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Application of Artificial Neural Networks to Project Reference Evapotranspiration under Climate Change Scenarios

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Abstract: Evapotranspiration, one of the major elements of the water cycle, is sensitive to climate change. The main objective of this study was to examine the response of reference evapotranspiration (ET_0) under various climate change scenarios using artificial neural networks and a general circulation model (GCM) - the Canadian Earth System Model Second Generation (CanESM2). The Hargreaves method was used to calculate ET_0 for western, central, and eastern parts of Prince Edward Island. The two input parameters of the Hargreaves method; daily maximum temperature (T_{max}), and daily minimum temperature (T_{min}) were projected using CanESM2. The T_{max} and T_{min} were downscaled with the help of statistical downscaling and simulation model (SDSM) for three future periods 2020s (2011-2040), 2050s (2041-2070), and

2080s (2071-2100) under three representative concentration pathways (RCP's) including RCP 2.6, RCP P4.5, and RCP 8.5, and the. Temporally, there were major changes in Tmax, Tmin, and ET₀ for the 2080s under RCP8.5. The temporal variations in ET₀ for all RCPs matched the reports in the literature for other similar locations and for RCP8.5 it ranged from 1.63 (2020s) to 2.29 mm/day (2080s). As a next step, a one-dimensional convolutional neural network (1D-CNN), long-short term memory (LSTM), and multilayer perceptron (MLP) were used for estimating ET₀ due to the non-linear behavior of ET₀ and the limited meteorological input data. High coefficient of correlation ($r > 0.95$) values for both calibration and validation periods showed the potential of the artificial neural networks in ET₀ estimation. The results of this study will help decision makers and water resource managers to quantify the availability of water in future for the island and to optimize the use of island water resources on a sustainable basis.

Keywords: Artificial neural networks; General circulation model; Hargreaves method; Reference evapotranspiration; Statistical downscaling

1 Introduction

Atmospheric increase of greenhouse gases from excessive use of the fossil fuels and human interventions have caused global warming (Huang et al. 2011). Atmospheric temperature is rising in numerous parts of the world (Abbas et al. 2018; Shi et al. 2020; Shafiq et al. 2019) included Canada (Zhai et al. 2019). All sectors of life like, agriculture, water resources, ecosystem, and human health have been badly affected due to climate variability globally (Abbas et al. 2018; Maqsood et al. 2020). Therefore, investigating and understanding future climate variability at a site-specific/regional scale is necessary to adapt, mitigate these changes.

It is imperative to analyze the effect of climate variability on the water cycle. Evapotranspiration (ET) is an essential element of the water cycle and consists of two processes:

evaporation (from the soil), and transpiration (from the plant leaves). Evapotranspiration from the reference crop surface is known as Reference evapotranspiration (ET_0). A comprehensive definition of ET and its components can be found in Allen et al. (1998). Accurate measurement of ET_0 is required for irrigation scheduling, water resources management, designing agricultural practices, and hydrological studies. Many empirical methods are used to measure ET that is used to estimate ET_0 (Almorox et al. 2015).

The Penman-Monteith method can accurately measure ET_0 in various climate conditions. It requires various climatic parameters like temperature, sunshine hours, wind speed, and vapor pressure for calculating ET_0 (Allen et al. 1998). However, this method challenging in many parts of the world due to the non-availability of the meteorological and climatic parameters data. Especially for future projection of ET_0 the downscaling of the input climatic parameters is not reliable (Randall et al. 2007), which also limits, its use. Therefore, temperature based empirical methods may be preferred for ET_0 estimation to overcome these limitations. Temperature data are easily accessible for almost all the world's meteorological stations and its projection by the available GCMs is more reliable than any other climatic parameters (Randall et al. 2007). Vicente-Serrano et al. (2014) stated that the Hargreaves method can be used as a quality method for estimating the ET_0 if input data for the Penman-Monteith method is not available. Numerous studies have compared the results of the Hargreaves method and standard Penman-Monteith method and reported that the first method performed well in both cold and arid climates (Almorox et al. 2015; Ren et al. 2016).

