Fuzzy Inference Systems as Geographic Patterns of Climatic Warming Over Mexico

Carlos Gay[1,2], Bernardo Bastien[3], Valeria Vidal[2] and Jessica Pelcastre[2]
[1]*Centro de Ciencias de la Atmosfera, Universidad Nacional Autónoma de México, Mexico City, Mexico*
[2]*Programa de Investigación en Cambio Climático, Universidad Nacional Autónoma de México, Mexico City, Mexico*
[3]*Geography Department, University College London, London, U.K.*
cgay@unam.mx, ucfabab@ucl.ac.uk, vva@ciencias.unam.mx, jesspesic@gmail.com

Keywords: Warming Patterns, Pattern Scaling, Climate Change Scenarios, Adaptive Neuro-Fuzzy Inference Systems.

Abstract: Local and regional temperature response to the global temperature rising is a matter of relevance in terms of climate change impacts assessment. However, in developing countries, the estimation of this response has been hampered, mainly, due to the lack of regional climate models and of higher computational power. This work analyzes the high-resolution warming signal over Mexico as function of the global mean temperature using Adaptive Neuro-Fuzzy Inference Systems. The geographical array of Fuzzy Inference Systems are presented as warming patterns that were used to project the temperature trend, in the 21st century, under the four Representative Concentration Pathways. We based on the assumptions that the global temperature increase is the dominant influence on future climate and that the local response is determined by the local geographic conditions. The resulting scenarios shows that the northwestern and south central regions present the highest warming values, likewise, all maps display a region where the projected warming remains uncertain. The proposed methodology is presented as an alternative pattern scaling technique whose results pretend to serve as an analysis tool of potential impacts of regional warming over Mexico, and lead to the generation and improvement of adaptation and mitigation strategies.

1 INTRODUCTION

The Global Circulation Models (GCMs) and Earth System Models (ESMs) are proper representations of the internal climate dynamics. Despite of their contribution to the better understanding of the climate system, models have reached the point in which even by adding more computational power, the uncertainty of the results continue to be high simply because of the system's natural variability ((Baumberger et al., 2017); (Knutti and Sedláček, 2013); (Flato et al., 2013)). For instance, (Deser et al., 2012) used 40 initial conditions to run the Community Climate System Model version 3, which projections were an example of the large influence of natural variability on the actual climate, whereas the global temperature increased for all the projections, the local temperature greatly differed among them, in fact, there were some places that even got cooler than the climatology.

The treatment of this variability requires tools able to work with complex and uncertain processes but, at the same time, sufficiently capable to communicate its results in an easy and efficient way. It is for this reason that the use of Fuzzy Logic is gaining ground in the climate change research field as it lets to analyze these complex processes and climate system variability from a different perspective since it works with no strict boundary values. In addition, Fuzzy Logic works with linguistic variables that allows to generate closer results to common language, from which the understanding and communication of climate change effects becomes more intuitive.

The high spread of the results coming from the GCMS has presented a major challenge to the implementation of action plans and decision making. This has compelled the improvement of the framework with which the topic has been approached and studied (Hallegatte, 2009; Heal and Millner, 2014; Runting et al., 2017), highlighting the importance of local scale research. For this reason, the geospatial distribution, also known as warming patterns, of the warming signal turns out to be a useful parameter for providing an indicative potential temperature for different world regions (Collins et al., 2013). These temperature patterns have been calculated by averaging, in every grid cell (usually $1^\circ \times 1^\circ$ latitude-longitude resolution), the projected mean temperature given by the GCMs with the global temperature, using the Coupled Model Intercomparison Project Phase 5 (CMIP5; (Taylor et al., 2012)) under the four Representative Concentration Pathways (RCPs; (van Vuuren et al., 2011)). The spatial resolution is coarse since it is given by the GCMs themselves and the temporal horizons are at the end of the 21st and 22nd century (Collins et al., 2013).

The role of warming patterns in vulnerable regions is fundamental to assess the regional implications of different degrees of warming (James et al., 2017), particularly over developing countries. Mexico, which due to its geographic and climatic characteristics, as well as its economic and social conditions, is a country that expects to be highly vulnerable to climate change effects. Therefore, projections at regional and local scale represent key pieces for the implementation of action plans at state and municipal levels.

