DEEJ (2018) 7 (2) 23-32

University of Kashan

Desert Ecosystem Engineering Journal

Journal homepage: http://deej.kashanu.ac.ir

Evaluation of Change in Bioclimatic Indices in South of Iran Under Climate Change Conditions*

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Received: 08/04/2018 Accepted: 28/08/2018

Abstract

In recent years, the issue of climate change especially its impacts investigate by use of world bioclimatic classification systems (WBCS) that are coupled with climate change models.The Rivas Martinez classification that is a hierarchical method, uses a set of climate variables and biochemical index, it has its own subgroups.; macrobioclimatology, bioclimate, thermotype and ambrotype. Indicators used in this method are: simple continentality index, annual ambrothermic index, thermal index and compensated thermicity index. In order to evaluate the change in bioclimatic index of the Martinez method under climate change conditions in south of Iran, we used the output data of the HadGEM2.ES model as one of the CMIP5 models with appropriate spatial resolution and the two scenarios RCP8.5 & RCP4.5 The strength of model is determined based on the weight gain method. The results of this study indicate that, generally, under the implementation of pessimistic and optimistic scenarios, the rate of ambrothermic decreases, which means that the environmental conditions become drier. The thermal index, which evaluates the cold intensity during the cold period, as a limiting factor for the growth and development of plant communities will increase. The core of increase of this indicator is relatively large and has an extension to the west of the provinces of Hormozgan, south of Fars and west of Kerman province. Also, the output of the model indicates that a decrease of continentality index for the future period. The reason for this decrease is due to an unbalanced temperature increase during the warm and cold seasons. The implementation of global climate change models also confirms this. The yearly positive temperature shows decreasing trend due to the transfer of periods that will experience a zero temperature threshold under the warming conditions.

Keywords: Bioclimate, Rivas Martinez, South Iran, Climate Change, Scenario.

* This article is the result of a joint research project with Payame Noor University

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DOI: 10.22052/jdee.2018.126500.1031

1. Introduction

Bioclimatologystudied the relationship between climate and living organisms (Pesaresi et al, 2014). Today, bioclimatic classification based on plant territories and known as the world bioclimatic classification system (WBCS) is used widely (Rivas-Martins et al., 2004 and 2008). Bioclimatic maps resulted from the implementation of these classifications is a good tool for evaluating environmental capabilities, especially in the analysis of the environment- vegetation relationship. Drawing ishobioclimatic lines in present conditions and emissionscenarios can help us monitor climate change (Torregrosaet al., 2013), and based on that, assess climatic sensitivity and climatic resilience. In addition, implementing different scenarios that cover a wide range of possible future changes help us better conduct sensitivity analysis (ShaemiBarzoki and HabibiNokhandan, 2009). Observing the change in capacity, land use, and, ultimatelythe degree of climatic sensitivity and resilience depends on the climate type and manner in the future. In recent years, the issue of climate change from different points, especially itsimpacts has increased use ofworld bioclimatic classification systems that are coupled with climate change models.

Pesaresi et al (2014) studied bioclimate of Italy using Rivas Martins method.They shows these maps are useful to build spatial predictive models for vegetation, and also for monitoring climate change. Mahlstein et al., (2013) reviewed the global climate change using Koppen-Geiger method and RCP8.5 scenario. They concluded that current climate projections suggest that the pace of shifting climate zones increases approximately linearly with increasing global temperature. Rubel and Kottek(2010) reviewed the map of climate change in the period of 1901 to 2100 using Koppen-Geiger climate classification method The main results comprise an estimation of the shifts of climate zones within the 21st century by considering different IPCC scenarios. Heubes et al., (2011) Modelling biome shifts and tree cover change for 2050 in West AfricaThey showed that forest degradation, a trigger for desertification processes, might play a crucial role in the future. Thus, it is essential to consider both climate change and direct human impact to generate realistic future tree cover projections, and both should generally be considered in predictive vegetation modellingAngela et al., (2010) survey the climate change impacts on blanket peatland distribution in Great Britain.This study show that the geographical distribution of blanket peatlands gradually retreats towards the north and the west. Gerald et al., (2009) designed bioclimatic model ofincrease and decrease in poplar species in western US forests under climate change conditions. Projecting the contemporary climate profile into the future climate provided by three General Circulation Models and two scenarios (SRES A2 and either B1 or B2) suggested that the area occupied by the profile should diminish rapidly over the course of the century, 6– 41% by the decade surrounding 2030, 40–75% for that surrounding 2060, and 46–94% for 2090. Gavilan (2005) used Martins methodology indices to determine how vegetation is distributed in the center of Spain. water availability in soils is alimiting factor for the development of vegetation in springor autumn as well as in summer.Garzon et al., (2013) provided vegetation bioclimatic map for Palma- canary islands, and used Rivas- Martins' thermal and ombrothermic indices in spatial analysis.They concluded multiple linear regression (MLR) with correction of interpolated residuals is an attractive interpolation method for bioclimatic mapping on this oceanic island since it permits one to fully account for easily available geographic information but also takes into account local variation of climatic data.