The outputs of the GCMs under different RCPs prescribed by the intergovernmental panel on climate change may only be used on a global or continental level (Wilby et al. 2000). Therefore, the outputs of the GCMs cannot present a credible view on the local/site-specific scale due to

parameterization limitations. Hence, useful dynamic and statistical downscaling techniques have been used to make the GCMs outputs useful at a local/site-specific scale.

Statistical downscaling technique offers immediate outputs of climate variables (precipitation and temperature) and is much simpler, cheaper and flexible than the dynamic technique (Zhang et al. 2020; Wilby et al. 2000). Empirical/statistical relationships between large-scale atmospheric predictors (e.g., surface mean temperature, surface precipitation, etc.) and local scale parameters (e.g., observed precipitation and temperature) have been established in this technique by using multiple linear regression (MLR). There exist various statistical downscaling models, but the SDSM has been selected for this study as it is most accurate and widely used to downscale and project the climate variables (Arshad et al. 2019; Birara et al. 2020). Wilby et al. (2002) presented a comprehensive review of SDSM to assess the regional climate change impacts.

The non-linear nature of ET_0 because of its contributing meteorological parameters (Landeras et al. 2008) requires non-linear problem-solving techniques for its accurate estimation. Artificial neural network techniques (ANNs) have a non-linear mathematical structure which is very useful in modeling complex non-linear problems (Sudheer et al. 2003). Hashemi and Sepaskhah (2020) estimated ET_0 with the Penman-Monteith method and ANNs namely MLP and the radial basis function (RBF) and reported that both the ANNs performed well as compared to the Penman-Monteith method. Zanetti et al. (2007) used MLP and RBF for estimating ET_0 from T_{max} , T_{min} , and/or different neural network architecture and found that MLP gave better results, with a single hidden layer, 10 neurons, and activation function type of hyperbolic tangent sigmoid, than RBF.

Long short-term memory has a chain-like structure that is capable of storing previous information and can also handle time series problems (Zhang et al. 2018). Afzaal et al. (2020a)

estimated ET_0 by using the recurrent neural networks (RNNs) namely LSTM and bidirectional LSTM and a limited number of meteorological parameters. They reported the high accuracy of these networks in estimating ET_0 . Majhi et al. (2020) used different combinations of meteorological parameters for computing the ET_0 and compared the results of LSTM with MLP and empirical methods (Hargreaves and Blaney-Criddle). They found that LSTM can estimate ET_0 with higher accuracy as compared to the other models. One-dimensional convolutional neural networks (1D-CNNs) are deep learning algorithms mostly used to analyzing visual imagery. These networks are the most advanced forms of the ANNs as they have more hidden layers as compared to the MLP and LSTM. These networks can also be used in time series problems if they are modeled properly (Ferreira and da Cunha 2020).

Evapotranspiration is not only the major climatic component that controls the water balance, but it is a major component that controlled the production of a crop. The variation in ET_0 may create problems especially in those areas, where most of the agricultural lands are rainfed such as Atlantic Canada. Future projections of ET_0 can help to make irrigation strategies for rainfed areas where the temperature is expected to increase, and rainfall may vary due to climate change. Future projections of ET_0 for Prince Edward Island, an important agricultural province of Atlantic Canada, have not yet been conducted and/or reported in the literature. The main reason might be the non-availability of the required climatic parameters for the calculation of ET_0 . Therefore, the main objective of this study was to predict ET_0 with the use of ANNs and a Canada-specific GCM (CanESM2).

2 Materials and methods

2.1 Description of the study area

Prince Edward Island (PEI) is one of the highly populated provinces of Atlantic Canada (Statistics Canada 2020). It covers approximately 5660 km² geographical area and is 225 km long and 3-65 km wide at its various transects. It is located between 62 to 64 °W longitude and 46 to 47 °N latitude. The climate of the province is humid continental and affected by the surrounding Northumberland Strait seas and the Gulf of Saint Lawrence. The summer season is moderately warm, and occasionally its Tmax reaches as high as 34 °C (Government of PEI 2015). The densely planted crops on the island are potatoes, grains, and oilseeds (barley, oats, wheat, canola, corn, and soybean), fruits (blueberries, cranberries, strawberries, grapes, and apple), vegetables (carrot, cabbage, cucumber, tomatoes, onion, and cauliflower) (Government of PEI 2020).