The aim of this paper is to present high-resolution ($0.5^\circ \times 0.5^\circ$ latitude-longitude) warming patterns over Mexico, of the climate scenarios given by the four RCPs, constructed through Adaptive Neuro-Fuzzy Inference Systems (ANFIS; (Jang, 1993)), as well as proposing an alternative method to the actual pattern scaling techniques. Consequently, these results may reinforce the assessment of the potential impacts of regional warming over Mexico and thus lead to the improvement and creation of local mitigation and adaptation strategies.

The following section depicts the methodology with which the warming patterns were constructed by inferring the local warming response to the global temperature increments observed in the 20th century and the beginning of the 21st century, it also outlines the procedure for the patterns validation. Section 3 portrays the projected temperature trends using the fuzzy patterns given the RCP2.6, RCP4.5, RCP6 and RCP8.5 scenarios. And finally, section 4 elaborates on the conclusions and the future work.

2 METHODS

We projected the local temperature changes over Mexico through the global mean temperature changes, during the observed period from 1901 to 2015, by inferring the local response to the global temperature increments. Basing on the assumption that the local response is mainly influenced by the local geographic conditions (e.g. latitude, longitude, height, orography, etc.), we assumed that the response during the 20th century and the beginning of the 21st century will be the same for the rest of the 21st century, since the geographic conditions will remain the same. The reason we used temperature changes and not the temperature itself was because, at evaluating the ANFIS with the RCP temperature scenarios, some values will be out of the temperature range with which the ANFIS was trained.

The global data used were the annual mean temperature anomalies of the CRUTEM4 (Osborn and Jones, 2014) and the HADCRUT4 (Morice et al., 2012) datasets. The first consists in anomalies over land and the latter in anomalies over land and ocean. For the local data, we used the CRU TS3.24 (Harris et al., 2014) database, composed by monthly absolute temperature values gridded at a $0.5^\circ \times 0.5^\circ$ latitude-longitude resolution, which was converted to temperature anomalies with respect to the 1961-1990 period.

First, we applied the algorithm proposed by (Rato et al., 2008) to filter the warming signal from the two global time series and the gridded dataset. Because some of the calculated trends still displayed oscillations and, because we wanted to work with the simplest trend curves, these were smoothed adjusting them to a quadratic polynomial.

Then, we computed 10 year temperature differences, in both global and local data, of thirteen different periods between 1901 and 2015. This time step election was made based on that the differences computed every 10 years during the observed period were expected to be similar in magnitude to the differences computed over the trends of the RCP temperature scenarios using a time step of 5 years.

Finally, using the Matlab's Fuzzy Logic Toolbox, we constructed one ANFIS per each grid cell of the CRU TS3.24 dataset. The created Fuzzy Inference Systems (FIS) consist in Sugeno type systems (Sugeno, 1985) that use the grid partition method for the fuzzy rules induction. We defined three triangular membership functions for each input and a linear function for each output. To train the FIS, we used three epochs and a hybrid optimization method, i.e., an integration of backpropagation and least squares method.

In every FIS, the domain of the input (global temperature change) is divided in three fuzzy sets that represent the linguistic categories defined as low, medium and high, so that every value in the domain has its membership degree to the fuzzy sets, ranging from zero (no membership) to one (full membership) (Zadeh, 1965).

Then, the adjusted IF-THEN rules (Zadeh, 1975; Takagi and Sugeno, 1985) relate the membership degree μ of the input parameters to a linear function.

