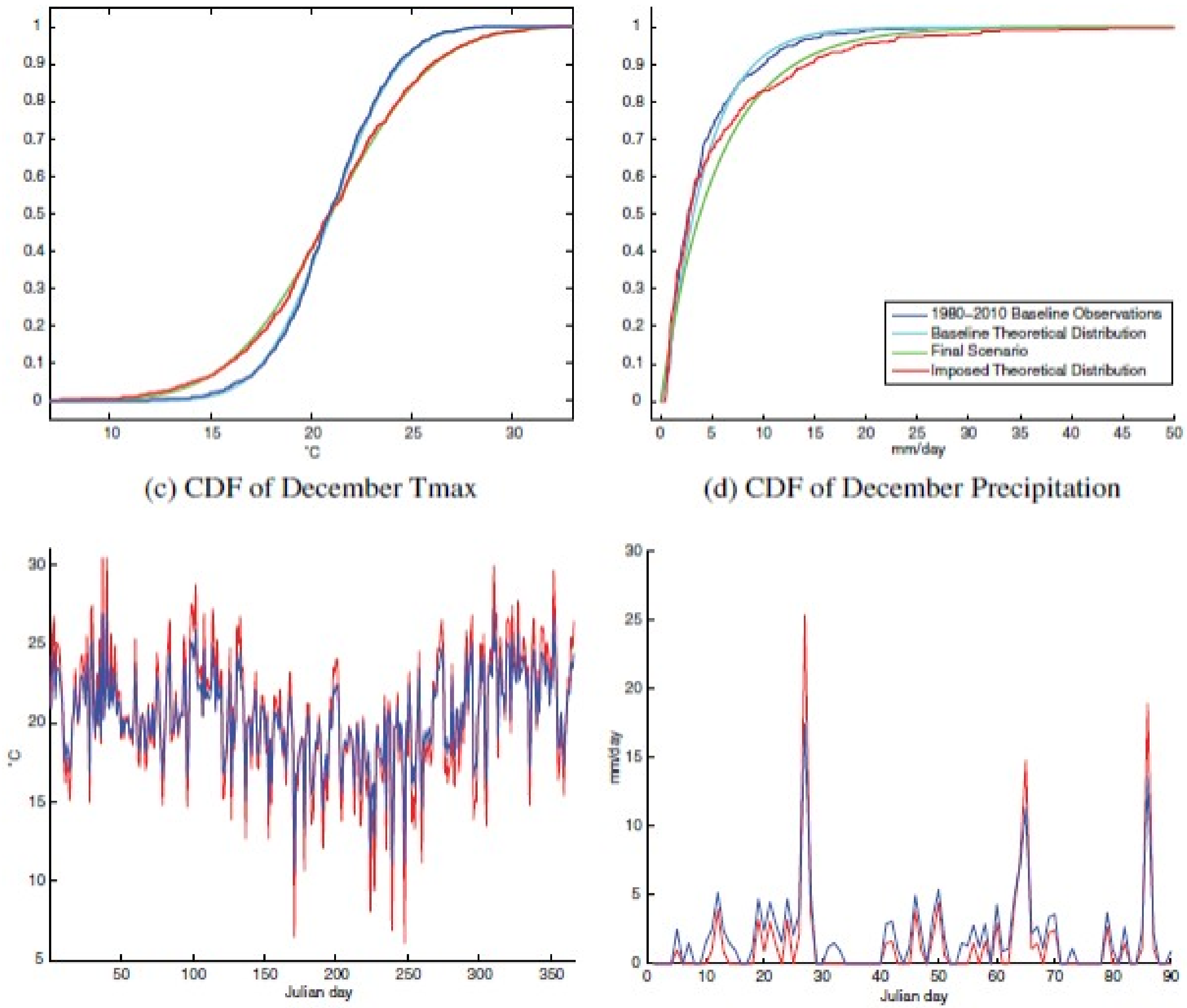
Slide provided by Alex Ruane

Enhanced Delta Method



(c) CDF of December Tmax

(d) CDF of December Precipitation

(e) Mean and Variability ΔT Example

(f) Mean and Variability ΔP Example

Recognizable historical time series adjusted to impose climate changes drawn from CMIP5 models.

Adjusts each month's:

- Mean Tmax, Tmin
- Standard deviation of daily temperatures
- Mean precipitation
- # rainy days
- Shape of rainfall distribution

Does not adjust:

- Solar radiation
- Wind speed
- Relative humidity at Tmax (although vapor pressure and VPD changes)

GCM Δvariability is less reliable than Δmeans

Shizukhuishi, Japan, hypothetical scenarios from Ruane et al., 2015