Fig.1 location map meteorological stations situated in Prince Edward Island used for this study.

2.2 Data sources and analysis activities

Meteorological data (Tmax and Tmin) on daily basis, GCM data (CanESM2), and National Center of Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) data were used in this study. The study objective was achieved by using the above data and through i. investigating the ability of the SDSM to downscale and assess the variation in Tmax and Tmin

for three future periods the 2020s, 2050s, and 2080s, ii. calculating ET_0 in baseline (1989-2005) and future three-time periods using limited meteorological data (Tmax and Tmin) in Hargreaves method, and iii. estimating the non-linear ET_0 with the help of artificial neural networks (MLP, LSTM, and CNN) for baseline and future periods.

2.2.1 Meteorological data

Three meteorological stations, namely North Cape, Charlottetown, and East Point were selected to assess the temperature and ET_0 changes in the study area (Figure 1, Table 1). The selection of these stations was based on the data quality, different locations on the island, and the length of the available daily data (1989-2005). The daily Tmax and Tmin for the baseline period were collected from Environmental Canada (Government of Canada 2017). These datasets were used as a predictand in calibration and validation of the SDSM.

Table 1 The attributes of the selected meteorological stations in Prince Edward Island, Canada.

Stations	Latitude (°)	Longitude (°)	Elevation (m)	Up.Thr. Tmax (°C)	Lo.Thr. Tmin (°C)	Data missing (%)
North Cape	47.06	-64.00	7.60	33.2	-33.0	1.68
Charlottetown	46.23	-63.17	13.7	33.0	-29.8	0.64
East Point	46.46	-61.99	7.70	33.5	-31.0	0.77

Up.Thr.Tmax: Upper threshold value of daily maximum temperature; Lo.Thr.Tmin.: Lower threshold value of daily minimum temperature.

The missing values of data were estimated using relevant neighboring station ($R^2 > 0.90$) data and adopting a linear regression model. The linear regression model was used to create a relation between target and neighboring stations which helped in estimating the missing values between the observed data.

2.2.2 The general circulation model data

The GCM model used in this study was CanESM2 developed by the Canadian Centre for Climate Modeling and Analysis (CCCma) of Environment Canada. The CanESM2 model outputs

between 2006 to 2100 were retrieved for three different climate scenarios RCPs of 2.6 (low forcing scenario), 4.5 (medium stabilization scenario), and 8.5 (very high emission scenarios). These scenarios are defined under the future projection of greenhouse gas emissions, and possible ranges of radiative forcing values of 2.6, 4.5, and 8.5 W/m² as well as CO₂ concentrations of 420, 540, and 940 mg/L in the 2100 year, respectively (van Vuuren et al. 2011). Moreover, CanESM2 has been reported to perform well with the SDSM in downscaling Tmax and Tmin as compared to other GCMs (Birara et al. 2020; Hassan and Hashim 2020). It also covers the study area with a relatively higher spatial grid resolution of 2.8125° × 2.8125°. It has been widely and most used GCM in climate change impact studies (lotfi et al. 2020; Shafiq et al. 2019)

Besides CanESM2 model outputs for three different climate scenarios, large-scale atmospheric variables from NCEP/NCAR were utilized for creating a statistical relationship with the historical Tmax and Tmin. CCCma also provides the NCEP/NCAR predictors for the (1961-2005) period. Both CanESM2 and NCEP/NCAR data have the same set of 26 predictors' variables (Table 2). Two tiles (Box_106X_49Y and Box_107X_49Y) of CanESM2 cover the study area. The data of these two tiles were retrieved from the Canadian climate data and scenarios website (Government of Canada 2019) and then processed by the SDSM to predict Tmax and Tmin for the future periods. The SDSM performed well in the projections of local climate variability (Al-Mukhtar and Qasim 2019; Birara et al. 2020).

