Improving regional climate projections by their prioritized aggregation through the OWA operator

Carlos Llopis-Albert[a]; José M. Merigó[b]; Yejun Xu[c], Huchang Liao[d]

[a] Universitat Politècnica de València, C/ Camí de Vera s/n, 46022 Valencia, Spain; email: cllopisa@gmail.com

[b] Department of Management Control and Information Systems, University of Chile, Av. Diagonal Paraguay 257, 8330015 Santiago Chile; email: jmerigo@fen.uchile.cl

[c] Research Institute of Management Science, Business School, Hohai University, Nanjing 211100, PR China; email: xuyejohn@163.com

[d] Business School, Sichuan University, Chengdu, Sichuan 610065, China; email: liaohuchang@163.com

Abstract

Decision-makers express a strong need for reliable information on future climate changes to come up with the best mitigation and adaptation strategies to address its impacts. These decisions are based on future climate projections simulated using different Representative Concentration Pathways (RCPs), General Circulation Models (GCMs) and downscaling techniques to obtain high-resolution Regional Climate Models (RCMs). RCPs defined by the Intergovernmental Panel on Climate Change (IPCC) entail a certain combination of the underlying driving forces behind climate and land use/land cover (LULC) changes, which leads to different anthropogenic Greenhouse Gases (GHGs) concentration trajectories. The projections of global and regional climate change should also take into account relevant sources of uncertainty and stakeholders' risk attitudes when defining climate polices.

The goal of this paper is to improve regional climate projections by their prioritized aggregation through the ordered weighted averaging (OWA) operator. The aggregated projection is achieved by considering the similarity of the projections obtained combining different GCMs, RCPs and downscaling techniques. The relative weights of the different projections to be aggregated by the OWA operator are obtained by regular increasing monotone fuzzy quantifiers, which allows modelling the stakeholders' risk attitudes. The methodology provides a robust decision-making tool to evaluate the performance of future climate projections and to design sustainable policies under uncertainty and risk tolerance, which has been successfully applied to a real-case study.

Keywords: OWA operators; climate change; General Circulation Models; aggregation; Representative Concentration Pathways; stakeholders; decision-making; uncertainty; risk

1. Introduction

Climate change and global warming is a major concern for societies and policy-makers in order to achieve a sustainable development. The climate change impacts are broadly categorized into three main areas: erratic climate and weather extremes (e.g., water scarcity, floods, droughts, melting of the cryosphere, sea level rise, higher temperatures, more severe storms, desertification, erosion, landslides, salt water intrusion), altered ecosystems and habitats (e.g., migration of species, damages to coral and shellfish, forests are more prone to deadly infestations, endangered species) and risks to human health and society (e.g., threats to agriculture and food availability, threats to tourism in coastal areas, significant health problems because the air and water are warmer and polluted, damages to infrastructure and transportation).

The decision-making process to design mitigation and adaptation strategies is hindered by the complex interactions among the driving forces of the climate change, ranging from natural causes, energy use, lifestyle and climate policies, to demographic, technological, socio-economic and environmental developments. A large number of methodologies have been developed to deal with decision-making processes in environmental problems (e.g., ; Llopis-Albert and Palacios-Marqués, 2016).

The assessment of the impacts of climate change relies on future climate projections obtained using different Representative Concentration Pathways (RCPs), General Circulation Models (GCMs) and downscaling techniques for obtaining high-resolution Regional Climate Models (RCMs). RCPs as adopted by the Intergovernmental Panel on Climate Change (IPCC) in its fifth Assessment Report (AR5) entail diverse driving forces behind anthropogenic Greenhouse Gases (GHGs) concentration trajectories (IPCC, 2014). Furthermore, this report establishes that humans through the GHGs trends are the main cause of current global warming.

The projections of global and regional climate change are hampered by the large existing uncertainties, which range from low confidence in climate variable observations, the underlying driving forces of climate and land use/land cover (LULC) changes, possible future climate change scenarios and anthropogenic impacts, GCMs assumptions and limitations, spatial resolutions, initial conditions to downscaling techniques to obtain regional projections. These uncertainties are translated into regional projections, which lead to dissimilar results and occasionally opposite to each other. Therefore, the IPCC (2014) recommends in climate change studies the use of stochastic approaches, i.e., the use of an ensemble of projections (e.g. Andersson et al., 2006) or a combination of those projections through different weighting methods (e.g., Gay and Estrada, 2010). Stochastic approaches are highly use to deal with many environmental problems, such as groundwater flow and mass transport (e.g., Llopis-Albert et al., 2015), saltwater intrusion (e.g., Llopis-Albert et al., 2016), hydro-economic models (e.g., Llopis-Albert et al., 2014).

As a rule of thumb, regional projections are key to understanding the climate change, but a methodology to deal with uncertainties and risk tolerance is advisable.

This paper is intended to improve regional climate projections by their prioritized aggregation by means of the ordered weighted averaging (OWA) operator. The heterogeneous and uncertain future climate projections (simulated using a variety of GCMs, RCPs and downscaling techniques) are aggregated in accordance with their similarity, where the relative weights of the projections are obtained by regular increasing monotone fuzzy quantifiers. In this way, the methodology also allows reducing uncertainty and modelling the risk tolerance when defining climate polices, i.e. the optimism/pessimism degrees of decision-makers. The procedure has been successfully applied to future regional projections for mainland Spain using the data provided by the State Meteorological Agency of Spain (AEMET, 2017).