Monterio-Henriques et al., (2015) evaluated the ambiguities indesigning Portuguese bioclimatic map, using thermotype and ombrotypeindices of Martins' classification system. F-test showed that the estimated mean squared errors for the maps of ombrothermic indices were significantly lower than those produced by the former methodological framework.

Other researchers also studied the consequences of climate change using CMIP5 models and RCP family scenarios including:

Dang et al, (2014), modeled the consequences of climate change on agriculture in the Mekong Delta. They used CMIP5 models, especially HadGEM2.ES model. The results showed that temperature will increase in the future and precipitation will be accompanied by a sharp decrease and increase. Traore et al. (2017) examined the risk of climate change for cereal products based on RCP8.5 and RCP4.5 scenarios in south of Mali. Their results showed that the minimum and maximum temperaturewill increase by 4.9 and 2.9 ° C until the middle of the 21st century. Alexander and Arblaster(2017) examined temperatures and precipitations based on RCP8.5 and RCP4.5 radiative forcing scenarios and CMIP5 models. Their results showed that, at the end of 21st century, cold temperature will decrease and warm temperature will increase, and precipitation would increase in the middle decades. Ishida (2017) used the output of general circulation models (CCSM4, HadGEM2-ES, MIROC5) based on the RCP8.5 and RCP4.5 radiation forcing scenarios for the modal downscale of future climate change in North California. His results showed that temperature will increase and precipitation will both increase and decrease. Also, Taylor et al (2012) examined the limitations and potential of CMIP5 data. The main objective of this research is to evaluate the change in biochemical indices under conditions of climate change in south of Iran.

2. Material and Methods

2.1. Study area

The study area extends between latitudes of 25°3′- 33°4′ N and longitudes of 47 °4′- 63°21′E Which includes the provinces of Sistan and Baluchestan, Kerman, Hormozgan, Fars, Bushehr and Khuzestan. Selected stations are located in dry and semi-arid southern Iran according to Kopen classification. Stations located near the beaches of the Persian Gulf and the Oman Sea, with sultry weather and whatever goes on in the Iranian plateau, reduces air humidity. The elevation range of the studied stations is 6 meters from Abadan Station to Kerman Station with a height of 1753 meters, also, the presence of complex Zagros topographic system contributes to the high climatic diversity.

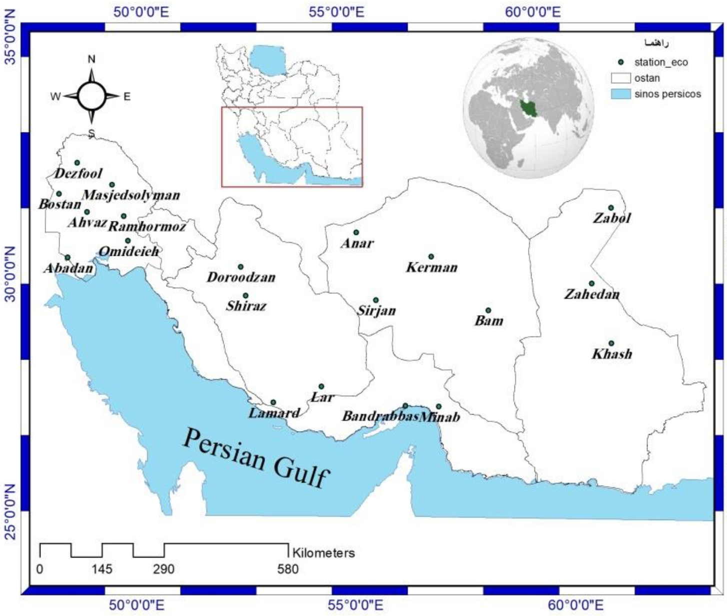

Figure 1: Study area

2.2. Methodology

Rivas- Martins'Bioclimatic Classification

Rivas- Martins' Classification is a hierarchical classification method withits own sub- groups which usesa set of climate variables and bioclimatic indices; its main bioclimatic divisions are: macrobioclimate, bioclimatic, thermotype, and ombrotype. This division is based on a set of climatic parameters and bioclimatic indices, with temperature and precipitation data as its main form. In this method, macroclima is the highest level of typing units(Rivas-Martines, 2011).

