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China's coastal zone vulnerability to climate change: impacts and economic assessment

By **Enrica De Cian**
Fondazione Eni Enrico Mattei and Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC), Italy
enrica.decian@cmcc.it

SUMMARY This technical report describes a methodology for the economic assessment of future climate change impacts and adaptation at the global scale, but taking explicitly into account the spatial dimension being based upon gridded information. The approach can thus be applied to the estimation of climate impacts and adaptation costs with high spatial resolution for large number of climate and socioeconomic scenarios. This document summarizes the general methodology, which will be described with greater detail in a dedicated paper under preparation[1], to then develop an application to characterize climate.

Keywords: Climate change impacts, adaptation, Energy Demand, Panel Data Models.

JEL: Q54, Q55, Q41, C23

[1] *De Cian E. and Sue Wing I. (2014) "Climate change impacts on energy demand", CMCC Research paper RP0240 and SISCLIMA Conference Proceedings*

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PRELIMINARY VERISION - PLEASE DO NOT CITE OR QUOTE

1. INTRODUCTION

As also mentioned in the latest IPCC 5th assessment report (IPCC, 2014), the econometric or statistical approach is one consolidated methodology used by economics to estimate both the economic consequences of climate change and to evaluate adaptation options (Heal et al. 2014). These approaches have been mostly applied to analyze climate change impacts in agriculture (Lobell & Burke, 2010, Schlenker and Roberts 2009) and responses of energy demand patterns (Auffhammer Mansur 2012, Barreca 2012, De Cian et al. 2013, Deschenes and Greenstone 2011).

Another vastly applied methodology to study the effects of climate change impacts and policies is model-simulation based analysis. However this approach, which is based on the explicit representation of the main behavioral or systemic features of the phenomenon analyzed, is extremely data intensive, and often cannot be pursued. Just to give an example think to a modelling approach to hydro-power generation responses to changes in average meteorological variables as well as in extreme events. Many different generation units are involved and for each the main "functioning" characteristics need to be specified. Likely they will all display a different sensitivity depending for instance on water reservoir characteristics (run-of-river versus dams with large storage reservoirs), the storage capacity, as well as the alternative (and competitive) uses for water in the area where they are located, and so on. Therefore the volume (and quality) of data is often an impediment to conduct such assessments on the large scale. Alternatively, when they are performed on the large scale, input and output information are highly aggregated and the spatial specificities are often lost.

Econometric approaches, on the contrary, do not try to describe all the mechanisms involved, but rather to identify robust relationships between the climate stressors and the endpoint of interest. In this sense, the data requirement is more limited, which makes these approaches easier to apply to broader scales.

The approach of combining statistical models for exploring a given system's sensitivity with scenario-based analysis of exposure has a large, yet unexplored potential. This is being amplified by the recently increasing number of spatially resolved data products becoming available referring to main climate change and environmental variables. The re-analysis of these data could allow the application of statistical/econometric approaches to get at a time information at the global scale, and, by determining geographically-scaled indicators to stratify the information, to get insights preserving the spatial relevant heterogeneity. In principle this methodology can be easily applied to different sectors, time, and countries. Moreover statistical models can also accommodate variables accounting for the role of adaptive capacity. A number of papers under publication in a Special Issue in Energy Economics[2] have identified some of the key areas where significant progress could be made.

The remaining of this document illustrates the potential of using empirical approaches, combined with spatial data and future climate projections, in the analysis of climate impacts on crops' productivity and energy demand , and adaptation, with a focus on China.

2. GENERAL METHODOLOGY

The empirical literature on climate change impacts has used mostly three different types of statistical models: cross-sections, time-series, and panel models. Cross-section models are based on the comparison of locations across space, and, in doing so, are able to implicitly capture the effect of adaptation strategies to different climates. In particular, albeit being based on one-point-in-time observations, they typically rely upon "between country" variations where climatic differences across observation units enable to capture the potential role of adaptation in the long term. Differently, time-series models examine the response to weather shocks, examining how this varied in time in a specific "location" that can

[2] Doi: 10.1016/j.eneco.2014.04.014

be a site or a country. Panel data models are somewhat in between: they are based on the observation of different units across time. In particular, fixed-effect panel models, which rely on the within variation, are closer to time-series models. However, in addition to the inter-annual variation they also capture the differences in average climate conditions across different locations allowing the estimation of a site-specific (constant) term. This term, that basically “shifts” the estimated relationship, captures how much the climate effect in each site differs from the group mean. A further advantage of panel data models is that they can control for differences in unobservable factors that are unit specific and constant over time (e.g. long-term average climate).