The rest of the paper is organized as follows. Section 2 presents the methodology based on the prioritized OWA operator. Section 3 shows an application to a case study, while section 4 concludes the paper.

2. Methodology

2.1. Overview

We have selected ordered weighted averaging (OWA) operators (Yager, 1988) to aggregate the future regional projections for analyzing the climate change because its capability to encompass a range of operators from minimum to maximum, including several averaging aggregation operations like arithmetic mean. In the aggregation of fuzzy sets several fuzzy numbers are combined to produce a single fuzzy number (Klir and Yuan, 1995). This combination can be performed by intersection, minimum, product (i.e., fuzzy t-norms or disjunctive quantifiers) and union, maximum, summation (i.e., s-norms or conjunctive quantifiers). In addition, there are other well-known operators for aggregation such as arithmetic, geometric and harmonic means. A review on the development of aggregation operators can be found in Yu (2015).

OWA operators (Yager, 1988; Yager et al., 2011) and prioritized multi-criteria decision-making problem has been widely tackled in the literature (e.g., Yu et al., 2012). OWA operator has been extended under a wide range of frameworks including probabilities (Merigó, 2010), distance measures (Merigó and Casanovas, 2011), linguistic information (Merigó and Gil-Lafuente, 2013), moving averages (Merigó and Yager, 2013) and continuous operators (Zhou et al., 2016). Wei and Tang (2012) developed generalized prioritized aggregation operators. Chen et al. (2014a) developed a weakly prioritized measure for multi-criteria decision making and Yu et al. (2013) with preference relations. In fuzzy environments, Verma and Sharma (2016) designed prioritized operators with triangular fuzzy numbers, Ye (2014) considered trapezoidal intuitionistic fuzzy sets, Chen (2014) used interval-valued intuitionistic fuzzy sets, and Dong and Wan (2016) focused on triangular intuitionistic fuzzy numbers. Some other authors have used hesitant fuzzy sets in the aggregation process (e.g., Jin et al., 2016). Additionally, other authors have considered other environments with interval numbers (Ran and Wei, 2015) and linguistic information (Zhao et al., 2014).

However, this technique has been scarcely applied to climate change. Rahmani and Zarghami (2013) developed a new approach to combine climate change projections by using OWA operators.

The methodology entails three main steps. First, based on the future regional climate projections provided by AEMET, the similarity of a specific projection (obtained using a certain GCM, RCP and downscaling technique) is determined by comparing it with other projections obtained using other GCMs and/or downscaling techniques. Second, the methodology finds the total similarity through OWA operators considering different stakeholders' risk tolerance. Third, it averages the regional climate projections based on their total similarity, thus minimizing uncertainty.

Another advantage of the OWA operator is that since the similarity of regionals projections depends on stakeholders' risk attitudes, a sensitivity analysis can be carried out based on their preferences.

2.2. Comparison of future regional projections.

The regional projections obtained with different GCMs and downscaling techniques leads to a wide range of uncertainties. They show dissimilar results and occasionally opposite to each other, which hinders their direct use by policy-makers.

This problem can be diminished by finding the weak projections and reducing their effects in averaging. In order to measure the weakness the unlikeness measure $U_{i,s}^{x}$ is used, which calculates the total distance and/or error of a prediction by comparing a regional projection i (obtained using a certain GCM, RCP and downscaling technique) with regard to the other regional projections, j, in a station s (Rahmani and Zarghami, 2013):

$$U_{i,s}^{x} = \sum_{j=1,i\neq j}^{m} \sum_{t=1}^{k} \left| x_{i,t,s} - x_{j,t,s} \right| \tag{1}$$

where $x_{i,t,s}$ is the change in variable of x (rainfall, minimum temperature or maximum temperature) predicted by regional projection i to the value of its baseline in month t; m represents the number of all projections; k is the number of all months; and s indicates the stations. The value of x expresses the percent of change for rainfall and the absolute change for temperature.

In order to facilitate the analysis, a conversion between the unlikeness measure to similarity and a normalization of values to be within the interval [0, 1] is carried out (Rahmani and Zarghami, 2013):

$$L_{i,s}^{x} = \frac{Max_i U_{i,s}^{x} - U_{i,s}^{x}}{Max_i U_{i,s}^{x} - Min_i U_{i,s}^{x}} \tag{2}$$

where $L_{i,s}^{x}$ is the normalized similarity of a regional projection i in station s on variable x regarding the other projections.