Indices and Variables

The primary variables required in this method are: average annual precipitation, average monthly precipitation, winter precipitation, summer precipitation, average monthly temperature, average temperature of warmest and coldest months, minimum and maximum temperature of the coldest months from 1985 to 2015 related to 20 stations in south of Iran (Figure 1).

secondary variables are: yearly positive temperature, yearly positive precipitation and Positive monthly precipitation (Table 1). Positive temperature and precipitation in a given period is defined as the sum of that variable in periods with positive temperature. In this study, outputs of HadGEM2.ES model and pessimistic (RCP8.5) and optimistic (RCP4.5) scenarios from 2020 to 2040 were used for evaluating change in bioclimatic indices of Martins' model.

Table 1: Station characteristics and some variables used in Martins Bioclimatic Method (Tmin cold = Minimum temperature of the coldest month, T max cold = Maximum temperature of the coldest month, average war = Average warmest month temperature, mean cold = average coldest month temperature, P = Annual precipitation, sum = Total annual temperature)

Station	longitude	latitude	elevation	T an	Tmin cold	T max cold	Mean war	Mean cold	P	sumTAT
Abadan	48 15	30 22	6	26/1	7/9	18/4	37/7	12/8	144/4	313/7
Omidieh	49 39	30 46	15	25/9	6/9	18/2	38/0	12/4	230/9	311/1
Anar	55 15	30 53	1408	20/8	-1/2	13/7	33/2	7/7	66/5	249/8
Ahwaz	48 40	31 20	22/5	26/4	8/4	18/0	38/6	12/7	207/9	316/4
Bostan	48 0	31 43	7	24/9	6/2	17/4	37/0	11/5	197/7	299/3
Bandar Abbas	56 22	27 13	10	27/1	12/0	23/3	34/3	17/5	159/5	325/2
Bam	58 21	29 6	1066	23/9	5/8	17/1	35/0	11/0	55/2	287/1
Khash	61 12	28 13	1394	21/3	1/9	15/4	31/9	9/0	152/8	255/6
Dezful	48 23	32 24	143	24/8	5/6	17/7	37/8	11/4	365/9	298/1
Ramhormoz	49 36	31 16	150	27/9	8/8	18/0	40/4	13/7	286/3	334/7
Zabol	61 29	31 2	489/2	22/7	1/8	15/8	35/4	8/3	48/8	271/9
Zahedan	60 53	29 28	1370	19/5	0/6	14/7	30/3	7/4	77/4	234/3
Sade Doroodzan	52 26	30 13	1620	18/5	0/0	10/4	30/7	5/3	457/4	221/9
Sirjan	55 41	29 28	1739	18/0	-0/9	12/7	29/8	5/7	134/7	215/5
Shiraz	52 36	29 32	1484	19/0	0/3	12/7	31/1	6/3	319/5	227/7
Kerman	56 58	30 15	1753	17/2	-2/6	12/9	28/8	5/0	128/5	206/2
Lamerd	53 15	27 22	411	27/5	7/2	20/4	38/3	14/7	206/9	329/7
MasjedSoleiman	49 17	31 56	320/5	25/7	7/4	17/0	38/8	11/7	384/7	308/3
Lar	54 17	27 41	792	25/2	4/6	18/7	36/7	12/2	188/8	302/3
Minab	57 5	27 6	29/6	28/5	12/2	23/9	35/7	18/9	203/0	342/0

Indices used in this method are: simple continentality index, annual ombrothermic index, thermicity index, compensated thermicity index (Table 2). These indices are the main components of Martins method. Simple continentality index is the difference between the temperature of the warmest and coldest months of the year and the ombrothermic index is: Ten times as much as the ratio of Positive annual precipitation to Positive annual temperature.The thermicity index is the sum of total annual temperature, the minimal average temperature of the coldest month and the average maximumtemperature of the coldest month of the year, multiplied by ten. The compensated thermicity index is a coefficient of an increase or a decrease in the thermicity index. If the continentality coefficient is less than or equal to 18, it can be equal to the thermicity index. The yearly Positive temperature is: sum monthly mean temperature of months with average temperature is more than zero. In this method, the continentality and ombromotermic indices are fundamental in determining macrobioclimatic types and are crucial in determining the conditions of large-scale bioclimate.

