

Changes in Mediterranean Climate Extremes: Patterns, Causes,
and Impacts of Change

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Abstract

The Northern Mediterranean region includes a wide range of climatic variability, and a spectrum of economies that have entered the EU at different times. This study attempts to increase understanding and predictability of both the Mediterranean climate and the potential for climate derived socio-economic impacts a selection of these economies may face. A methodology is detailed whereby the target region is assessed for the patterns and causes behind extreme climatic events (that may challenge current adaptation strategies), and the kinds of socio-economic outcomes that they may produce.

In order to explore the behaviour of floods, droughts, heatwaves, and cold snaps, across the Northern Mediterranean region (35° - 45° N, -10° - 30° E) with a selection of hemispheric circulation predictors (drawn from the NCEP/NCAR reanalyses), two differing models have been used. Orthogonal Spatial Regression (OSR) is an inversion of a dendroclimatology technique that relies on spatial variability, with Principal Components Analysis (PCA) at its core. Radial Basis Function Artificial Neural Networking (RBF ANN) is a machine-learning pattern matching approach, capable of non-linearity. The two have been applied as direct downscaling methods to the STARDEX (STATistical and Regional dynamical Downscaling of EXtremes for European regions) indices of extremes, across the target area. Analysis suggests that there may be significant departures between regional and seasonal contrasts in extreme behaviour, and those evident for mean climate. In addition, where warming occurs, extreme high temperatures generally show a trend of greater magnitude than the mean. Modelled links between circulation predictors and extreme climate are consistent with these results, statistically significant, largely linear, and are (in many cases) stronger for extremes than the mean. Distinct circulation regimes have been identified, as described by groups of predictors (representative of Atlantic influence, for instance), each with effects that are relevant to a particular region, season, and type of Mediterranean extreme climate.

This thesis also explores direct relationships between extreme events (quantified by the indices of extremes) and socio-economic indicators (i.e., agricultural yield, energy consumption, and excess mortality). OSR and ANN are applied again, as

econometric upscaling models, between climate indices and socio-economic indicators, to provide the final link in a chain of potential predictability. Long-term (i.e., decadal) trends in the socio-economic indicators considered are consistent with non-climatic influences. However, regional variations in sensitivity to extreme climate have been identified (on a seasonal basis) that demonstrate both the advantages of using upscaling technique, and the use of station-scale predictors over spatially aggregated data. The model functions (e.g. linear, gaussian, or quadratic) most useful for modeling relationships are seen to vary between regions and seasons. Furthermore, regions that display strong trends in extreme behaviour and significant links to sensitive sectors of activity have been highlighted. This study suggests that Mediterranean climate extremes are changing over time, and that policy concerning the socio-economic impacts of those changes must be specified with regional concerns in mind.

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Phil Jones and Keith Briffa wrote the original Orthogonal Spatial Regression Fortran program developed here, Colin Harpham wrote the Radial Basis Function Artificial Neural Network C++ program, and Malcolm Haylock wrote the Indices of Extremes program (for the STARDEX project), used to calculate climate indices in Chapter 3.