2.3. Aggregation of future regional projections by OWA operators.

The aggregation of the similarity measures for all stations is carried out by OWA operators, which is a well-known technique to deal with uncertain and complex environments in multi-person and multi-criteria problems. The methodology aims to consider stakeholders' risk preferences when defining climate polices, and to minimize the existing uncertainties. The risk tolerance define the optimism/pessimism degrees of decision-makers, i.e., if they are willing to accept risk or, conversely, they are risk averse. Climate change is a global challenge that can only be effectively addressed through a global effort. The stakeholders involved in the decision-making process for defining climate policies may cover the governments and governmental agencies, experts and opinion formers in climate change, civil society, non-governmental organization (NGOs), mass-media, economic sectors, and the IPCC. The risk attitude or optimism degree of the decision-makers can be collected through public government information, meetings, surveys, polls, conferences, workshops, round tables, personal interviews, debate forums, expert panels and mass-media information.The priority of a regional projection is ranked through its total similarity measures considering all stations, TL_i^x, while an n-dimensional OWA operator is used to determine the aggregation value:

$$TL_i^x = OWA\left(L_{i,1}^x, L_{i,2}^x, \dots, L_{i,n}^x\right) = \sum_{g=1}^{n} \omega_g b_g \tag{3}$$

where $\left(b_{i,1}^x, b_{i,2,}^x, \dots, b_{i,n}^x\right)$ is the sorted vector in descending order of the $\left(L_{i,1}^x, L_{i,2}^x, \dots, L_{i,n}^x\right)$ vector, in which n is the numbers of stations. The weight vector $(\omega_1, \omega_2, \dots, \omega_n)$ indicates the order weights, and each component ω_g satisfies that $\omega_g \in [0,1]$ and $\sum_{g=1}^{n} \omega_g = 1$. The weights can be obtained by different techniques, such as fuzzy linguistic quantifiers, orness measure, dispersion measure, O'Hagan's maximum entropy measure, normal distribution based method, training etc. (e.g., Yager, 1988; O'Hagan, 1988; Xu, 2005; Sadiq and Tesfamariam, 2010).

Two characterizing measures called orness measure and dispersion measure associated with the weighting vector ω of an OWA operator were introduced by Yager (1988). The orness measure of the aggregation operator is defined as:

$$\alpha = \frac{1}{n-1} \sum_{i=1}^{n} \omega_i (n-1) \tag{4}$$

with $\alpha \in [0,1]$.

It characterizes the degree to which the aggregation is like an *or* operator. When $\alpha = 0$ the vector ω becomes $(0, 0, \dots, 1)$, which means that minimum value in the vector $\left(L_{i,1}^{x}, L_{i,2}^{x}, \dots, L_{i,n}^{x}\right)$ is assigned the complete weight (i.e., the OWA behaves as a minimum operator). Likewise, when $\alpha = 1$ becomes $(1, 0, \dots, 0)$, which means that maximum value in the vector $\left(L_{i,1}^{x}, L_{i,2}^{x}, \dots, L_{i,n}^{x}\right)$ receives the complete weight (i.e., the OWA behaves as a maximum operator). If all elements in the vector $\left(L_{i,1}^{x}, L_{i,2}^{x}, \dots, L_{i,n}^{x}\right)$ are assigned equal weights (i.e., arithmetic average) the vector ω becomes $(1/n, 1/n, \dots, 1/n)$ and $\alpha = 0.5$. Between the two extreme values (i.e., $\alpha = 0$ and $\alpha = 1$) there is an infinite number of possible α values, which lead to different weights distributions. Note that $\alpha = 0.5$ does not assure that weights are uniformly distributed (i.e., $\omega_i = 1/n$), instead it means that weights are distributed symmetrically regarding the mean. Then any symmetric probability density function (PDF) like uniform or normal presents an $\alpha = 0.5$.

The weight distribution for a given α can be analyzed through the dispersion measure $Disp(\omega)$ as presented by Yager (1998):

$$Disp(\omega) = -\sum_{i=1}^{n} \omega_i \ln(\omega_i) \tag{5}$$

where $0 \leq Disp(\omega) \leq \ln(n)$. It provides a degree to which the information in the arguments is used. In this way, when $\alpha = 0$ or $\alpha = 1$ (i.e., $\omega_i = 1$) the dispersion is zero and when $\omega_i = 1/n$ (i.e., a uniform distribution) it takes its maximum value (i.e., $\ln(n)$).

In this study, we use a fuzzy linguistic quantifiers (Q) to obtain the weights, such as a regular increasing monotone (RIM) quantifier (Yager, 2009):

$$\omega_g = Q\left(\frac{g}{n}\right) - Q\left(\frac{g-1}{n}\right), g = 1,2, \dots, n \tag{6}$$

The quantifier is defined as $Q(r) = r^{\beta}$, where r≥ 0 and β is a parameter that depends on the risk tolerance of the stakeholder, which is represented using fuzzy terms. Then, values of $\beta < 1$ expresses stakeholders' optimism (risk acceptance), $\beta = 1$ for risk neutral and $\beta > 1$ for pessimism (risk aversion).

This is because the RIM function is bounded by two linguistic quantifier "there exists" $Q^*(r)$ (OR) and "for all", $Q_*(r)$ (AND). Therefore, for a given $Q(r)$ the relationship $Q^*(r) \leq Q(r) \leq Q_*(r)$ is always fulfilled.

For β = 1, the RIM quantifier becomes a uniform distribution (i.e., weight distribution is similar to an arithmetic mean, which means that $\omega_i = {}^1/_n$). For β > 1, it leans towards right (i.e., ''And-type'' operators showing negatively skewed OWA weight distributions). Likewise, for β < 1, it leans towards left and becomes a regular decreasing monotone (RDM) quantifier (i.e., ''Or-type'' operators showing positively skewed OWA weight distributions).

Additionally, the OWA operator has some important properties, i.e., monotonicity, commutativity and boundary (e.g., Wang et al., 2014). Furthermore, note that many other aggregation operators could also be considered in the analysis (Yager, 2011).