DownscalingTools and Validation of the model

Given that the outputs of global climate models are not feasible for small and local scales, downscaling methods should be used to compensate for this problem. In order to simulate the future climate, MarkSIMGCM tool was used for modal downscaleof outputs of AOGCM models. MarkSIMGCM software, a web-based tool, downscalesminimum and maximum temperature data, daily precipitation and sunshine using Markov third- rank and random model (Jones & Thornton, 2013; Nouri et al., 2017).MarkSimGCM,a directional fortranprogram is developed to examine the output of modal downscale, and it is linked with a graphical user internuncial (GUI) in Google Earth The outputs of the text file format show annual and monthly results. This software considers the 1961-1990 modal downscaleas the basicperiod. This software is run on the basis of 17 AOGCM models of the CMIP5 model series, based on the latest climate change report (Fifth Report), asradiation forcing scenarios. This software is easily available in any part of the world, considering that it is web-based. The models included in this software are the most appropriate models of spatial separation(http://gismap.ciat.cgiar.org/MarkSimGCM). In this research, HadGEM2.ES model is used as one of the most suitable CMIP5 models with spatial separation.

HadGEM2.ES model incorporates major components such as atmosphere, oceans, and ice-sea with and without vertical dimension in the atmosphere to the stratosphere model and the components of the ground system, including dry and oceanic carbon cycle, and atmospherein chemistry (Martin et al., 2011).

Most of the past studies on the consequences and effects of climate change have been based on the models derived from the fourth inter pannel governmentof climate change. Now, a new generation of general circulation models used in the fifth inter pannelgovernment ofclimate change(IPCC) is known as the coupled model intercomparison phase 5 (CMIP5). A series of new emission scenarios, called representative concentration pathway of greenhouse gases density represent the fifth report models (AghaKhaniAfshar et al., 2017). The purpose of these models is to provide a framework for climate change experiments in the form of simulations based on the fifth IPCC report. In general, these models (1) evaluate how models simulate the recentpast (2) provide predictions of future climate change in two time scales: short-term period (up to 35 years) and long-term period (up to 2100) (3) understanding factors that contribute to model predictions, for example, in evaluating feedbacks such as clouds and the carbon cycle (Jones et al., 2013).

As mentioned above, in this study two pessimistic (RCP8.5) and optimistic scenarios (RCP4.5) resulted from the fifth report or the most recent report were used to assess the effects of climate change. The two scenarios are among the most common scenarios for assessing climate change effects. The basis for evaluations of the latest inter panel government of climate change (2013) report is four major scenarios known as RCPs, which are the consequences of human-made emissions and changes in land use and their effect on climate system. These scenarios are expressed in terms of average global forcing, ie change in the radiant flux above the atmosphere due to variations in atmospheric composition (carbon dioxide concentration as an instance), which do not include socioeconomic information.

Validation of the model

In this research, weight gain method was used to determine the validity and capability of coupled AOGCM models. In this regard, simulated values were compared with the observed value of the base period(1985-2013).

The strength of each model is determined based on the weight gain method. The weight of each model is calculated according to equation (1):

$$W_{i,j} = \frac{\frac{1}{\Delta F_{i,j}}}{\sum_{i=1}^{n} (1/\Delta 1_{i,j})} \quad (1)$$

In the above equation, F is the measured meteorological variable, ΔF is the difference between the simulated variable under different scenarios with the observation value in the base period and W is the simulation mass of each general flow model for the scenario. i and j represent the month and the general circulation model of the atmosphere, respectively(Ahmadi,2017).

These formula were calculated on BCC-CSM1.1,HadGEM2-ES,GFDL-ESM2M & MIROC5 models as atmospheric models of the CMIP5 model series. The operation of this process was run in the form of a developed program in the Excel software environment.

3. Results and Discussion

Select a Model

The results show that the HadGEM2-ES model has a higher ability to simulate temperature and precipitation behavior under the radiation inductive scenarios in the future due to its higher weight than other models. Therefore, the model data was used as one of the AOGCM-coupled models of the CMIP5 model series based on RCP radiative induction scenarios to assess and detect the effects of climate change in the future period. The verification of the AOGCM models studied based on the weighting method showed in Table (2).