Table 2 The List of 26 predictors of NCEP

No.	Predictors	No.	Predictors
1	Surface precipitation (ncepprcpgl)	14	Vorticity at Surface (ncepp1_zgl)
2	Surface specific humidity (ncepshumgl)	15	Vorticity at 500 hPa (ncepp5_zgl)
3	Mean sea level pressure (nceppmslpgl)	16	Vorticity at 850 hPa (ncepp8_zgl)
4	Surface mean temperature (nceptempgl)	17	Wind direction at Surface (ncepp1thgl)

5	Air flow strength at surface (ncepp1_fgl)	18	Wind direction at 500 hPa (ncepp5thgl)
6	Air flow strength at 500 hPa (ncepp5_fgl)	19	Wind direction at 850 hPa (ncepp8thgl)
7	Air flow strength at 850 hPa (ncepp8_fgl)	20	Divergence at Surface (ncepp1zhgl)
8	Zonal velocity at surface (ncepp1_ugl)	21	Divergence at 500 hPa (ncepp5zhgl)
9	Zonal velocity at 500 hPa (ncepp5_ugl)	22	Divergence at 850 hPa (ncepp8zhgl)
10	Zonal velocity at 850 hPa (ncepp8_ugl)	23	Geopotential height at 500 hPa (ncepp500gl)
11	Meridional velocity at surface (ncepp1_vgl)	24	Specific humidity at 500 hPa (nceps500gl)
12	Meridional velocity at 500 hPa (ncepp5_vgl)	25	Geopotential height at 850 hPa (ncepp850gl)
13	Meridional velocity at 850 hPa (ncepp8_vgl)	26	Specific humidity at 850 hPa (nceps850gl)

2.3 Description of Statistical downscaling and simulation model

The SDSM was developed by Wilby et al. (2002). It is a hybrid model of MLR and stochastic weather generator (SWG). The MLR creates an empirical/statistical relationship between the predictand (Tmax and Tmin) and NCEP predictors (large scale parameters) which produce regression parameters from the input data. These calibrated parameters of MLR are used in SWG to generate time series data up to 100 years. The detail of getting outputs is described in (Wilby et al. 2002). The steps for downscaling GCM data included 1. quality control analysis, 2. screening of the predictors, 3. model calibration, 4. generation of weather, 5. model validation, 6. scenario generation using GCM data.

Quality control deals with filling in missing values present in a dataset and replace the missing values with code -999 as per model provisions.

Screening of the NCEP predictors is a crucial and most important step for all the statistical downscaling methods as these predictors highly influence the output of the SDSM (Huang et al. 2011). Partial correlation, p-value, and correlation matrix are mostly used in combination for the

screening of the predictors (Huang et al. 2011; Wilby et al. 2002). The steps described by Mahmood and Babel (2013) were used for the screening of NCEP predictors:

First, NCEP predictors were extracted for the baseline period (1989-2005) for better correlation results. The procedure adopted for the screening of NCEP predictors for Tmax at the central part of the island is shown in Table 3. A correlation matrix was computed between predictand (Tmax and Tmin) and the 26 NCEP predictors. Predictors that have the highest correlation (R₁) in this matrix with the predictand (12 in this case) were separated and arranged in descending order. The first NCEP predictor that has (R₁) value was selected and called a super predictor (SP). The predictor nceptemp was the SP for Tmax at the central part of the island as it had the highest correlation (0.93) with the predictand.

Table 3 Procedure adopted in the screening of NCEP predictors for Tmax at the central part of the island.