2.3. Average of regional projections based on their total similarity.

A simple additive weighting is used to average the regional projections based on their total similarity. The weight for each projected variable, v_i, is calculated in accordance with the order of total similarity regarding a specific regional projection i, TL_i^x (Rahmani and Zarghami, 2013):

$$v_i^{x,\alpha} = \frac{m + 1 - ord(TL_i^{x,\alpha})}{\sum_{i=1}^{m} i} \tag{7}$$

where m is the number of regional projections and $\mathrm{ord}()$ represents the rank, i.e., one for the highest similarity and m for the lowest one. The weights v_i are defined to add up the unity. It is worthwhile mentioning, that ω_g indicates the order in the OWA methodology based on the stakeholders' risk preferences, while ν_i represents the effect of similarity.

As a result, the average projection of a certain variable $x_{i,t,s}$ (i.e., rainfall, minimum temperature or maximum temperature) using different regional projections is defined as follows:

$$\bar{x}_{t,s}^{\alpha}=\sum_{i=1}^{m} \nu_i^{x,\alpha}\, x_{i,t,s} \quad (8)$$

3. Application to a case study

Spain is a country located in southwestern Europe occupying about 85 percent of the Iberian Peninsula. It has an area of 504,030 km², of which 499,542 km² is land and 5,240 km² is water. Spain is the second largest country in Western Europe and with an average altitude of 650 m, the third highest country in Europe. It lies between latitudes 36° and 44° N, and longitudes 19° W and 5° E, and its Atlantic coast is 710 km long.

The climate of Spain varies across the country and presents three main climatic zones, based on the geographical situation and orographic conditions. The Mediterranean climate is characterized by dry and warm summers and cool to mild and wet winters. The oceanic climate is located in the northern part of the country, especially in the regions of Basque Country, Asturias, Cantabria and Galicia. The semiarid climate is located in the south eastern part of the country, especially in the region of Murcia and in the Ebro valley. In contrast to the Mediterranean climate, the dry season continues beyond the end of summer.

We use regional projections for mainland Spain as provided by the State Meteorological Agency of Spain (AEMET, 2017). These projections are obtained following the guidelines of the fifth Assessment Report (AR5) of the Intergovernmental Panel on

Climate Change (IPCC, 2014). This study uses a set of 42 future regional projections encompassing 24 GCMs, 3 RPCs scenarios and 2 downscaling techniques. These regional climate projections are obtained for the 21st century and comprise the variables precipitation (using 2321 weather stations), and maximum and minimum temperature (using 374 weather stations).

All GCMs models used to obtain regional projections are from CMIP5 Project (Coupled Model Intercomparison Project Phase 5) and within the framework of the AR5-IPCC. They provide daily information for the variables precipitation, and maximum and minimum temperature (AEMET, 2017). The AR5 (IPCC, 2014) defines four new scenarios in comparison with the AR4 and the ENSEMBLES (Stream 1 y Stream 2) project (IPCC, 2007). On the one hand, the ENSEMBLES project generated a collection of regionalized climate change projections based on a set of global models, regional models and emission scenarios. These projections were generated under the emission scenarios named as SRES (Special Report Emissions Scenarios), which cover four possible emission scenarios: high emissions (A2), average emissions (A1B), low emissions (B1) and a scenario of aggressive mitigation in order to avoid the possibility of exceeding 2ºC of global warming (E1) with regard to pre-industrial levels (Van der Linden and Mitchell, 2009).

On the other hand, the four new emission scenarios provided by the AR5, called Representative Concentration Pathways (RCPs), are considered as plausible scenarios depending on different Greenhouse Gases (GHGs) concentration trajectories. The four RCPs (i.e., RCP 2.6, RCP 4.5, RCP 6, and RCP 8.5) entail a different range of radiative forcing values in the year 2100 relative to pre-industrial values (+2.6, +4.5, +6.0, and +8.5 W/m^2, respectively). An important difference of the new RCPs regarding the emission scenarios used in the AR4 is that the latter did not contemplate the effects of possible policies or international agreements with the aim of mitigating emissions. Instead, they represent potential socio-economic developments without restrictions on emissions. On the contrary, some of the new RCPs consider the effects of policies to limit climate change over the 21st century. Each RCP has an associated high spatial resolution database of emissions of pollutants (classified by sector), emissions and concentrations of GHGs and land use/land cover (LULC) changes until the year 2100, based on a combination of models of different complexity of atmospheric chemistry and the carbon cycle. As a result, this is translated into different range of radiative forcing values.

RCP 2.6 entails an extremely low scenario that reflects aggressive GHGs reduction and sequestration efforts. RCP 4.5 implies a low scenario in which GHGs emissions stabilize by midcentury and fall sharply thereafter. RCP 6.0 assumes a medium scenario in which GHGs emissions increase gradually until stabilizing in the final decades of the 21st century. Finally, RCP 8.5 postulates increasing GHGs emissions until the end of the 21st century, i.e., atmospheric CO^2 concentrations are more than triple by 2100 relative to pre-industrial levels.