The present exercise uses a panel regression model to estimate the parameters characterizing a reduced-form relationship between the selected impact endpoint at country level (in the specific case, crops productivity and energy demand), a set of meteorological indicators, and a number of other covariates controlling for time-invariant country-specific heterogeneity (country effect), unspecified exogenous influences affecting all countries and units (time effects), and other confounding factors (such e.g. the electricity generation mix in the case of energy demand). Equation (1) offer a general representation of the model specification: the relationship of interest is (F), which specifies how a vector of meteorological variables (Mi,t) affects the impact endpoint (Yi,t):

$$Y_{i,t} = \mu_i + \tau_t + F\left[M_{i,t}\right] + Z_{i,t}\gamma + \varepsilon_{i,t} \qquad (1)$$

$(\boldsymbol{\mu}_\mathbf{i})$ is the time-invariant individual heterogeneity, $(\boldsymbol{\tau}_\mathbf{t})$ is the unspecified exogenous influences affecting all units, $(\mathbf{Z}_{\mathbf{i,t}})$ other confounding factors, and $\boldsymbol{\varepsilon}_{\mathbf{i,t}}$ a random disturbance term. The coefficients in model (1) are identified from the inter-annual variations and therefore they represent the short-term response to annual variation in the meteorological indicators considered. The model needs to be specified in a slightly different form to take into account long-term effects.

The methodology is used to estimate two sets of response functions, those related to:

1. Rice, Wheat, Maize, and Sorghum productivity;
2. Sectoral energy demand;

The set of confounding factors include real per capita GDP in the model for crop productivity and energy demand, because we found there is a long-term relationship of cointegration between yields and real per capita GDP on the one hand, and energy demand and real per capita GDP on the other hand. The empirical model used for the estimation of the response function of agriculture and energy demand is then specified in an “error correction model” (ECM) form, which enables the estimate of both short- and long-run elasticities.

3. DATA

The novelty of the methodology is the use of various spatial datasets to stratify the gridded meteorological data from reanalysis datasets. In this way we are able to stratify the climate variables and identify the spatial heterogeneity that is relevant to each sector. In the case of agriculture we combined the climate data with a mask of the spatial distribution of harvested area by crop type and irrigation regime (Portmann et al. 2010), and with a dataset providing the growing season for each crop (Sacks et al. 2010), in each grid cell. For the spatially-relevant grid cells to impact endpoint considered - in the case of agriculture the grid cells where crops are grown - we computed the annual distribution of daily temperature and precipitation during the growing season. The meteorological variables used in the empirical model are the count of day of exposure to hot days (defined as number of days with daily mean temperature above 27.5°C) , wet and dry days (defined as number of days with daily mean precipitation above 15mm/day or below 5mm/day).

A similar approach is used to spatially identify the relevant grid cells for the domain of energy demand. In the case of energy demand the spatial attribute usd is population density by grid cell. The relevant variables here are exposure to cold and hot days, as well as to dry and humid days.

Although the input historical climate data are defined on a daily basis and at the grid cell level, the meteorological variables stratified and computed as just described are ultimately aggregated to country level, which is the scale at which the econometric model is estimated. This is also the resolution of the dependent variables. In the study of agriculture, the dependent variable is crop yield defined at the national scale, on a yearly base. In the case of energy demand we used sectoral final energy use. Data sources of all date used are summarized in Table 1.

Crop gridded harvest area	Portmann, F. T., Siebert, S., and Doll, P. MIRCA2000Global monthly irrigated and rain-fed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling. Global Biogeochemical Cycles 24, 1 (2010).
Crop calendar data	Sacks, W. J., Deryng, D., Foley, J. a., and Ramankutty, N. Crop planting dates: an analysis of global patterns. Global Ecology and Biogeography 19, 607-62 (2010).
Yields	Food and Agriculture Organization of the United Nations (FAO), FAO Statistical Databases; available at http://faostat.fao.org (2013).
Gridded population	Center for International Earth Science Information Network - CIESIN - Columbia University, International Food Policy Research Institute - IFPRI, The World Bank, and Centro Internacional de Agricultura Tropical - CIAT. 2011. Global Rural-Urban Mapping Project, Version 1 (GRUMPv1): Population Count Grid. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). http://sedac.ciesin.columbia.edu/data/set/grump-v1-population-count.
Climate historical data	Compo, G.P. et al. The Twentieth Century Reanalysis Project. Quarterly Journal of the Royal Meteorological Society 137, 1-28 (2011). Rodell, M., Houser, P. R., Jambor, U., Gottschalck, J., Mitchell, K., Meng, C.-J., … Toll, D. (2004). The Global Land Data Assimilation System (GLDAS). Bulletin of the American Meteorological Society, 85(3), 381–394. doi:10.1175/BAMS-85-3-381
Future climate projections	Climate models used for the design of future climate change projections. All data was accessed from the http://pcmdi9.llnl.gov/esgf-web-fe/between June 1st and August 31st, 2013. Models used: CCSM4, CNRM-CM5, GFDL-CM3, MIROC5, MPI-ESM-MR
GDP	Heston, A., Summers, R., and Atenm, B. Penn World Table Version 7.1 Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania (2013).
Energy demand data	International Energy Agency (IEA) database[3]

Table 1: Spatial dataset used to stratify climate variables by sector

[3] Accessed on November 2012.