Table 2: Results of the verification of of AOGCM models from the CMIP5 series based on weighting method

MIROC5	GFDL-ESM2M	HadGEM2-ES	BCC-CSM1.1	
0.29	0.21	0.41	0.20	Minimum temperature
0.31	0.23	0.38	0.28	Maximum temperature
0.35	0.22	0.35	0.25	Precipitation

Ombrotype and Thermotype Indices

Ombrothermic index

Ombrothermic index (IO) is in fact a symbol of the Positive ratio ofprecipitation to temperature, and if it increases in an area, it can be regarded as a positive trend and an improvement in the environment conditions. As can be seen in Fig. 2, the two maximaldecrease of this indexis in northof Khuzestan and Fars. In general, pessimistic and optimistic scenarios will decreaseombrothermic index by -4 ° and -5 °, respectively, which means that the environmental conditions are getting drier and drier. Except Anar, Zahedan and Shiraz stations which have significant positive changes, the remaining stations have slight positive or negative change (Table 2).

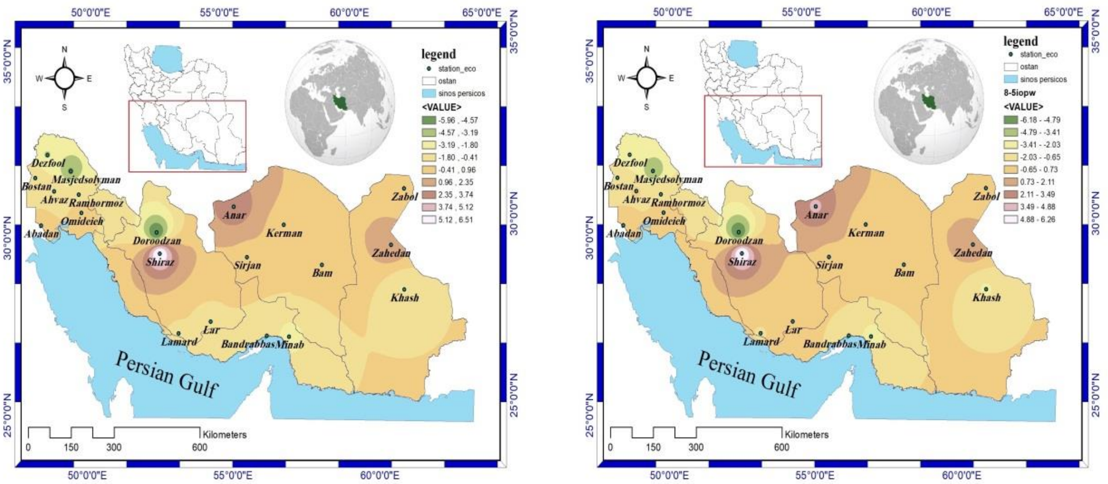

Figure 2: Change in the ombrothermic index of south of Iran based on HadGEM2.ES model and RCP8.5 (Right) and RCP4.5 (left) scenarios

Thermal Index

The thermal index (IT) evaluates cold intensity of the cold period as a limiting factor for the growth and development of plant communities (Pesaresi et al., 2014). Outputs of scenarios and the above model indicates that thermicity index will increase by 16.8 and 17.4 ℃ respectively, and with the exception of Anar, Shiraz and Lar stations with a decreasing trend, the remaining stations show an increasing trend. As seen in Fig. 3, the maximal range of increase in thermicity index, which is relatively large, surrounds west of Hormozgan, south of Fars to the west of Kerman. There is also a secondary range of increase in north of Khuzestan.