The downscaling techniques to obtain high-resolution RCMs from the GCMs are based on statistical downscaling methods (such as linear regression or synoptic analogue methods, e.g., Wilby et al., (2002), Wilby and Dawson, (2004)) or dynamical downscaling methods (e.g., Wang et al., 2014). On the one hand, statistical downscaling methods provide results at any scale, down to station-level information, are computationally inexpensive and efficient, and require low volume of data inputs. The main disadvantages are that they assume that the derived relationships do not change as the climate is perturbed, require a sufficient amount of good quality of observational data to produce reliable projections, and cannot explicitly describe the physical processes affecting the climate change. On the other hand, dynamic downscaling methods provide

20-50 km grid cell information, including information at sites with no observational data, i.e., they are not constrained to historical records. The main advantage is that they are physically based but are more complex and with a high computational cost and volume of data inputs (Murphy, 1999). Both approaches provide good results in terms of reproducing the observed variability of the local climate variables, but the lower computational cost of statistical downscaling has led to their greater use.

In addition, a review of downscaling methods for climate change projections with regard to advantages, disadvantages, outputs, requirements, and applications can be found in Trzaska and Schnarr (2014).

Further information about the generation of regional scenarios of climate change for Spain can be found in Brunet et al. (2009) and Morata-Gasca (2014).

Fig. 1 and Fig. 2 show the changes for different climatic variables and for an ensemble of future climate regional projections in comparison with the historical data for the period 1981-2010 (AEMET, 2017). Fig. 1 presents these changes for the annual average maximum and minimum temperature during the 21st century, while Fig. 2 depicts these changes for precipitation. As aforementioned, the changes of the climatic variables are obtained using a set of 42 future regional climate projections encompassing 24 GCMs, 3 RPCs scenarios and 2 downscaling techniques. Fig 1 and Fig. 2 present future reginal projections obtained using a specific GCM, RPC and downscaling technique. Therefore, the future projections show a wide range of climatic variables changes. Temperature changes may differ several degrees centigrade from one future projection to another, and the differences regarding the precipitation changes are also important. The largest differences are mainly due to the underlying assumptions of each GCM considered. The GCM with lower emission scenarios and implementing policies or international agreements with the aim of mitigating emissions lead to lower changes in the climatic variables and vice versa. The same can be enunciated for the different RCPs, those with higher radiative forcing values lead to higher changes of the climatic variables, and conversely, for lower values. The downscaling techniques used in the future regional projections lead to less important but non-negligible differences. It is worth mentioning that results strongly depend on how many projections based on each GCM, RCP or downscaling technique are used for obtaining the aggregated projections. Then, if more future projections with higher RCP values are used, the aggregated projection would be biased towards the higher values and vice versa. However, the aggregate projection with risk acceptance ($\beta < 1$) would lead to a lower bias towards the higher values.

The proposed methodology is applied to properly tackle with those large uncertainties while considering different degrees of optimism of decision-makers. In this sense, these figures also show the changes of the aggregated future regional projections, obtained using prioritized OWA operators, for different stakeholders' risk tolerances. That is, since the similarity of regionals projections obtained using OWA operators depends on stakeholders' risk preferences, a sensitivity analysis has been performed using three different values of risk tolerance. Specifically, for $\beta = 0.5\,(\text{risk acceptance})$, $\beta = 1\,(\text{risk neutral})$, and $\beta = 2$ (risk aversion).According to these premises, Fig. 1 shows for the set of future projections that there is a growing trend regarding the maximum temperature changes over the whole period, but with a wide range of values depending on which GCM, RPC and downscaling technique are based on. This upward trend reaches an increase among 1-4 ºC at the end of the 21st century, and is less pronounced in some coastal areas. The largest increase corresponds to summer months with up to 4-7 ºC. In the winter the expected average values show an increase of around 3 °C. The percentage of warm days keeps a constant growing trend throughout the period. The aggregated projections also show the growing trend in the maximum temperature changes to a greater or lesser extent, but with higher changes and with greater variations between successive years for larger risk acceptance attitudes (i.e., for β=0.5). That is, with more risk acceptance, temperatures or precipitations closest to the extreme values among all of future projections for a certain time are achieved. On the contrary, with risk aversion attitudes values closest to the average of all future projections are obtained. Furthermore, the changes may differ significantly at some years of the series for the different risk acceptance preferences. This shows the worth of the methodology to model those attitudes and uncertainties, which allows to come up with better policies and with more consensus among decision-makers.

Results show that there is also a growing trend of the annual minimum temperature change, with increasing values for the set of future projections and the aggregated projections of around 1-4 ° C at the end of the 21st century (Fig. 1). This increase is greater in southern peninsular and during the summer months, while the days of frost decreases and the percentage of warm nights increases. Similar results regarding the aggregated projections can be drawn, i.e., higher risk tolerance leads to higher temperature changes and variations between successive years.

The percentage change in precipitations is on a downward trend for the aggregated projections, with reductions ranging from 3 to 23% at the end of the 21st century (Fig. 2). In general, a downward trend in precipitations is observed throughout the peninsular area, although is lower in the northern half of the peninsula. The number of rainy days decreases, and the duration of dry periods tend to be longer, which would increase the risk of droughts especially in summer and the southern half peninsula. That is, the seasonal cycles are more noticeable.

Again, results show that for stakeholders' with risk acceptance (β = 0.5) higher changes for the climatic variables are achieved, while for risk aversion (β = 2) lower changes are obtained.

Finally, these results are in line with that obtained by other authors, which show that there will be a more intense heat in the summer months, together with increases in the intensity and frequency of heat waves over southern Europe and the Mediterranean and a decrease in precipitation (e.g., Fischer and Schär, 2010; Morata-Gasca, 2014).