4. EMPIRICAL MODELS

The two sets of response functions are estimated using national annual data for different sized-panel datasets, depending on the case considered. Here we summarize the specific empirical model estimated in each case, while details are described in dedicated papers under preparation[4].

MODEL 1. AGRICULTURE

In the specific case of agriculture the general framework introduced in Eq. (1) reads as follows:

$\mathbf{Y_{i,t}}$: $\mathbf{y_{i,t}}$, yield (ton/hectare)

$\mathbf{M_{i,t}}$: $\mathbf{DT^{k}_{i,t}}$, $\mathbf{DP^{j}_{i,t}}$

$\mathbf{F}[\quad]$: $\boldsymbol{\Sigma}$

$\mathbf{Z_{i,t}}$: real GDP per capita

$$\Delta \ln y_{i,t} = \alpha_i + \Delta Z_{i,t}\eta + \sum_{k=1}^{K}\sum_m \beta_1^{k,m}\Delta T_{i,t}^{k,m} + \sum_{j=1}^{J}\sum_m \beta_2^{j,m}\Delta P_{i,t}^{j,m}$$

$$+\gamma\left[\ln y_{i,t-1} - Z_{i,t-1}\lambda - \sum_{k=1}^{K}\sum_m \theta_1^{k,m} T_{i,t-1}^{k,m} - \sum_{j=1}^{J}\sum_m \theta_2^{j,m} P_{i,t-1}^{j,m}\right] + \varepsilon_{i,t} \quad (2)$$

$\mathbf{y_{i,t}}$ indicates the yield of rice, wheat, maize, and sorghum in country $\mathbf{i}$ and year $\mathbf{t}$. The weather variables $\mathbf{T^{k,m}_{i,t}}$ and $\mathbf{P^{j,m}_{i,t}}$ are annual counts of growing season days with average temperature in interval $\mathbf{k}$ and precipitation in interval $\mathbf{j}$ in areas with irrigated or rain-fed management regimes, $\mathbf{m}$. The count of days of exposure to k temperature and j precipitation range in country i in year t is weighted with the share of harvested area by management type (Portmann et al. 2010):

$$T^{k,m}_{cell\epsilon i,C} = \sum_{c\in i} T^{k,m}_{cell\epsilon i,C} * \frac{ha^{m}{}_{j,cell\epsilon i,2000}}{\sum_j ha^{m}{}_{j,cell\epsilon i,2000}}$$

[4] De Cian E. and Sue Wing I. (2014) "Climate change impacts on energy demand", CMCC Research paper RP0240 and www.sisclima.it/wp-content/uploads/2013/10/SISC_Conference_Proceedings.pdf

$\mathbf{Z}$ is a vector of socio-economic variables (real per capita gross domestic product) which control for the potentially confounding effects of unobserved historical adaptations to changing climate and weather. On the right-hand side, $\boldsymbol{\alpha}_{\mathbf{i}}$ is a country-specific intercept that captures the influence on yields of unobserved heterogeneous time-invariant factors, the $\boldsymbol{\Delta}$ terms capture the short-run effects of inter-annual shocks, the lagged effect of the deviation from the long-run equilibrium relationship between crop yield and meteorology is given in square brackets, and $\boldsymbol{\varepsilon}_{\mathbf{i,t}}$ is a random disturbance term. The error-correction speed of adjustment parameter, $\boldsymbol{\gamma}$, measures countries' average rate of adjustment toward long-run equilibrium. The yield response to weather is indicated by the vectors of short-run semi-elasticity parameters $\boldsymbol{\beta}_{\mathbf{1}}$ and $\boldsymbol{\beta}_{\mathbf{2}}$, and to climate by the vectors of long-run semi-elasticity parameters $\boldsymbol{\theta}_{\mathbf{1}}$ and $\boldsymbol{\theta}_{\mathbf{2}}$. The long-run response is the cumulative effect during the adjustment period until the system returns to the long-run equilibrium and is computed using the long-term elasticities, $\boldsymbol{\theta}_{\mathbf{1}}/-\boldsymbol{\gamma}$ and $\boldsymbol{\theta}_{\mathbf{2}}/-\boldsymbol{\gamma}$.

MODEL 2. ENERGY DEMAND

In the specific case of energy demand the general framework introduced in Eq. (1) reads as follows:

$\mathbf{Y}_{\mathbf{i,t}}$: $\mathbf{q}_{\mathbf{i,t}}$, per capita energy (Ktoe), $\frac{\mathbf{Q}_{\mathbf{i,t}}}{\mathbf{POP}_{\mathbf{i,t}}}$

$\mathbf{M}_{\mathbf{i,t}}$: $\mathbf{DT}^{\mathbf{k}}_{\mathbf{i,t}}$, $\mathbf{DH}^{\mathbf{j}}_{\mathbf{i,t}}$