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List of Acronyms

AIR	All India Averaged Rainfall	EU-ETS	EU Emission Trading Scheme
ANN	Artificial Neural Networks		
AYA	Agricultural Yield per hectare Anomaly	FAO	Food and Agricultural Organization
BLUE	Best Linear Unbiased Parameters	FIC	Fundación para la Investigación del Clima
BOSR	Basin OSR	GBF	Gaussian Basis Function
CAP	Common Agricultural Policy	GCM	General Circulation Model
CCA	Canonical Correlation Analysis	GDP	Gross Domestic Product
CDD	Cooling Degree Days	GNP	Gross National Product
CLR	Classical Least-squares Regression	HadCM	Hadley Centre Coupled Model
CO ₂	Carbon Dioxide	HadRM3	Hadley Centre Regional Model 3
CRU	Climatic Research Unit	HDD	Heating Degree Days
DEFRA	Department for Environment, Food, and Rural Affairs	hPa	hectoPascals
	Diurnal Temperature Range	HGT	Geopotential HeiGhT
DTR	East-Atlantic West-Russia pattern	IPCC	Intergovernmental Panel on Climate Change
EAWR	European Climate Assesment	ITCZ	Inter-Tropical Convergence Zone
ECA	ECA and Dataset	JJA	June, July, August
ECA&D	Commerical Electricity Consumption	KNMI	Koninklijk Nederlands Meteorologisch Instituut
ECC	European Centre for Medium-range Weather Forecasting	LBF	Linear Basis Function
ECMWF	European Coal and Steel Community	MAM	March, April, May
ECSC	European Economic Community	mb	millibars
EEC	Emergency Disasters Data Base	MEI	Multivariate Enso Index
EM-DAT	Excess Mortality Index	MICE	Modelling the Impact of Climate Extremes
	El Niño-Southern Oscillation	MLP	Multi-Layer Perceptron
EMI		MO	Mediterranean Oscillation
ENSO	Empirical Orthogonal Function	MO(AC)	MO for Algiers and Cairo
EOF	ECMWF ReAnalysis	MO(GI)	MO for Gibraltar and Israel
	Residential Electricity Consumption	MPI	Mediterranean Pressure Index
ERA		MSLP	Mean Sea Level Pressure
ERC	European Union	NADW	North Atlantic Deep Water
		NAO	North Atlantic Oscillation
		NCAR	National Center for Atmospheric Research
		NCDC	National Climatic Data Center
		NCEP	National Centers for Environmental Prediction
		NOAA	National Oceanic and Atmospheric Administration

NCPI	NSCP Index	TAR	IPCC Third Assessment Report
NSCP	North-Sea Caspian Pattern		
OLS	Ordinary Least Squares	TAVG	Mean Temperature Index
OSR	Orthogonal Spatial Regression	TPF	Thin Plate spline basis Function
PC	Principal Component	THC	Thermohaline Circulation
PCA	Principal Component Analysis	TMAX	Maximum Temperature Index
PDF	Probability Density Function	TMIN	Minimum Temperature Index
PDSI	Palmer Drought Severity Index	TNFD	Frost Days Index
PF90	Fraction Of Rainfall Due To Wet Days Index	TN10	Cold Nights Index
PINT	Rainfall Intensity Index	HWDI	Heat Wave Duration Index
PN90	Number Of Days Classed As Wet Index	TX90	Warm Days Index
PQ90	Wet Days Index	UCTE	Union for the Co-ordination of Transmission of Electricity
PREC	Mean Total Daily Rainfall Index	UEA	University of East Anglia
PX5D	Five Day Maximum Rainfall Index	UKMO	United Kingdom Met Office
PCDD	Consecutive Dry Days Index	UM	Unified Model
RBF	Radial Basis Function	UN	United Nations
RCM	Regional Climate Model	UNDP	United Nations Development Programme
RMSE	Root Mean Squared Error	UNEP	United Nations Environment Programme
ROSR	Regional OSR	UNESCO	United Nations Education, Scientific and Cultural Organisation
SRES	IPCC Second Assessment Report	USD	United States Dollars
SH	Siberian High	WDCGG	World Data Centre for Greenhouse Gasses
SHI	Siberian High Index	WG1	Working Group 1 of the TAR
SHM	Specific Humidity		
SLP	Sea Level Pressure	WMO	World Meteorological Organization
SOI	Southern Oscillation Index		
SON	September, October, November	WHO	World Health Organization
SPI	Standardized Precipitation Index		
SRES	IPCC Special Report on Emission Scenarios		
SST	Sea Surface Temperature		
STARDEX	STatistical And Regional dynamical Downscaling of Extremes for European regions		
SVD	Singular Value Decomposition		