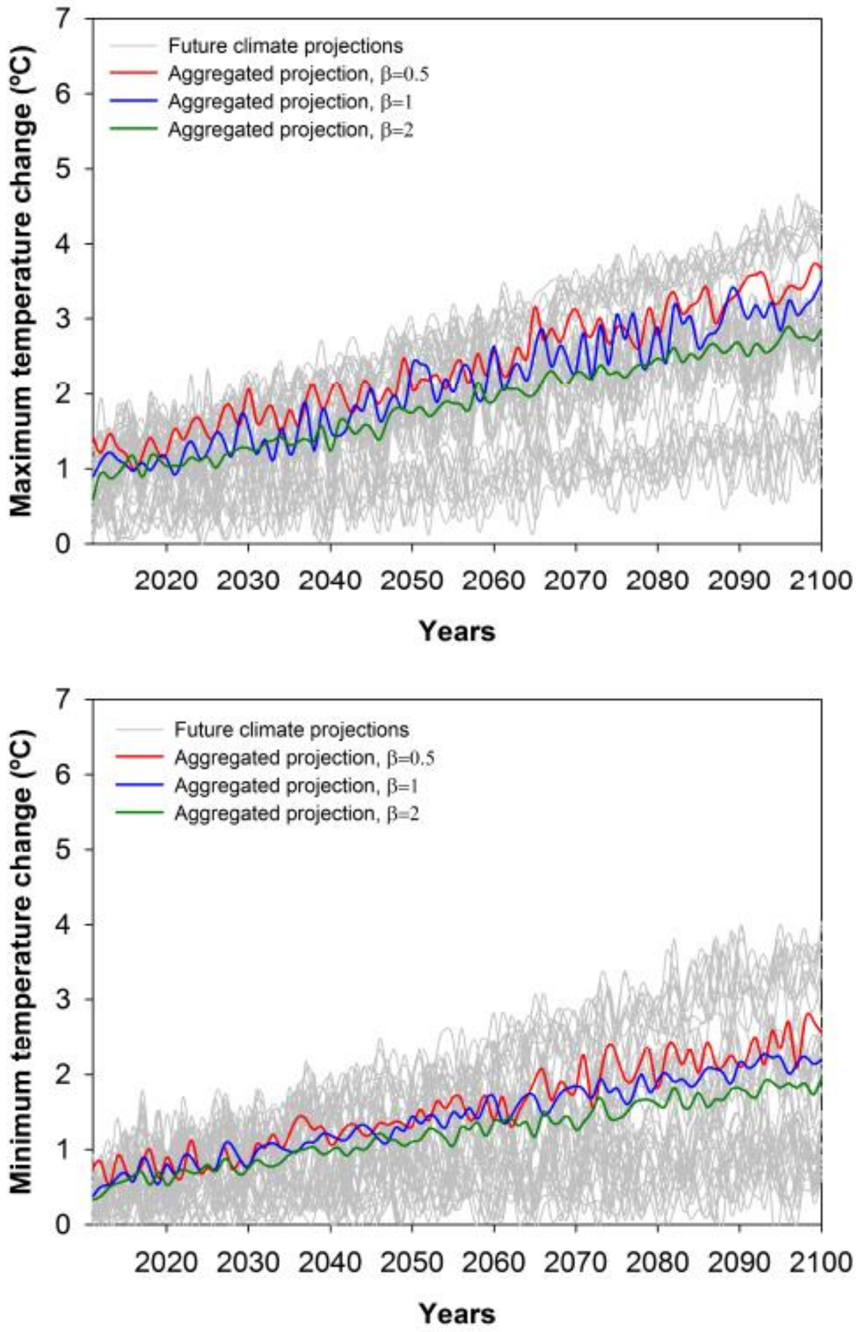

Figure 1. Annual maximum and minimum temperature change (ºC) for an ensemble of future climate regional projections and aggregated projections with different stakeholders' risk attitude (β) obtained for mainland Spain and the 21st century (i.e., the period 2011-2100).

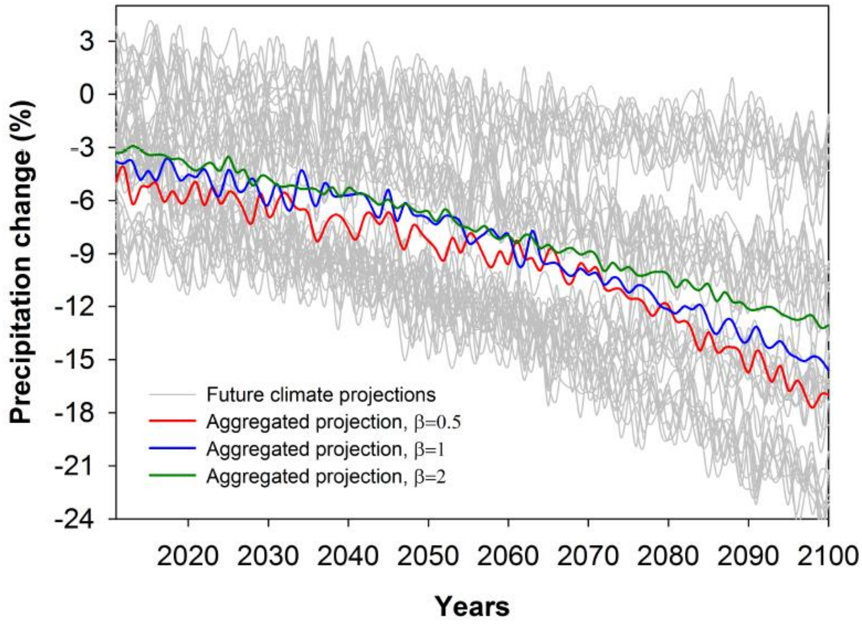

Figure 2. Annual precipitation change (%) for an ensemble of future climate regional projections and aggregated projections with different stakeholders' risk attitude (β) obtained for mainland Spain and the 21st century (i.e., the period 2011-2100).