$\mathbf{F}[\quad]: \boldsymbol{\Sigma}$

$\mathbf{Z}_{\mathbf{i,t}}$: real GDP per capita

$$\Delta \ln q_{i,t} = \alpha_i + \Delta Z_{i,t}\eta + \sum_{k=1}^{K} \beta_1^k \Delta T_{i,t}^k + \sum_{j=1}^{J} \beta_2^j \Delta SH_{i,t}^j$$

$$+\gamma\left[\ln q_{i,t-1} - Z_{i,t-1}\lambda - \textstyle\sum_{k=1}^{K} \theta_1^k T_{i,t-1}^k - \sum_{j=1}^{J} \theta_2^j SH_{i,t-1}^j\right] + \varepsilon_{i,t} \tag{3}$$

Here, $\mathbf{q}_{\mathbf{i,t}}$ indicates the sectoral energy demand in country $\mathbf{i}$ and year $\mathbf{t}$. The meteorological variables $\mathbf{T}^{\mathbf{k,m}}_{\mathbf{i,t}}$ and $\mathbf{SH}^{\mathbf{j,m}}_{\mathbf{i,t}}$ are annual counts of days with average temperature in interval $\mathbf{k}$ and specific humidity in interval $\mathbf{j}$. The count of days of exposure to k temperature range in country i in year t is computed as the weighted sum of days of exposure to k temperature range in the grid cell c belonging to country i:

$$\mathbf{T^k_{i,t}} = \sum_{\mathbf{cell\in i}} \mathbf{T^k_{cell\in i,t}} * \frac{\mathbf{POP_{c,i,2000}}}{\mathbf{POP_{i,2000}}} = \sum_{\mathbf{c\in i}} \mathbf{T^k_{cell\in i,t}} * \boldsymbol{\omega}_{\mathbf{cell\in i,2000}}$$

The control variable, in this case real per capita gross domestic product, controls for the effects of potentially confounding historical factors. A country-specific intercept, $\boldsymbol{\alpha_i}$, captures the influence on energy demand of unobserved heterogeneous time-invariant factors and $\boldsymbol{\varepsilon_{i,t}}$ is a random disturbance term. The error-correction speed of adjustment parameter, $\boldsymbol{\gamma}$, measures countries' average rate of adjustment toward the long-run equilibrium. The beta coefficients capture the short-run effects of inter-annual shocks, while the theta ones capture lagged feedback of the disequilibrium into the change in energy demand. The long-run response is the cumulative effect during the adjustment period until the system returns to the long-run equilibrium and is computed using the long-term elasticities, $\boldsymbol{\theta_1}/-\boldsymbol{\gamma}$ and $\boldsymbol{\theta_2}/-\boldsymbol{\gamma}$.

5. EMPIRICAL RESULTS

Table 2 and 3 summarize the estimated elasticities of the impact endpoint considered (cereal productivity and energy demand) to climate variables using historical data. The details of the estimation are described in dedicated papers[5]. Here we only discuss the response functions that are used to compute the future impacts. Moreover, here we illustrate the potential impact of climate change, without considering the potential interaction with economic growth.

Table 2 shows the sensitivity of cereals to dry, wet, and hot days by region and management system. The effect of temperature is always negative for rain-fed crops whereas it is smaller or even positive for irrigated crops. The effect of high precipitation can be positive in tropical areas for maize and rice, which grow under average high precipitation conditions, whereas it is negative for wheat.

Table 3 highlights the heterogeneity in the demand of the different energy vectors (electricity, oil products and gas) in the different sectors (agriculture, commercial, industry and residential) in response to an increase in frequency of cold days (heating effect) and to an increase in frequency in hot days (cooling effect). Electricity handles virtually the entire cooling load, whereas the heating load is distributed among a wider range of fuels (natural gas and fuel oil). Our results in fact show that the cooling effect, which is observed in the sector of electricity, is stronger in temperate regions in residential and commercial sectors. The heating effect is found to be stronger for fuel oil and natural gas. Concerning industry, we find a significant response of electricity for cooling in tropical countries and of fuel oil and electricity for heating in temperate countries.

[5] De Cian E. and Sue Wing I. (2014) "Climate change impacts on energy demand", CMCC Research paper RP0240 and www.sisclima.it/wp-content/uploads/2013/10/SISC_Conference_Proceedings.pdf

	Maize				Sorghum		Rice				Wheat			
	Tropical		Temperate		Trop-ical	Temp-erate	Tropical		Temperate		Tropical		Temperate	
	Rain-fed	Irri-gated	Rain-fed	Irri-gated			Rain-fed	Irri-gated	Rain-fed	Irri-gated	Rain-fed	Irri-gated	Rain-fed	Irri-gated
<5	**0.05**		-0.4		0.11		**0.21**		-0.51				0.01	
>15	0.09		**-0.86**			-0.19			**1.36**		-1.39		0.58	
17.5-22.5	-0.09	0	**-0.35**	**0.39**							-0.66	**0.11**	**0.22**	**-0.3**
22.5-27.5	**-0.15**	**0.1**	**-0.35**	**0.41**	-0.52	**0.26**			**-0.4**	**0.19**	-2.25	**-0.75**	-0.02	**-0.06**
>27.5	**-0.16**	**0.12**	**-2.32**	0.85	-0.21	0.65	-0.03	-0.02			-2.25	**-0.84**	-1.27	-1.08

Table 2: Agriculture. Estimated long-run elasticities to precipitation and temperature from Model 1 (eq. 2). Underlined: p < 10%, bold italic: p < 5%.