Sr	NCEP Predictors	R ₁ (%)	R ₂ (%)	p.r (%)	p-value	PRP
1	nceptempgl	0.93				
2	ncepp500gl	0.87	0.85	0.37	0.00	0.57
3	ncepshumgl	0.86	0.92	0.05	0.00	0.95
4	nceps850gl	0.71	0.76	0.03	0.06	1.04
5	ncepp850gl	0.63	0.58	0.21	0.00	1.33
6	nceps500gl	0.47	0.52	0.17	0.00	1.37
7	ncepp1_vgl	0.44	0.36	0.38	0.00	0.13
8	ncepp5_fgl	0.35	0.31	0.02	0.20	0.95
9	ncepp5_zgl	0.36	0.31	0.25	0.00	1.70
10	ncepp8_zgl	-0.29	0.19	0.22	0.00	1.75
11	ncepp5_ugl	0.26	0.23	0.07	0.00	0.73
12	ncepp1_fgl	0.24	0.21	0.08	0.00	0.66

R₁: correlation coefficient between NCEP predictors and predictand; R₂: correlation coefficient among the NCEP predictors; p.r.: partial correlation between predictand and predictors and in the presence of SP; PRP: Percentage reduction in partial correlation to the correlation coefficient. Bold values were the screened predictor for Tmax at Charlottetown station.

After finding the SP, the correlation coefficient between the remaining selected NCEP predictors (11 in this case) and predictand (R₁), correlation coefficient among NCEP predictors (R₂), partial correlation (p.r), and p-value were calculated in the presence of SP. The predictors having a high correlation (R₂) coefficient with the SP (0.5 in this study) were eliminated to

minimize the multicollinearity between predictors. The R_2 between two predictors up to 0.7 is acceptable (Pallant, 2007). In this study, the predictors (ncepp500gl, ncepshumgl, nceps850gl, ncepp850gl, and nceps500gl) had the highest correlation ($R_2 > 0.5$) with the SP and were eliminated from the list to minimize multi co-linearity. Then, the predictors having a high p-value > 0.05 were also eliminated to keep the results statistically significant. So, ncepp5_fgl and nceps850gl were also eliminated from the list as they had a p-value higher than 0.05.

The percentage of reduction in partial correlation to the correlation coefficient (PRP) was used to find the second most appropriate NCEP predictor and was calculated by the following equation.

$$PRP = \frac{\rho.r - R_1}{R_1} \quad (1)$$

where, R_1 is correlation coefficient, and $\rho.r$ is the partial correlation between predictand and predictors.

A predictor with the lowest PRP value was selected as the second most suitable predictor and it had very low multi co-linearity with the SP. The predictor ncepp1_vgl was selected as the second-most appropriate predictor for Tmax at the central part of the island as it had the lowest PRP value (0.13) and it did not have a strong correlation with the SP. The next predictors were selected by repeating these steps.

2.3.1 Model calibration, validation, and future scenarios generation

The complete dataset of the baseline period (1989-2005) with screened NCEP predictors was split into 70% for calibration (1989 to 2000) and 30% for validation (2001-2005). The options of ordinary least square (OLS), unconditional and monthly sub-models were chosen in the model interface for calibration purposes. Validation was carried out with the output of the calibration run. Then, 20 ensembles of synthetic daily future weather series had been generated by SWG. The

average of these 20 daily ensembles had been compared with the historical data for the validation period. The calibrated model was used to project Tmax and Tmin for the future period 2006-2100 under different RCPs (2.6, 4.5, 8.5). The pattern of climatic variables was modeled for three future periods namely the 2020s, 2050s, and 2080s.

2.4 Hargreaves method

Various methods are used for predicting the ET₀ but the Penman-Monteith method is the standard and most precise method to estimate the ET₀. It required various weather parameters such as temperature, moisture content, wind velocity, and solar radiation. Many meteorological stations do not have a complete dataset of the meteorological parameters and the required data set mostly unavailable. So, alternate ET₀ methods like Hargreaves, Blaney-Criddle, FAO-56 reduced set, and Turc methods are used which required only a few meteorological parameters. It was found from previous studies that the Hargreaves method was performed well in predicting the ET₀ as compared to other ET₀ methods like BC, FAO-56 reduced method (Fisher and Pringle 2013; Hafeez et al. 2020). That's why, Hargreaves method was used in this study due to its accuracy over other methods and non-availability of the required dataset, and non-reliability of downscaling and projecting the meteorological parameters required for the Penman-Monteith method.