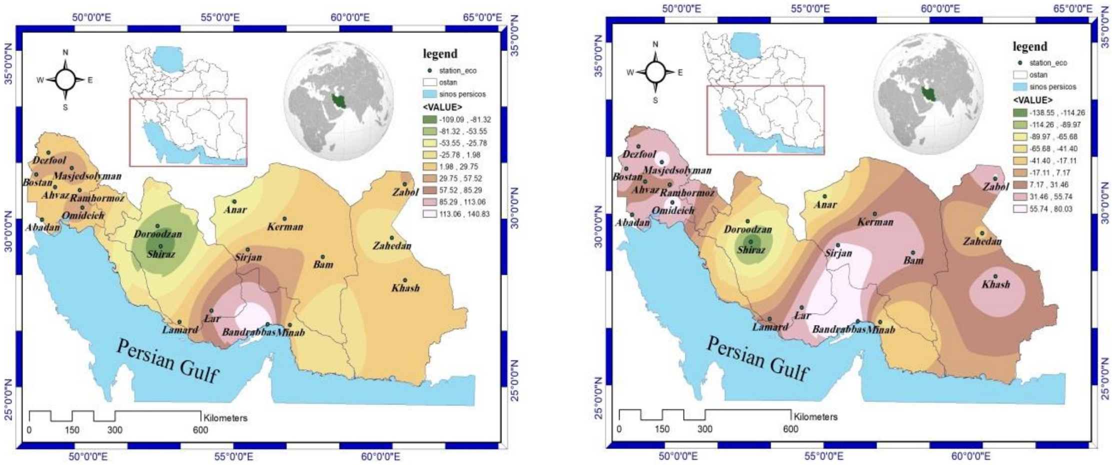

Figure 3: Change in the thermal index of south of Iran based on HadGEM2.ES model and RCP8.5 (right) and RCP4.5 (left) scenarios

Continentality Index

The continentality index (IC), which is in fact a symbol of seasonal fluctuations of temperature at the peak of heat and cold clearly illustrates the degree of continentality. This index simply shows the range of temperature variations between the warmest and coldest months of the year. The analysis of the outputs from the implementation of HadGEM2.ES model in the selected stations based on the implementation of dual scenarios shows that this index will decrease by 1.9 and 1.7 ℃, with its maximum, 6.7,in LAR station in south of Fars and its minimum in Kerman and Khash stations in eastern region (Fig. 4). The reason for this decrease is the unbalanced increase in temperature during warm and cold seasons . "World climate models also show that the amount of heating in the cool season will be higher than that in the warm season (Shamei&Habibi, 2011)."

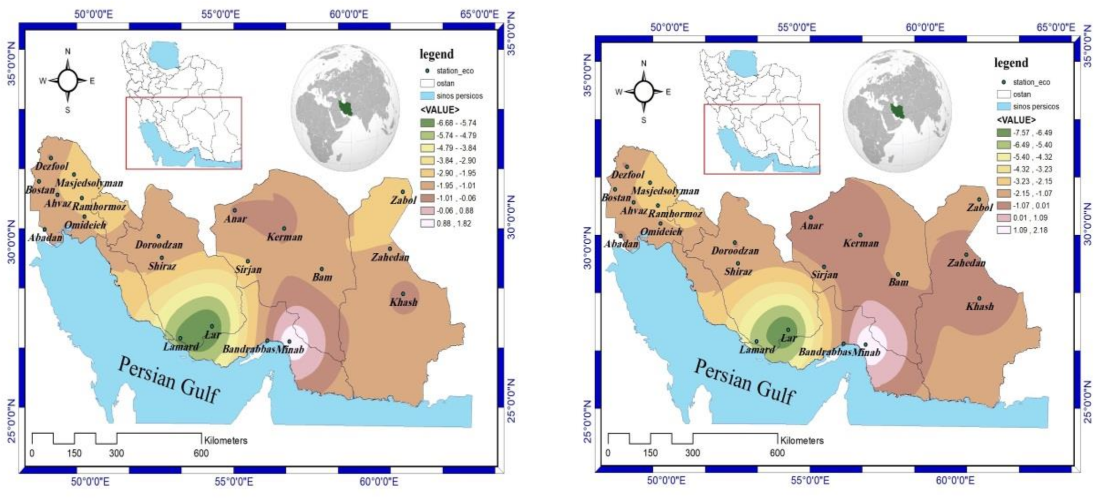

Figure 4: Changes in the continentality index of south of Iran based on HadGEM2.ES model and RCP8.5 (right) and RCP4.5 (left) scenarios

Yearly Positive Temperature

This index actually represents the thermal potential of different stations, since its amount is sum of the average temperature of months with above zero. The Positive annual temperature in selected stations will be reduced by 2.1 and -3.3℃ based on the implementation of the above scenarios. Of course, this does not mean absolute reduction in temperature, because this conclusion is the result of transfer and movement of periods with zero temperature threshold under thermal conditions. In fact, it can be said that this is the result of an increase in periods in which the temperature in the selected stationsis positive in the forecast period. In other words, these months have a lower average temperature than similar periods when added to previous periods. Therefore, stations with lower altitudes and positive temperature in all months of the year under basic conditionsshow an increasing trend. Comparing change in some initial parameters makes this clearer. (Table 3). The average temperature of the coldest month in the triple scenarios of the base period, the optimistic and pessimistic scenario is 10.8, 11.3, and 11.7 respectively, and the average minimum temperature for the coldest month is 4.6, 5.2, and 5.4, respectively, which confirms the trend of temperature rise with the implementation of dual scenarios based on HadGEM2.ES model (Table 4).