	Agriculture				Commercial				Industry				Residential				
	Tropical		Temperate		Tropical		Temperate		Tropical		Temperate		Tropical		Temperate		
	Ely	FuelOil	Ely	FuelOil	Ely	Gas	Ely	Gas	Ely	FuelOil	FuelOil	Ely	FuelOil	Gas	Ely	FuelOil	Gas
Heating (<12.5)	ns	**0.046**	ns	**0.046**	ns	**0.009**	**-0.006**	**0.009**	**-0.023**	ns	**0.059**	ns	**0.099**	ns	**0.011**	**0.099**	**0.016**
Cooling (<27.5)	**0.021**	ns	**0.021**	ns	ns	ns	**0.019**	ns	**0.004**	ns	ns	**0.006**	ns	ns	**0.013**	ns	ns

Table 3: Energy. Estimated long-run elasticities to temperature from Model 2 (eq. 3). Underlined: p < 10%, bold italic: p < 5%.

6. FUTURE IMPACT CALCULATION

The impact of future climate change is calculated by combining the estimated parameters with Representative Concentration Pathway trajectories (RCP 4.5 and 8.5) simulated by an ensemble of five climate models in the CMIP5 project[6] , CCSM4, CNRM-CM5, GFDL-CM3, MIROC5, MPI-ESM-MR. For every model-scenario combination we calculate producer countries' current (2006-15) and future (2046-55) distributions of simulated daily temperature ($\overline{T}^{k,m}_{cell \in ii,C}$ and $\overline{T}^{k,m}_{cell \in ii,F}$) and precipitation ($\overline{P}^{j,m}_{cell \in ii,C}$ and $\overline{P}^{j,m}_{cell \in ii,F}$) at the grid cell level. Combining these variables with the fitted long-run equilibrium response, we obtain the climate shocks, defined as the ratio between future and current yields, in the case of agriculture, and between future and current energy demand, in the case of energy, at the grid cell level:

$$\frac{y^{CC,m}_{cell,F}}{y^{CC,m}_{cell,C}} = \exp\left\{\sum_{k=1}^{K} \hat{\theta}_1^{k,m} \Delta\overline{T}^{k,m}_{cell \in i,F} + \sum_{j=1}^{J} \hat{\theta}_2^{j,m} \overline{\Delta P}^{j,m}_{cell \in i,F}\right\}$$

$$\frac{q^{CC}_{cell \in i,F}}{q^{CC}_{cell \in i,C}} = \exp\{\sum_{k=1}^{K} \hat{\theta}_1^{k} \left[DT^{k}_{cell \in i,F}\omega_{cell \in i,F} - DT^{k}_{cell \in i,C}\omega_{cell \in i,C}\right]$$

Note that in the case of energy demand we here focus on the future impacts due to changes in temperature.

[6] All data was accessed from the http://pcmdi9.llnl.gov/esgf-web-fe/between June 1st and August 31st, 2013.

7. FUTURE DATA AND CLIMATE PROJECTIONS

Figure 1 shows the change in future exposure to cold days (with daily average temperature below 12.5°C) and to hot days (with daily average temperature above 27.5°C) centered in 2050, considering the 2045-2055 decade, according to the multi-model pattern of exposure in China. Chinese inland areas will experience a reduction in cold days, whereas coastal, southern areas will face an increased exposure to hot days. Consistently, the exposure to hot days is stronger in RCP 8.5, which is also the scenario with the stronger temperature increase, than in RCP 4.5.