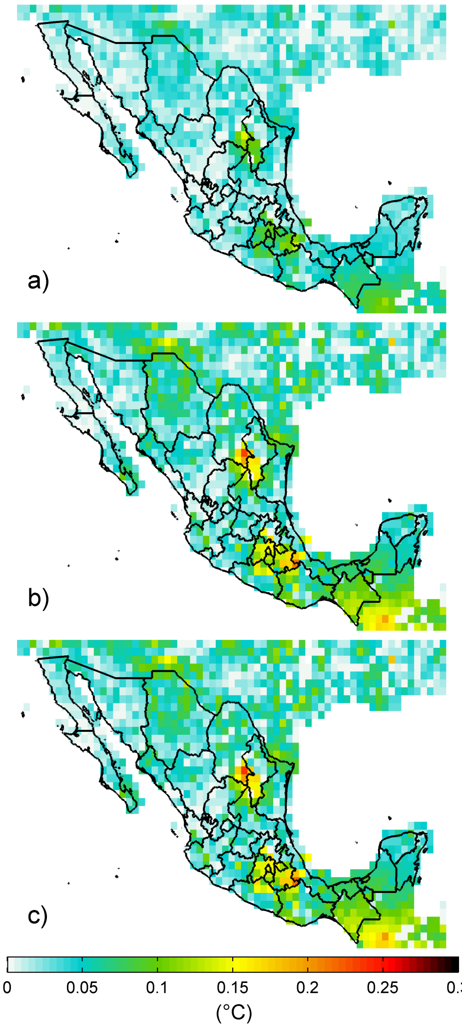

Figure 1: Absolute error between the observed temperature trends and the ones projected with the fuzzy warming patterns, of year 2015, using the global time series of the a) CRU-Global, b) GISTEMP and c) GHCN v3.0.0 datasets.

Since the domain is divided in three fuzzy sets, there are three IF-THEN rules and three linear functions. The local temperature change trend is computed by a weighted mean of the IF-THEN rules' results, in which the weight is given by the membership degree that characterize the rule (eq. 1).

$$dT_{local} = \sum_{i=1}^{3} \frac{(a_i(dT_{global}) + c_i)\mu_i}{3} \tag{1}$$

Where a_i and c_i are the scalars adjusted by the ANFIS and, altogether eq. 1, determine the scale factor. The linear relation between the local temperature change and the global change allows to analyze this relationship through a simple model, even though, it have a limited capacity to represent the real complexity of the climate parameters interaction since the climate is not a linear system. However, this is counteracted by the fuzzy inference process, as it infers the interactions between parameters which can be linear or not. In this way, the FIS of every grid cell represents the local climate response to the global temperature increments, which is determined by the local geographic conditions.

In order to validate the set of FIS, optimized through the ANFIS, we projected the local change trends using the temperature fuzzy patterns of the observed period 1901-2015. The historic global temperature time series used were the CRU TS3.24 (hereafter called CRU-Global, to avoid confusion with the spatially disaggregated values of CRU TS3.24 used to train the ANFIS) and the global means of the combined land-surface air and sea-surface water temperature anomalies of the GISTEMP ((GISTEMP Team., 2017); (Hansen et al., 2010)) and the GHCN v3.3.0 (Mitchell and Jones, 2005) datasets. The trend of the three time series was filtered and, by repeating the same procedure mentioned above, we projected the local temperature trends. For this, the initial year of the projections was 1905, from which the results of the 10 year local temperature changes were added up until the final temperature trend, at year 2015, was obtained. The validation metrics used were the absolute error and the linear correlation coefficient, along with Taylor diagrams (Taylor, 2001), with which we analyzed the performance of the projections at all time steps.

The cumulative absolute error between the observed (CRU TS3.24 dataset) and the projected temperature trends, after projecting more than 100 years, is around 0.05°C for most of the country using the CRU-Global (fig. 1a), GISTEMP (fig. 1b) and GHCN (fig. 1c) global means. In the three experiments, the absolute error is higher over the northeastern and the south central regions. With the CRU-Global the error values are around 0.1°C and 0.15°C while, with the GISTEMP and the GHCN, the error stays predominantly around 0.1°C and 0.25°C.

The correlation coefficient of the observed and projected temperature trends (fig. 2a) and of the observed and projected temperature change trends (fig. 2b) present high values, staying always above 0.85 and 0.98 respectively. Meanwhile, the Taylor diagram (fig. 2c) shows the performance of the last projection, the temperature trend of year 2015, with the three datasets. All the datasets present a correlation coefficient above 0.99 and a RMSD less than 0.1. The performance of the projections of all the time steps (fig. 5, sec. Appendix) also present a correlation coefficient above 0.9 and a RMSD less than a 0.1.