The Hargreaves method was used to estimate the ET₀ from Tmax and Tmin data (Hargreaves and Samani 1985). The equation used in this method is:

$$ET_0 = 0.408(0.0023)(17.8 + T_{mean})(T_{max} - T_{min})^{0.5} R_a \quad (2)$$

where R_a is extraterrestrial radiation (MJm⁻²) and 0.408 is an empirical factor to convert MJm⁻² to mm.

The solar radiation at the top of the earth's atmosphere is used as R_a . Its values range from ~12 to ~31 MJm^{-2} in PEI with winter months reflecting the lower values and vice versa. It is calculated, based on the latitude of the location and the calendar day of the year, by the given equation:

$$R_a = \frac{24(60)}{\pi} \times G_{sc}(d_r)[(\sin(\varphi) \times \omega_s \times \sin(\delta)) + (\cos(\varphi) \times \cos(\omega_s) \times \cos(\delta))] \quad (3)$$

where, G_{sc} is the solar constant (0.0820 MJm^{-2}). The value of G_{sc} showed the amount of solar energy per unit time, at the mean distance of the earth from the sun, received on a unit area of a surface normal to the sun outside the atmosphere. In equation 3, φ is the latitude of the location (radians). Latitudes for North Centre, Charlottetown, and East Point locations were used as 0.8214, 0.8079, 0.8109 radians. Similarly, d_r is the inverse relative distance from the earth to the sun and calculated based on the calendar day of the year as:

$$d_r = 1 + [0.33 \times \cos\left(\frac{2\pi}{365}J\right)] \quad (4)$$

where J is the calendar day of the year.

In equation 3, ω_s represents the sunset hour angle (radians). Its values range from ~1 to ~2 radians in Prince Edward Island with winter months reflecting the lower values and vice versa. It is calculated as:

$$\omega_s = \arccos(-\tan(\varphi) \times \tan(\delta)) \quad (5)$$

where, δ = solar declination (radians), and is calculated as:

$$\delta = 0.409 \times \sin\left(\left(\frac{2\pi}{365} \times J\right) - 1.39\right) \quad (6)$$

Its values range from ~ -0.4 to ~ 0.4 radians in Prince Edward Island with winter months reflecting negative values and vice versa.

2.5 Deep learning algorithms

Three artificial neural networks (1D-CNN, LSTM, and MLP) were used to estimate the daily ET_0 for baseline (1989-2005) and future periods (the 2020s, 2050s, and 2080s) under three RCPs for western, central, and eastern parts of the island. The ANNs were trained by using 70% of data in each period under every RCP and validated by the remaining 30% of data at all the parts of the island. The hyperparameters (learning rate, optimizer, and batch size) were found by the trial-and-error method. Learning rate (l.r) is a configurable hyperparameter that controls how quickly the model is adapted to the problem and it has small positive values (0 to 1.0). Batch size is the hyperparameter that refers to the number of samples used in one iteration. The most used batch sizes are 32, 64, and 128. Optimizers are the methods that reduced the losses by changing the attributes (learning rates or weights) of the neural network. The highest performing combination of the learning rate, optimizer, and batch size was used for calibration and validation of the networks (Afzaal et al. 2020b). It was found that in this study CNN and MLP performed well at learning rate = 0.01, batch size = 64, and optimizer = Adam, while LSTM performed well at batch size = 128 and with the same learning rate and optimizer as CNN and MLP. The network's estimated ET_0 values were compared with the Hargreaves method output (ET_0) by naming it as the actual ET_0 . The main reason for adopting these networks was the non-linear behavior of the ET_0 and limited meteorological data availability.

(a)

(b)

(c)

Fig.2 (a) Block diagram of the one-dimensional convolutional neural network; (b) memory block of the long-short term memory network, and (c) Structure of multilayer perceptron neural network.