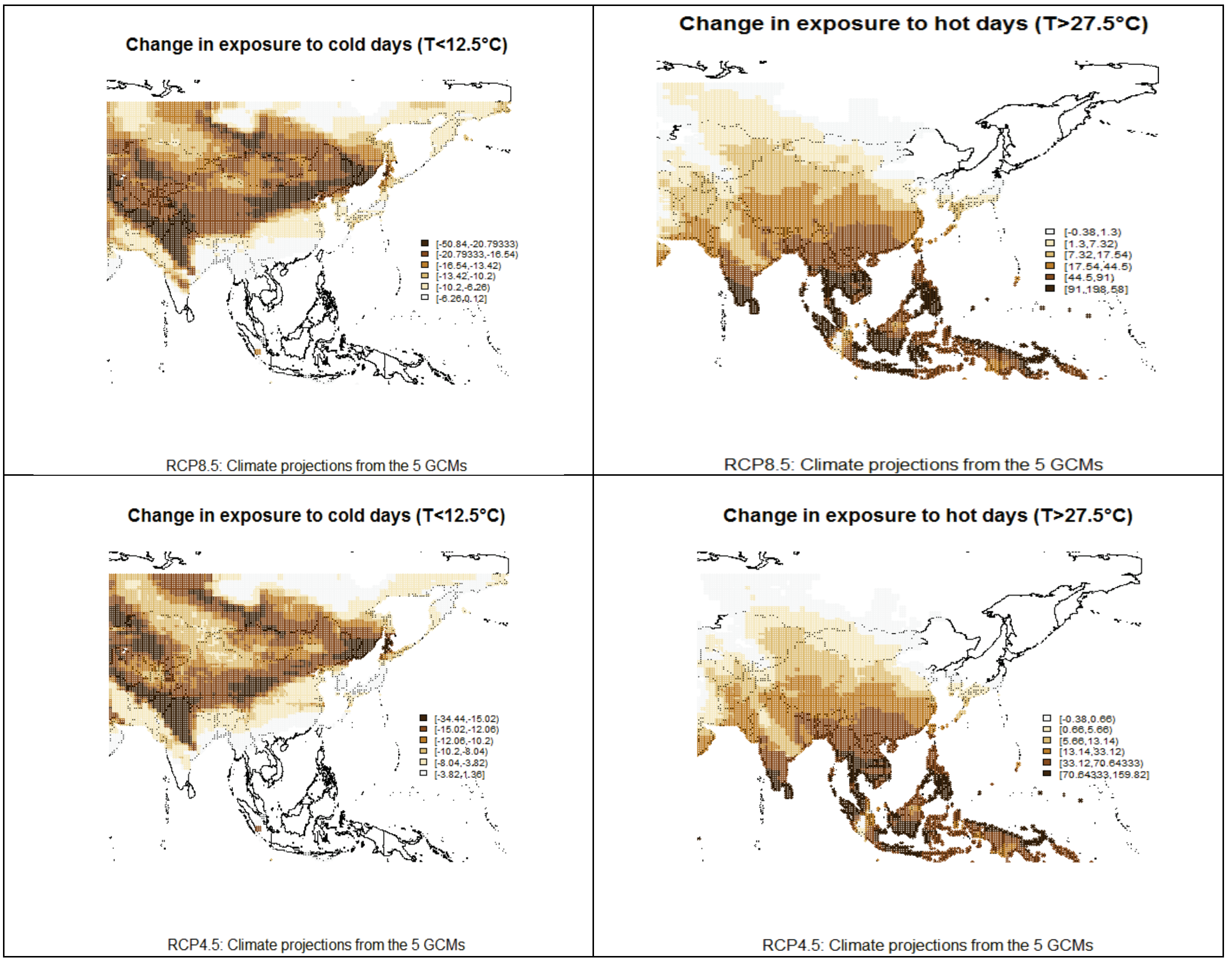

Figure 1: Change in future exposure to hot and cold days around 2050 (2045-2055) using 5 GCMs models (multi-model mean).

Figure 2 shows how the productivity of maize, rice, wheat and sorghum could change in RCP 8.5. This is done under the assumption that the areas where these crops are grown today are not going to change in the future. Red areas denote potential reduction in yields, whereas blue indicate potential increases.