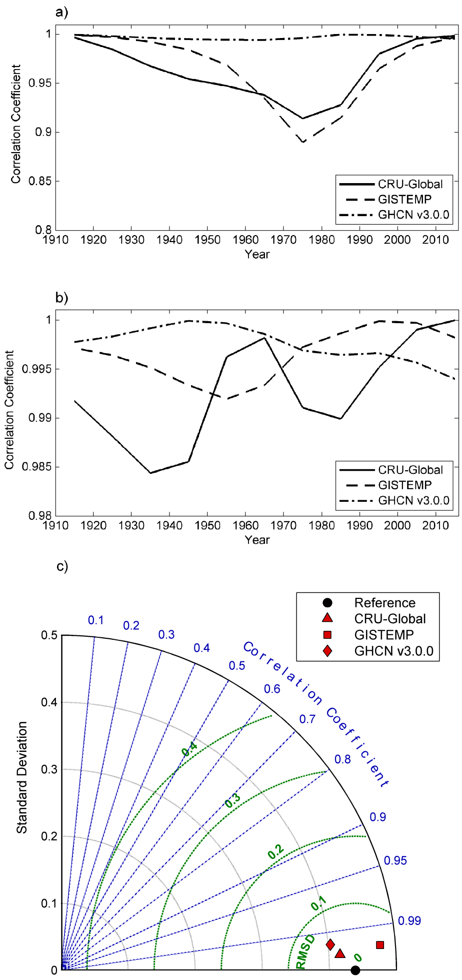

Figure 2: Validation of the fuzzy patterns using the global temperature time series of the CRU-Global, GISTEMP and GHCN v3.3.0 datasets where a) shows the correlation coefficient of the observed and projected temperature trends, b) the correlation coefficient of the observed and projected temperature change trends and c) the Taylor diagram of the last temperature trend projection (year 2015).

3 RESULTS

With the global temperature scenarios, derived from the GCMs runs corresponding to the CMIP5, we projected the future temperature trend over Mexico using the fuzzy patterns. This means that for RCP2.6 we got 32 projections; for RCP4.5, 42; for RCP6, 25 and for RCP8.5, 39. In total, we got 138 trend projections.

We adjusted the projections time step to obtain the local temperature trend changes every 5, 3, 3 and 2 years for the RCPs 2.6, 4.5, 6 and 8.5 respectively, and not every 5 years as it was already established (sec. 2). This adjustment was done because the changes in global temperature computed with these time steps

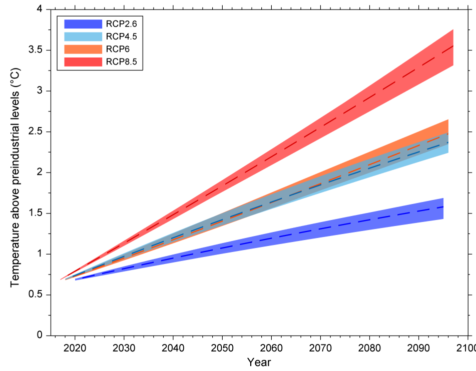

Figure 3: Temperature trend projections in Mexico over one grid cell given the GCMs runs corresponding to the CMIP5, for the RCP2.6 (blue), the RCP4.5 (clear blue), the RCP6 (orange) and the RCP8.5 (red) scenarios. The shaded areas represent the distribution of the individual models and the dashed lines represent the mean of the GCMs runs.

were equivalent to the changes computed every 10 years during the last century, the same time step used to train the FIS.

Taking a random grid cell as example, the projected temperature trends (fig. 3) result to be quite well defined, given each RCP, as they stay confined inside the same curve envelopes. The distribution of the individual models (shaded areas) can be seen as the uncertainty, i. e., as the range of possible values a grid cell can take under each RCP scenario. Also, it can be seen that this range becomes more spread along with every projection.

Likewise, the warming spatial distribution (fig. 4) shows that the projected scenarios are clearly differentiated between each other. They were computed by averaging all the models runs of every RCP. Since for each one we used a different time step, the year of the last projection was also different in every one of them, this is, for RCP2.6 the last projection was at year 2095, for RCP4.5 and RCP6 it was at 2096, and for RCP8.5 it was at 2097.

In all the scenarios, the largest temperature increments are localized in the northwestern region as well as over the south central region. Under RCP2.6 (fig. 4a) the temperature increments are between 2°C and 4°C over the northeast and between 0°C and 2°C over the south, with maximum values of 5°C. The warming patterns in RCP4.5 (fig. 4b) and in RCP6 (fig. 4c) are between 4°C and 8°C in the northwest and between 2°C and 4°C over the south, being slightly higher in the RCP6 scenario. In both, the maximum warming is about 8°C. RCP8.5 (fig. 4d) is the scenario where it is observed a warming between 6°C and 10°C over almost the whole country, being the maximum warming of 12°C.