4. Conclusions

Long-term climate change projections may provide a wide range of possible outcomes. The selection of climate policies based on these projections should take into account relevant sources of uncertainties and stakeholders' risk attitudes. Furthermore, studies of climate change rarely yield consensus among stakeholders because their different perceptions about the expected impacts and preferences about the adopted policies.

We have presented a methodology that makes use of prioritized OWA operators to provide an effective way to address stakeholders' risk attitudes and preferences regarding the measures to be undertaken. The methodology also allows minimizing the uncertainties associated to GCMs, RCPs and downscaling techniques, which are translated into future regional projections. These projections are combined by considering their similarity in such a way that the relative weights of the different projections are obtained by regular increasing monotone fuzzy quantifiers. The methodology provides a robust and effective decision-making tool to design sustainable climate policies under uncertainty and risk tolerance. Furthermore, it has been successfully applied to evaluate the climate change in Spain. The future aggregated regional projections have shown that a global warming is observed with a growing trend in maximum and minimum average temperatures and a downward trend in precipitations over the 21st century and throughout the peninsular area.

References

- AEMET (2017). State Meteorological Agency of Spain. http://www.aemet.es/en.

- Andersson, J.W., Todd, M.C., Hughes,D.A., Earle, A., Kniveton, D., Layberry, R., Savenije, Hubert H.G. (2006). Impact of climate change and development scenarios on flow patterns in the Okavango River. Journal of Hydrology 331 (1–2), 43–57.

-Brunet, M., Casado, M.J., Castro, M., Galán, P., López, J.A., Martín, J.M., Pastor, A., Petisco, E., Ramos, P., Ribalaygua, J., Rodríguez, E., Sanz, I., Torres, L. (2009). Generación de escenarios regionalizados de cambio climático para España. Ministerio de Medio Ambiente Medio Rural y Marino. 158 pp.

-Chen, L.H., Xu, Z.S., Yu, X.H. (2014). Weakly prioritized measure aggregation in prioritized multicriteria decision making. International Journal of Intelligent Systems, 29, 439-461.

-Chen, T.Y. (2014). A prioritized aggregation operator-based approach to multiple criteria decision making using interval-valued intuitionistic fuzzy sets: A comparative perspective. Information Sciences, 281, 97-112.

-Dong, J.Y., Wan, S.P. (2016). A new method for prioritized multi-criteria group decision making with triangular intuitionistic fuzzy numbers. Journal of Intelligent & Fuzzy Systems, 30, 1719-1733.

-Fischer, E.M., Schär, C. (2010). Consistent geographical patterns of changes in high-impact European heatwaves. Nature Geoscience, 3(6), 398-403.

- Gay, C., Estrada, F. (2010). Objective probabilities about future climate are a matter of opinion. Climate Change 99 (1–2), 27–46.

- IPCC (2014). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

-IPCC, 2007: Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, Pachauri, R.K and Reisinger, A. (eds.)]. IPCC, Geneva, Switzerland, 104 pp.

-Jin, F.F., Ni, Z.W., Chen, H.Y. (2016). Note on "Hesitant fuzzy prioritized operators and their application to multiple attribute decision making". Knowledge-Based Systems, 96, 115-119.

- Klir, G.J., Yuan, B. (1995). Fuzzy Sets and Fuzzy Logic: Theory and Applications. Prentice Hall International, Upper Saddle River, NJ.

-Llopis-Albert, C., Palacios-Marques, D., (2016). Applied Mathematical Problems in Engineering. Multidisciplinary Journal for Education, Social and Technological Sciences 3(2), 1-14. doi: 10.4995/muse.2016.6679.

-Llopis-Albert, C., Palacios-Marqués, D., Merigó, J.M., 2016. Decision making under uncertainty in environmental projects using mathematical simulation modeling. Environmental Earth Sciences 75(19), 1-11. doi: 10.1007/s12665-016-6135-y.

-Llopis-Albert, C., Merigó, J.M., Xu, Y., (2016). A coupled stochastic inverse/sharp interface seawater intrusion approach for coastal aquifers under groundwater parameter uncertainty. Journal of Hydrology, 540, 774–783. doi: 10.1016/j.jhydrol.2016.06.065.

-Llopis-Albert, C., Palacios-Marqués, D., Merigó, J.M. (2014). A coupled stochastic inverse-management framework for dealing with nonpoint agriculture pollution under groundwater parameter uncertainty. Journal of Hydrology 511, 10–16. doi: 10.1016/j.jhydrol.2014.01.021.