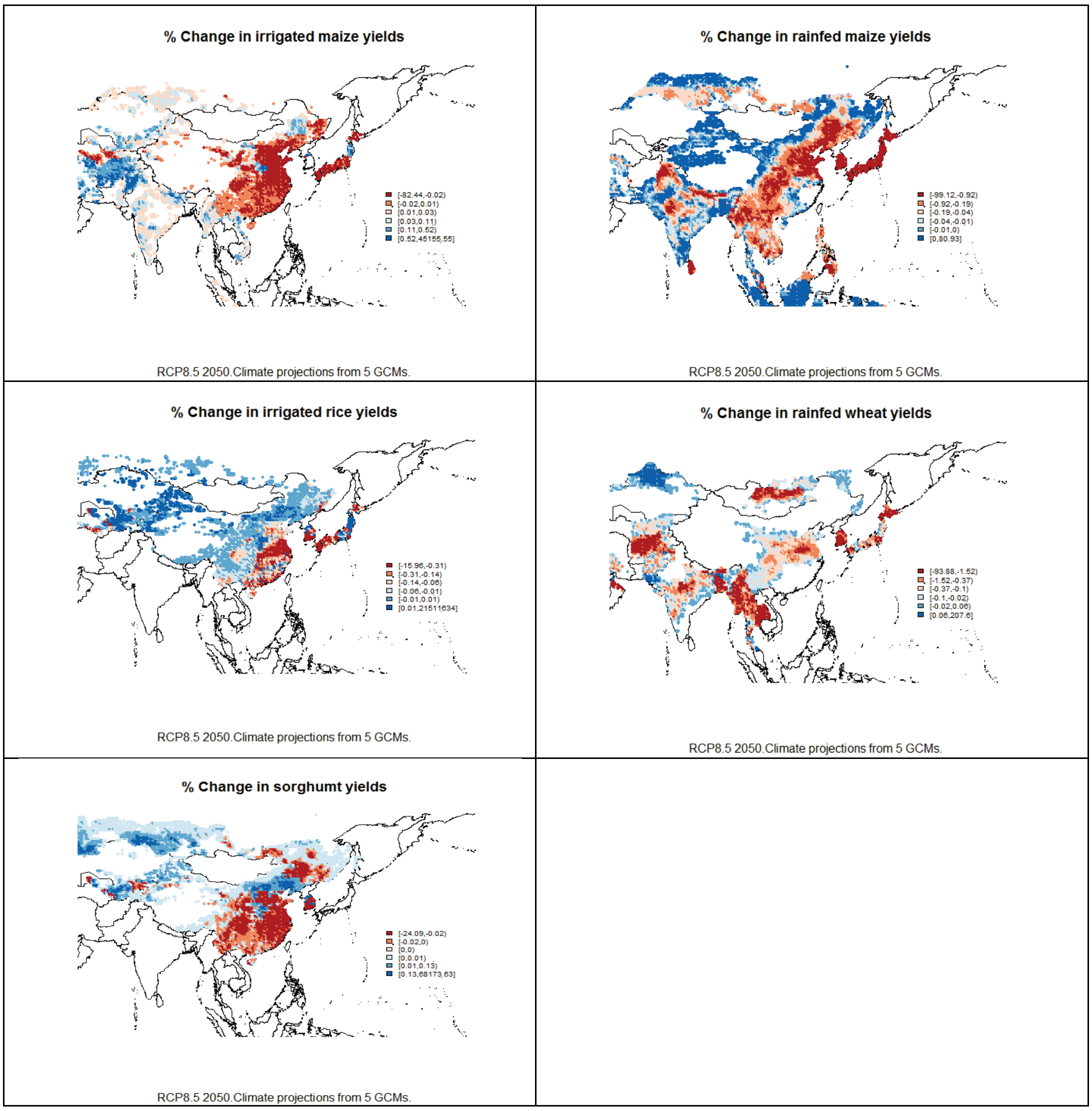

Figure 2: Change in crop yields due to temperature change in 2050 (2045-2055) , RCP 8.5, 5 GCMs models (multi-model mean).

China's coastal areas show a moderate decline in main cereal yields, that however remain within the range of the -1%. These are higher in rain-fed than in irrigated crops (note that in Figure 2 the categorization in the maps are different across rain-fed and irrigated agriculture).

Figure 3 shows the potential impact on sectoral energy demand, for those sectors and energy vectors where temperature played a statistically significant role. As can be seen in the residential sector of China's coastal areas there is a clear dominance of the cooling effect with increase in electricity demand often higher than the 66%. On the contrary gas and oil for heating purposes decline in a range between the 11% and 15% the former and the 34% and 70% the latter. A similar pattern in electricity demand can be observed in the agriculture and commercial sectors where it demonstrates a generalized increase larger than the 40%. The demand of energy for heating purposes declines everywhere, but less in the southern and coastal areas than in the inner regions of the country.

All in all, Chinese coastal areas depict a stronger increase in electricity demand and a lower decrease in oil and gas demand than interior regions. This seems to suggest that in the former there is a higher probability to observe a net increase in energy demand than in the latter.