Contrary to the rest of the country, the northeast-

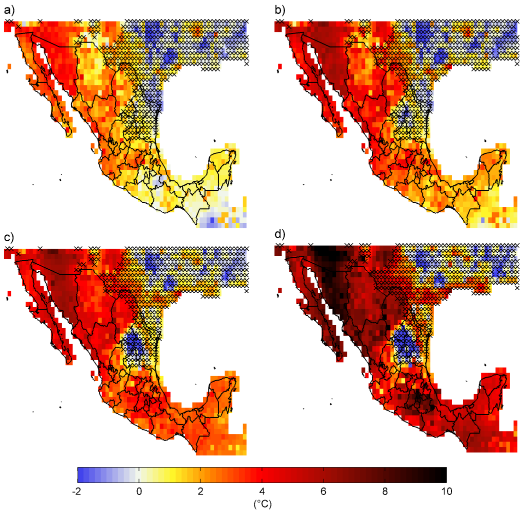

Figure 4: Warming signal over Mexico of the last projected year for a) RCP2.6 (2095), b) RCP4.5 (2096), c) RCP6 (2096) and d) RCP8.5 (2097) using the fuzzy warming patterns. Cross hatched areas represent regions where the warming trend is not significant due to the high climatic variability.

ern region shows negative temperature trends. However, this region corresponds to the grid cells where, according with the method in (Collins et al., 2013), the internal variability has a strong influence (cross-hatched areas) so that the projected trends are not significant and the local warming remains uncertain.

4 CONCLUSIONS

Climate change has been cataloged as one of the most important challenges threatening humankind, the anticipated knowledge about its probable impacts will let to the implementation of proper measures to face them. Particularly, the knowledge of the local warming and its impacts is crucial for developing countries like Mexico, where the climate change effects will enhance their priority problems.

One of the main methods used to estimate regional climate signals associated with global mean temperature increases is the pattern scaling, which assumes a linear relationship between the global temperature and local change. However, even though some processes can be understood through the assumption of a linear relation, the climate is such a complex system that many other climate processes can not, which provides little validity to models and conclusions based on a linear behavior (Stocker et al., 2001). Here is where Fuzzy Logic importance lies, since it can deals, through a different approach, with the complexity and the uncertainty of the climate system processes, being thus, a powerful tool in the absence of high computational capacity.

The methodology, with which we constructed the warming patterns presented here, lets the visualization of the local evolution of the temperature change over Mexico at different time scales under the four RCPs. Basically, once having the GCM runs, it is relatively simple to generate any future scenario. Also, it is necessary to remark that the produced results are temperature trends, as it is only projected the warming signal, thereby, it can not produce the maximum and minimum values that the climate variability could generate. Another issue that can be seen as a limitation is that the linear relationship, between the local and global temperature, implies that the temperature changes will be independent of the emission pathways and, consequently, of the type of forcing.

Therefore, for being the first attempt of its kind in Mexico, future efforts will focus in the enhancement of this methodology. Furthermore, the purport is to compare these results with the official scenarios that the Mexican government uses in its national communication on climate change, generated by (Cavazos et al., 2013), as well as to develop maps directed to identify the years in which specific warming levels are going to be reached and outstripped.

With this in mind, we expect that this temperature patterns may support the assessment of potential local impacts and serve as a basis for policy makers to develop adaptation and mitigation strategies.

ACKNOWLEDGEMENTS

We want to thank the Programa de Investigación en Cambio Climático of the Universidad Nacional Autónoma de México for the support to this work.

REFERENCES

Baumberger, C., Knutti, R., and Hirsch Hadorn, G. (2017). Building confidence in climate model projections: an analysis of inferences from fit. *Wiley Interdisciplinary Reviews: Climate Change*, 8(3):1–20.

Cavazos, T., Salinas, J., Martínez, B., Colorado, G., De Grau, P., Prieto González, R., and Bravo, M. E. (2013). Actualización de escenarios de cambio climático para México como parte de los productos de la Quinta Comunicación Nacional. *Informe final del proyecto al INECC*:150.

Collins, M., Knutti, R., Arblaster, J., Dufresne, J.-L., Fichefet, T., Friedlingstein, P., Gao, X., Gutowski, W., Johns, T., Krinner, G., Shongwe, M., Tebaldi, C., Weaver, A., and Wehner, M. (2013). Long-term climate change: projections, commitments and irreversibility. In *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, pages 1029–1136. Cambridge University Press.