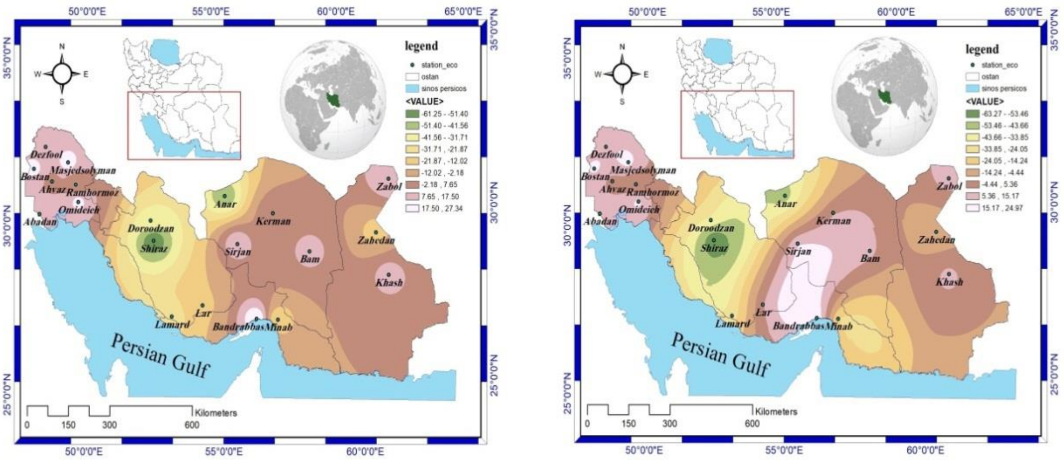

Figure 5: Changes in the Positiveannual temperature in the south of Iran based on HadGEM2.ES model and RCP8.5 (right) and RCP4.5 (left) scenarios

Table 3: Changes in Rivas Martins bioclimaticindices by implementing HadGEM2.ES model and pessimistic (RCP8.5) and optimistic(RCP4.5)scenariosin selected stations

Station	tp8.5- p	tp4.5- p	ic4.5-p	ic8.5-p	it4.5-p	it8.5-p	io4.5-p	io8.5-p
Abadan	13/7	10/6	-0/9	-1/0	27/1	35/9	0/5	0/3
Omidieh	21/0	18/0	-1/9	-1/9	63/5	72/2	0/4	0/2
Anar	-49/8	-49/8	-0/5	-0/9	-79/6	-79/6	3/7	3/7
Ahwaz	3/5	0/5	-1/9	-1/8	2/1	10/2	-0/6	-0/5
Bostan	20/7	17/8	-1/9	-1/8	47/1	55/1	-1/0	-1/0
Bandar Abbas	27/7	25/1	-0/8	-0/8	217/9	81/2	-1/1	-1/0
Bam	11/5	9/5	-1/2	-1/6	33/2	45/2	0/0	-0/1
Khash	11/2	8/7	-0/3	-0/7	35/0	48/0	-1/8	-2/1
Dezful	15/0	11/9	-1/0	-0/9	27/4	36/0	-3/3	-3/3
Ramhormoz	-3/2	-6/2	-2/9	-2/4	14/6	23/0	-0/9	-0/9
Zabol	15/1	12/2	-1/9	-2/3	43/7	57/4	0/2	-0/2
Zahedan	-16/7	-14/4	-0/3	-1/9	-38/9	-24/1	2/1	1/8
Sade Doroodzan	-32/9	-35/2	-1/1	-1/1	-71/9	-64/1	-6/0	-6/2
Sirjan	16/1	13/9	-0/9	-2/0	50/1	59/6	0/8	0/6
Shiraz	-61/3	-63/8	-1/4	-1/5	-148/5	-139/9	6/6	6/3
Kerman	6/4	4/2	-0/4	-0/7	9/5	25/0	0/7	0/4
Lamerd	-27/2	-29/8	-6/0	-6/1	9/9	18/9	-0/5	-0/7
MasjedSoleiman	23/0	20/2	-3/2	-2/8	60/7	68/9	-4/8	-4/8
Lar	-13/5	4/0	-7/6	-6/7	98/3	48/3	-0/9	-0/2
Minab	-21/4	-23/9	2/2	1/8	-53/4	-42/1	-2/3	-2/5