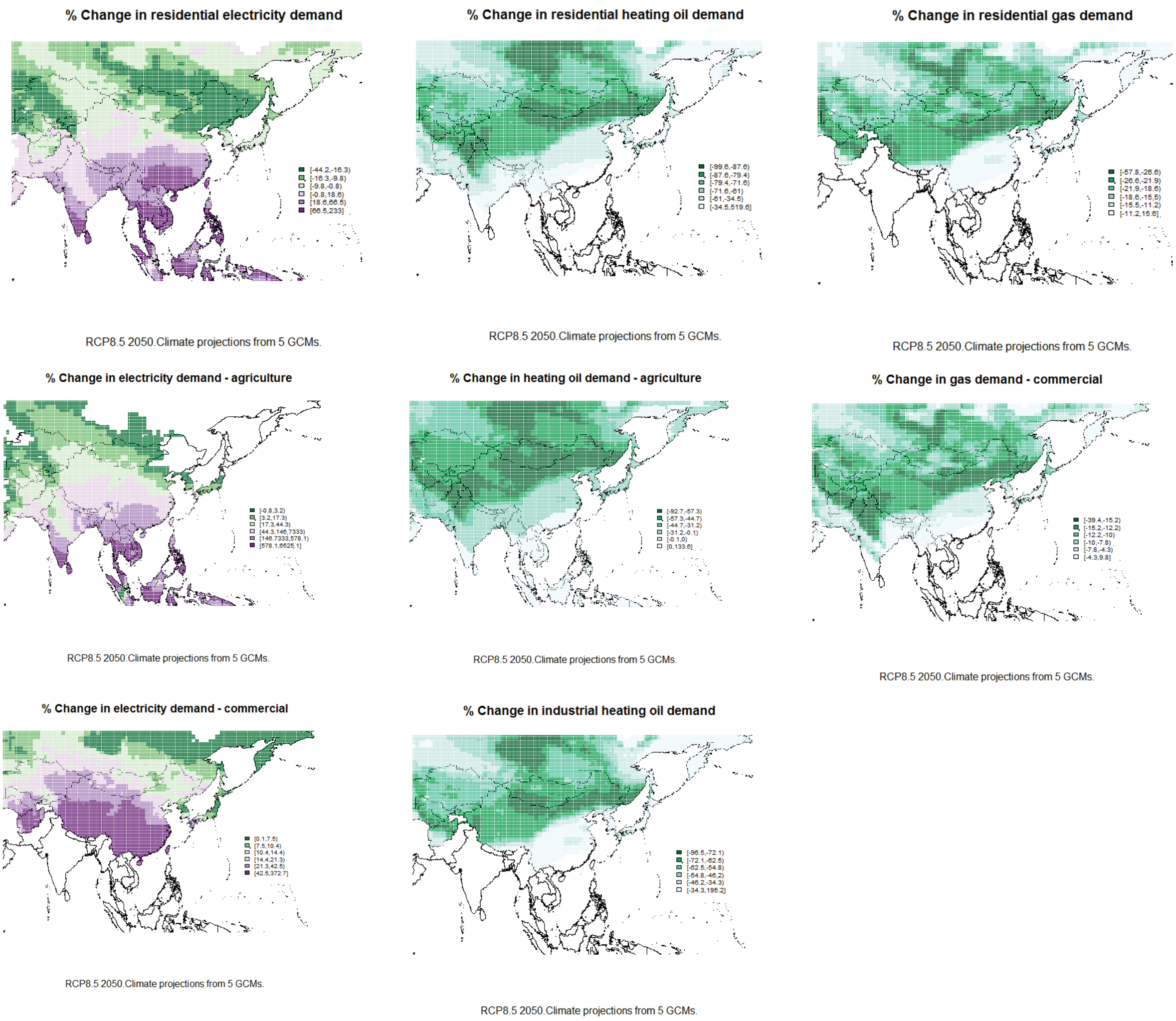

Figure 3: Change in energy demand due temperature change in 2050 (2045-2055) , RCP 8.5, 5 GCMs models (multi-model mean).

8. PRELIMINARY CONCLUSIONS AND NEXT STEPS

This exercise presents a preliminary application of a statistical/econometric technique to estimate the potential future impact of climate change on agriculture and energy demand in China. In a first step, a relation has been estimated between the two variables of interest, and a set of explanatories: temperature, precipitation, and GDP, using a world panel data set. In addition to estimate how much the climate effect in each country differs from the group mean, the error correction model used, enables to identify short and long-term responses to the changing climate. Estimates identify a negative effect of temperature for rain-fed crops yields, and a smaller or even positive one for irrigated crops. High precipitation can exert a positive effect in tropical areas for maize and rice, which grow under average high precipitation conditions, whereas it is negative for wheat. Estimates of the responses of energy demand point out a cooling effect, observed in electricity, which is stronger in temperate regions in residential and commercial sectors. Also a heating effect has been identified for fuel oil and natural gas. The industrial sector highlights a significant response of electricity for cooling in tropical countries and of fuel oil and electricity for heating in temperate countries.

In a second step, the relation identified has been projected to the future (2050) and then downscaled with a resolution of 0.5° x 0.5° grid for China, using spatially resolved climatic characteristics (temperature and precipitation) in the country, based upon projections of an ensemble of 5 climate models for two different climate change scenarios: RCP 8.5 and 4.5.

Main results, referred to RCP 8.5, highlight that China coastal areas may highlight a moderate reduction in cereal yields, with higher losses in rain-fed than in irrigated agriculture. These preliminary outcomes also show that productivity decrease are not higher than the 1% in 2050.

When energy demand is concerned, coastal areas in China show a clear dominance of the cooling effect for electricity as its demand increases in the residential, commercial and agricultural sectors. This effect is present, but milder in the inner areas of the country. On the contrary, the demand of fossil energy (oil and gas) for heating purposes declines everywhere, but less in the southern and coastal areas than in the inland. This seems to suggest that in the former there is a higher probability to observe a net increase in energy demand than in the latter because of climate change stressors.

These are just preliminary results and further refinements are expected:

- firstly, and trivially a better characterization of impacts at the grid level choosing carefully the interval categories to display such that to obtain more informative maps and allow a deeper analysis of the outcome obtained;
- secondly, identification of the net regional (i.e. coastal area wide) effect both for agriculture and energy demand in order to characterize the region as a whole and highlight its specificity compared to other areas of the country;
- thirdly, by coupling this spatial analysis with information about the economic structure of the region analyzed, recovering data at the provincial level, deriving higher order implication for the economic activity at the provincial level itself.

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