Convolutional Neural Networks are mostly used for two-dimensional (2D) images in machine vision applications while 1D-CNN has many applications in natural language processing and time series classification problems. Five layers were used in this study followed by appropriate hyperparameter selection by the hit-and-miss method (Figure 2a). The first layer was the convolutional layer which takes input (T_{max} , T_{min} , and T_{mean}). This layer connects with a max-pooling layer to extract the features. The third (flatten) layer was used to join the max-pooling and last two fully connected layers.

The LSTM is a form of recurrent neural network (RNN) that predicts time series problems. It's a sequence-based model that can store the previous information and relate it to a sequence for predicting the time series. Longer sequences cannot be saved in RNNs due to the problem of gradient vanishing in the early layers. The gradient vanishing problem is due to short-term memory. RNNs have chain like composition which helps the data to flow from them. RNNs store the information, based on the time or sequence steps, as a hidden state (h_t) at every stage. i.e., h_t for every input (X_t). Hyperbolic tangent function ($\tanh$) also presents in the structure of the RNN that scales the input date from -1 to 1. The problems of short-term memory of the RNN are solved by adding more states into its memory.

The temporal and sequel dependence of the previous blocks retained by adding the forget state (f_t) and cell state (C_t) in LSTM. The f_t of LSTM keeps or discards the information, and it depends on the output values of the sigmoid function. Those values which are closer to 1 are kept while the closer values to 0 are discarded. The previous hidden state (h_{t-1}) and X_t processed and giving out a new input (i_t) using the sigmoid activation function. The i_t is also given in the range of 1 to 0 without ignoring any information like f_t . C_t is calculated by adding the f_t and the dot

product of the sigmoid and tanh functions. The detailed review of information flow in the LSTM memory block is shown in Figure 2b.

An MLP is a common type of feedforward artificial neural network, which is mostly used in hydrology and water resources problems for modeling non-linear processes (Afzaal et al. 2020b). In this study, it was used for estimating the ET_0 . It contains multiple layers including input, hidden, and output layers (Figure 2c). Neurons are the fundamental processing unit of the ANNs that connect all these layers. The input layer takes all the variables like T_{max} , T_{mean} , and T_{min} for the prediction of output i.e., ET_0 . The hidden layers added the inputs and used an activation function for creating the output. The most common activation functions are sigmoid, tanh, and rectified linear unit. A rectified linear unit was used in this study due to its better performance relative to others.

In this study, 100 neurons and two hidden layers were selected by the trial-and-error method. A comparison of different learning algorithm was used in many studies and Levenberg-Marquardt was reported to be faster and had higher accuracy relative to the other algorithm (Kisi and Demir 2016; Tabari and Hosseinzadeh Talaei 2013). Therefore, the Levenberg-Marquardt learning algorithm was chosen for this study to find out the loss function due to its best performance.

2.6 Statistical evaluator

Two statistical evaluators, coefficient of correlation (r) and root mean square error (RMSE), were used for assessing the performance of the SDSM and the machine learning algorithms as suggested and used by Afzaal et al. (2020a) and Al-Mukhtar and Qasim (2019). Closure the value of r to '1' showed the better performance of the model.

$$r = \frac{\sum_{i=1}^N (y_i - \bar{y})^2 - \sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sqrt{\sum_{i=1}^N (y_i - \bar{y})^2}} \quad (7)$$

The RMSE, an error index, is used to calculate the differences between the observed and predicted data. Closure the value of RMSE to '0' showed the better performance of the model.

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{N}} \quad (8)$$

where $\hat{y}_i$ is the estimated value at the i th time; y_i is the actual value at the i th time; $\bar{y}$ = mean value of the y_i ; N = number of values and i ranges from 1 to N .

3 Results and discussion

3.1 Predictors selection

The screened NCEP predictors for Tmax were nceptemp and ncepp1_v, while nceptemp and ncepp5_z were the screened predictors for Tmin at all the parts of the island. It was observed that the nceptemp was the SP for both Tmax and Tmin variables at all the parts of the island. The nceptemp was also found as SP in different studies (Arshad et al. 2019; Mahmood and Babel 2013). These screened predictors of Tmax and Tmin were used for calibrating the SDSM.