-Merigó, J.M. (2010). Fuzzy decision making using immediate probabilities. Computers & Industrial Engineering, 58, 651–657.

-Merigó, J.M., Casanovas, M. (2011). Decision making with distance measures and induced aggregation operators. Computers & Industrial Engineering, 60, 66–76.

-Merigó, J.M., Gil-Lafuente, A.M. (2013). Induced 2-tuple linguistic generalized aggregation operators and their application in decision-making. Information Sciences, 236, 1–16.

-Merigó, J.M., Yager, R.R. (2013). Generalized moving averages, distance measures and OWA operators. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 21, 533–559.

-Morata-Gasca, A. (2014). Guía de escenarios regionalizados de cambio climático sobre España a partir de los resultados del IPCC-AR4. Ministerio de Agricultura, Alimentación y Medio Ambiente. Agencia Estatal de Meteorología (AEMET). NIPO: 281-14-002-7.

- Murphy J. (1999). An evaluation of statistical and dynamical techniques for downscaling local climate. Journal of Climate 12, 2256–2284.

-O'Hagan, M. (1988). Aggregating Template Rule Antecedents in Real-time Expert Systems with Fuzzy Set Logic. In, Proceedings of 22nd annual IEEE Asilomar Conference on Signals, Systems and Computers, IEEE and Maple Press, Pacific Grove, 681-689.

-Rahmani, M.A., Zarghami, M., (2013). A new approach to combine climate change projections by ordered weighting averaging operator; applications to northwestern provinces of Iran. Global and Planetary Change, 102, 41–50.

-Ran, L.G., Wei, G.W. (2015). Uncertain prioritized operators and their application to multiple attribute group decision making. Technological and Economic Development of Economy, 21, 118-139.

-Sadiq, R., Rodríguez, M.J., Tesfamariam, S., (2010). Integrating indicators for performance assessment of small water utilities using ordered weighted averaging (OWA) operators. Expert Systems with Applications, 37, 4881–4891.

- Trzaska, S., Schnarr, E., 2014. A review of downscaling methods for climate change projections. African and Latin American Resilience to Climate Change (ARCC). United States Agency for International Development by Tetra Tech ARD.

-Van der Linden, P, Mitchell, JFB. 2009. ENSEMBLES: Climate Change and its Impacts: Summary of research and results from the ENSEMBLES project. Met Office Hadley Centre, FitzRoy Road, Exeter EX1 3PB, UK. 160pp.

-Verma, R., Sharma, B. (2016). Prioritized information fusion method for triangular fuzzy information and its application to multiple attribute decision making. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 24, 265-290.

-Wang, H.M., Xu, Y.J., Merigó, J.M., (2014). Prioritized aggregation for non-homogeneous group decision making in water resource management. Economic Computation and Economic Cybernetics Studies and Research, 48(1), 247-258.

-Wang, Y., Leung, L. R., McGregor, J. L., Lee, D. K., Wang, W. C., Ding, Y., Kimura, F. (2004). Regional climate modeling: progress, challenges, and prospects. Journal of the Meteorological Society of Japan. Ser. II, 82(6), 1599-1628.

-Wei, C.P. Tang, X.J. (2012). Generalized prioritized aggregation operators. International Journal of Intelligent Systems, 27, 578-589.

-Wilby R.L., Dawson C.W., Barrow E.M. (2002). SDSM - a decision support tool for the assessment of regional climate change impacts. Environmental Modelling Software, 17, 145-157.

-Wilby, R., Dawson, C. (2004). Using SDSM version 3.1- A decision support tool for the assessment of regional climate change impacts. England, UK.

-Xu, Z.S., (2005). An Overview of Methods for Determining OWA Weights. International Journal of Intelligent Systems, 20, 843-865.

-Yager, R.R. (1988). On ordered weighted averaging aggregation operators in multi-criteria decision making, IEEE Transactions on Systems, Man and Cybernetics B 18 (1988) 183-190.

-Yager, R.R. (2009). Prioritized OWA Aggregation. Fuzzy Optimization and Decision Making, 8, 245-262.

-Yager, R.R., Kacprzyk, J., Beliakov, G. (2011). Recent developments on the ordered weighted averaging operators: Theory and practice, Springer-Verlag, Berlin.

-Ye, J. (2014). Prioritized aggregation operators of trapezoidal intuitionistic fuzzy sets and their application to multicriteria decision-making. Neural Computing & Applications, 25, 1447-1454.

-Yu, X.H., Xu, Z.S., Liu, S.S. (2013). Prioritized multi-criteria decision making based on preference relations. Computers & Industrial Engineering, 66, 104-115.

-Yu, D. (2015). A scientometrics review on aggregation operator research. Scientometrics, 105(1), 115-133.

-Yu, D., Wu, Y., Lu, T. (2012). Interval-valued intuitionistic fuzzy prioritized operators and their application in group decision making. Knowledge-Based Systems, 30, 57-66.

-Zhao, X.F., Li, Q.X., Wei, G.W. (2014). Some prioritized aggregating operators with linguistic information and their application to multiple attribute group decision making. Journal of Intelligent & Fuzzy Systems, 26, 1619-1630.

-Zhou, L.G., Merigó, J.M., Chen, H.Y., Liu, J.P. (2016). The optimal group continuous logarithm compatibility measure for interval multiplicative preference relations based on the COWGA operator. Information Sciences, 328, 250–269.