Deser, C., Knutti, R., Solomon, S., and Phillips, A. S. (2012). Communication of the role of natural variability in future north american climate. *Nature Climate Change*, 2(11):775–779.

Flato, G., Marotzke, J., Abiodun, B., Braconnot, P., Chou, S. C., Collins, W. J., Cox, P., Driouech, F., Emori, S., Eyring, V., Forest, C., Gleker, P., Guilyardi, E., Jakob, C., Kattsov, V., Reason, C., and Rummukainen, M. (2013). Evaluation of Climate Models. In *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, pages 741–866. Cambridge University Press.

GISTEMP Team. (2017). *GISS Surface Temperature Analysis (GISTEMP)*. NASA Goddard Institute for Space Studies. Dataset accessed 2017-01-15 at https://data.giss.nasa.gov/gistemp/.

Hallegatte, S. (2009). Strategies to adapt to an uncertain climate change. *Global environmental change*, 19(2):240–247.

Hansen, J., Ruedy, R., Sato, M., and Lo, K. (2010). Global surface temperature change. *Reviews of Geophysics*, 48(4):1–29.

Harris, I., Jones, P. D., Osborn, T. J., and Lister, D. H. (2014). Updated high-resolution grids of monthly climatic observations–the CRU TS3. 10 Dataset. *International Journal of Climatology*, 34(3):623–642.

Heal, G. and Millner, A. (2014). Reflections uncertainty and decision making in climate change economics. *Review of Environmental Economics and Policy*, 8(1):120–137.

James, R., Washington, R., Schleussner, C., Rogelj, J., and Conway, D. (2017). Characterising half a degree difference: a review of methods for identifying regional climate responses to global warming targets. *Wiley Interdisciplinary Reviews: Climate Change*, 8(2):1–23.

Jang, J. S. (1993). ANFIS: adaptive-network-based fuzzy inference system. *IEEE transactions on systems, man, and cybernetics*, 23(3):665–685.

Knutti, R. and Sedláček, J. (2013). Robustness and uncertainties in the new CMIP5 climate model projections. *Nature Climate Change*, 3(4):369–373.

Mitchell, T. D. and Jones, P. D. (2005). An improved method of constructing a database of monthly climate observations and associated highresolution grids. *International journal of climatology*, 25(6):693–712.

Morice, C. P., Kennedy, J. J., Rayner, N. A., and Jones, P. D. (2012). Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: The HadCRUT4 data set. *Journal of Geophysical Research: Atmospheres*, 117(D8):1–22.

Osborn, T. J. and Jones, P. (2014). The CRUTEM4 land-surface air temperature data set: construction, previous versions and dissemination via Google Earth. *Earth System Science Data*, 6(1):61–68.

Rato, R. T., Ortigueira, M. D., and Batista, A. G. (2008). On the HHT, its problems, and some solutions. *Mechanical Systems and Signal Processing*, 22(6):1374–1394.

Runting, R. K., Bryan, B. A., Dee, L. E., Maseyk, F. J., Mandle, L., Hamel, P., Wilson, K. A., Yetka, K., Possingham, H. P., and Rhodes, J. R. (2017). Incorporating climate change into ecosystem service assessments and decisions: a review. *Global change biology*, 23(1):28–41.

Stocker, T., Clarke, G., Le Treut, H., Lindzen, R., Meleshko, V., Mugara, R., Palmer, T., Pierrehumbert, R., Sellers, P., Trenberth, K., and Willebrand, J. (2001). Physical climate processes and feedbacks. In *Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change*, pages 419–457. Cambridge University Press.

Sugeno, M. (1985). Industrial applications of fuzzy control. Elsevier Science Inc.

Takagi, T. and Sugeno, M. (1985). Fuzzy identification of systems and its applications to modeling and control. *IEEE Transactions on systems, man, and cybernetics*, SMC-15(1):116–132.

Taylor, K. E. (2001). Summarizing multiple aspects of model performance in a single diagram. *Journal of Geophysical Research: Atmospheres*, 106(D7):7183–7192.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, 93(4):485–498.

van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G. C., Kram, T., Krey, V., Lamarque, J.-F., Masui, T., Meinshausen, M., Nakicenovic, N., Smith, S. J., and Rose, S. K. (2011). The representative concentration pathways: an overview. *Climatic change*, 109(1-2):5–31.

Zadeh, L. A. (1965). Fuzzy sets. *Information and control*, 8(3):338–353.