Table 4: Comparison of some variables in the present conditions and the output of the HadGEM2.ES model and RCP8.5 scenario

Station	Mean cold		mean warm		Tmin cold		T max cold		T anual	
	present	RC8.5	present	RC8.5	present	RC8.5	present	RC8.5	present	RC8.5
Abadan	12/8	14/4	37/7	38/3	7/9	8/5	18/4	20/2	26/1	27/3
Omidieh	12/4	15/3	38/0	39/0	6/9	9/9	18/2	20/7	25/9	27/7
Anar	7/7	4/4	33/2	29/0	-1/2	-3/2	13/7	11/9	20/8	16/7
Ahwaz	12/7	13/6	38/6	37/6	8/4	7/7	18/0	19/4	26/4	26/7
Bostan	11/5	13/7	37/0	37/4	6/2	7/8	17/4	19/5	24/9	26/7
Bandar Abbas	17/5	20/6	34/3	36/5	12/0	15/4	23/3	25/7	27/1	29/4
Bam	11/0	13/2	35/0	35/6	5/8	6/3	17/1	20/2	23/9	24/9
Khash	9/0	10/6	31/9	32/7	1/9	3/5	15/4	17/7	21/3	22/2
Dezful	11/4	12/8	37/8	38/3	5/6	6/7	17/7	18/9	24/8	26/1
Ramhormoz	13/7	14/7	40/4	39/0	8/8	8/9	18/0	20/5	27/9	27/6
Zabol	8/3	11/1	35/4	35/8	1/8	4/0	15/8	18/1	22/7	23/9
Zahedan	7/4	7/2	30/3	28/2	0/6	0/0	14/7	14/3	19/5	18/1
Sade Doroodzan	5/3	3/4	30/7	27/7	0/0	-3/3	10/4	10/1	18/5	15/8
Sirjan	5/7	8/2	29/8	30/3	-0/9	1/1	12/7	15/2	18/0	19/3
Shiraz	6/3	2/1	31/1	25/4	0/3	-4/4	12/7	8/6	19/0	13/9
Kerman	5/0	6/2	28/8	29/2	-2/6	-1/7	12/9	14/1	17/2	17/7
Lamerd	14/7	15/9	38/3	33/4	7/2	10/7	20/4	21/0	27/5	25/2
MasjedSoleiman	11/7	14/7	38/8	39/0	7/4	8/9	17/0	20/4	25/7	27/6
Lar	12/2	14/6	36/7	32/4	4/6	8/9	18/7	20/4	25/2	24/1
Minab	18/9	16/8	35/7	35/5	12/2	11/3	23/9	22/3	28/5	26/7
Average	10/8	11/7	35/0	34/0	4/6	5/4	16/8	18/0	23/5	23/4

4. Conclusion

In this study, the primary and secondary variables required by Martins method were implemented in two stages including the baseline or current status (1985- 2015) and the forecast period (2020-2040) and performing HadGEM2.ES model in the 20 arid and semi-arid stations in south of Iran and change in 5 bioclimatic indices of Rivas Martins were made based on that. These indices, includingthermicity index, compensated thermicity index, simple continentality index and Positive annual heat, were run under two pessimistic (RCP8.5) and optimisticscenarios (RCP4.5), and then widening was done withKriging interpolation. The most common method used in environmental sciences is the usual Kriging method. Of course, it should be noted that because the values of the above indices have a small correlation with height, the outputs of the applied DEM map are not significant and Kriging method is preferred in designing shapes.

Implementing dual scenarios at the area of the study shows that the mean of ombrothermicindicesdecreases and the thermotype indices increases. This means that environment is warning more and more in the future. Therefore, land preparation and planning for future should be done by considering bioclimatic capabilities under climate change conditions. Sensitivity analysis under climate models and scenarios embedded with empirical models, such as Martins method reveals a range of possible future bioclimatic changes and should be considered in land use and land potential in the future.

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