Zadeh, L. A. (1975). The concept of a linguistic variable and its application to aproximate reasoning-III. *Information sciences*, 9(1):43–80.

APPENDIX

The temperature from 1905 to 2015, projected every 10 year with the fuzzy warming patterns, shows a high performance at every time step (fig. 5). In all the Taylor diagrams it can be seen that the correlation coefficient keeps near or above 0.9. Also, the RMSD is maintained under 0.1 and the standard deviations are always near around the ones of the references. The dataset which shows the best performance is the GHCN v3.0.0 as the correlation coefficient is always above 0.95, the RMSD keeps always under

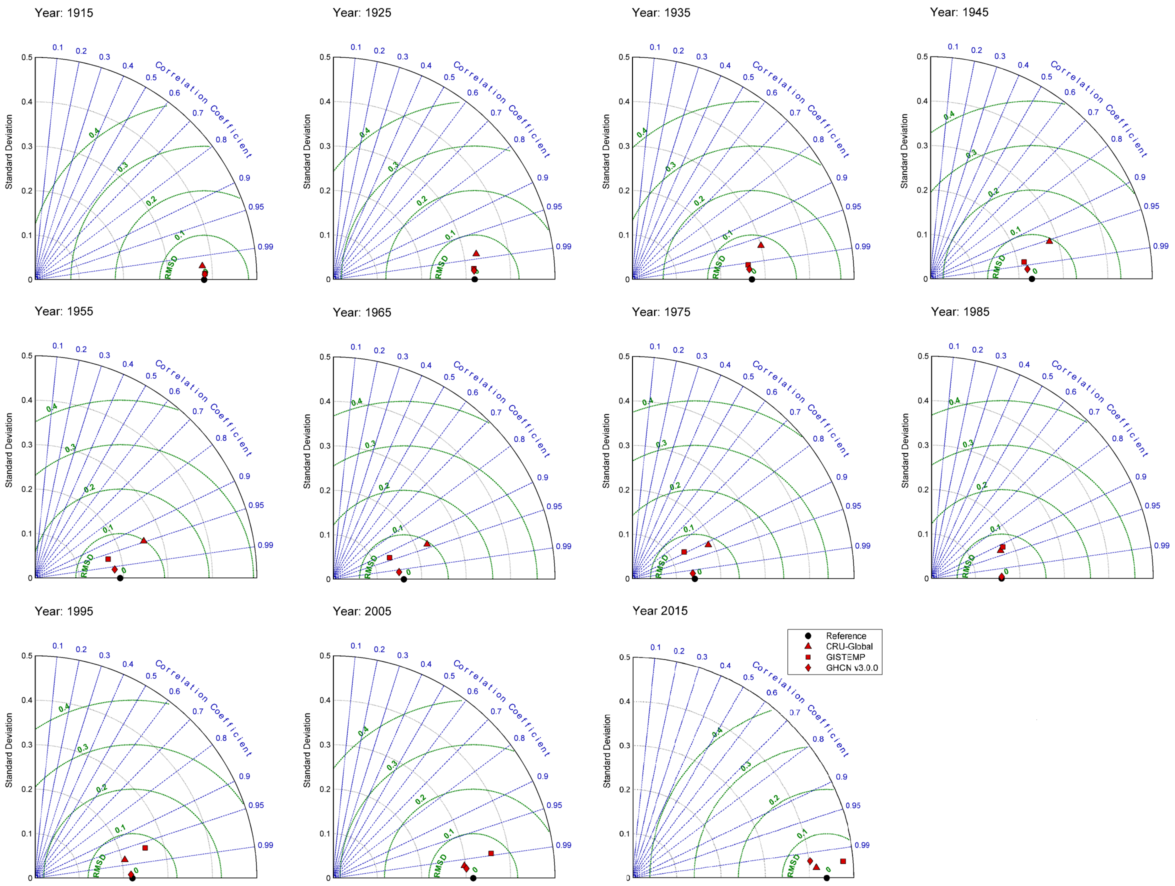

Figure 5: Taylor diagrams displaying the performance of the temperature projections from 1905 to 2015, projected every 10 years, for the validations of the fuzzy warming patterns using the CRU-Global, GISTEMP and GHCN v3.3.0 datasets.

0.1 and the standard deviations are the nearest ones to the references, except in the last projection, where its standard deviation differ more than the other two datasets.