3.2 Evaluation, calibration, and validation of SDSM

The selected predictors of NCEP were used for the calibration and validation period of the SDSM. The results of Tmax and Tmin simulated by SDSM were compared with the observed values for calibration (1989-2000) and validation (2001-2005) period. The simulated results of both Tmax and Tmin variables at all the parts of the island had a high correlation with their respective observed Tmax and Tmin during the calibration and validation periods. The values of r for Tmax and Tmin at all the parts of the island were greater than 0.95. The simulated results of

the Tmax and Tmin were in a better agreement with the observed mean monthly values and can be observed in visual presentation (Figure 3) where simulated results during the validation period were very near to the observed values at all the parts of the island. It indicated the better efficiency of the SDSM in simulating the Tmax and Tmin, its reliability, and applicability of the model in Prince Edward Island, Canada for climate change prediction.

Fig. 3 Comparison between observed and simulated mean monthly Tmax (daily maximum temperature) and Tmin (daily minimum temperature) during the validation period (2001-2005).

3.3 Change of climate factors under different future climate scenarios

The developed SDSM of climate factors at each part was utilized to project the future daily Tmax and Tmin for the 2006-2100 period. The projected Tmax and Tmin were used in the

Hargreaves method for calculating the ET_0 . These variations in average annual T_{max} , T_{min} , and ET_0 were illustrated in Figure 4 for the baseline and future periods (2020s, 2050s, and 2080s) based on the RCPs (2.6, 4.5, and 8.5) for western, central, eastern parts of the island. The middle line of the boxes in Figure 4 shows the median value, while the lower and upper boundaries of the boxes indicate 25% and 75% of the data sets, respectively. The lower and upper whiskers show the 10th and 90th percentiles, respectively. Results presented in these figures showed an increment in the future average annual T_{max} , T_{min} , and ET_0 irrespective of the RCPs and parts of the island.

RCP2.6 showed less change in the average annual values of T_{max} , T_{min} , and ET_0 as compared to RCP4.5 and RCP 8.5 at all the parts of the island. The increment in the average annual values of T_{max} , T_{min} , and ET_0 became larger as the time increased into the future periods. RCP8.5 showed maximum variations of T_{max} , T_{min} , and ET_0 in future periods.

Fig. 4 Projected changes in the average annual Tmax (°C), Tmin (°C), and ET₀ (mm/day) for baseline (1989-2005) and future periods the 2020s (2011-2040), 2050s (2041-2070), and 2080s (2071-2100) at western, central, eastern parts of the island under different RCPs (2.6, 4.5, and 8.5). The (*) asterisk symbol represents the presence of outliers in the data.

A larger average annual increment in Tmax, Tmin, ET₀ was found under RCP 8.5 in all the parts as compared to the RCP 4.5 and RCP 2.6 in future periods. The projected change in the average annual Tmax was approximately varied from 11.74 (2020s) to 16.55 (2080s) at the western part, 12.86 (2020s) to 19.52 (2080s) at the central part, and 11.93 (2020s) to 18.02°C (2080s) at the eastern part of the island under RCP8.5. The variation in the average annual Tmin was observed from 3.53 (2020s) to 8.90 (2080s) at the western part, 4.50 (2020s) to 11.33 (2080s) at the central

part, 5.21 (2020s) to 11.36°C (2080s) at the eastern part of the island under RCP8.5. The calculated average annual ET_0 changed in the range of 1.64 (2020s) to 1.92 (2080s), 1.64 (2020s) to 2.03 (2080s), and 1.63 (2020s) to 2.29 mm/day (2080s) at all the parts of the island under RCP2.6, RCP4.5, and RCP8.5 respectively.

These results are in concurrence with the findings of the literature. For example, Richards and Daigle (2011) predicted that the T_{max} and T_{min} values are likely to increase in the future periods for Prince Edward Island. Shi et al. (2020) projected the ET_0 , T_{max} , and T_{min} in southeastern Australia, and reported that the changes in these parameters were increased over time and maximum changes were observed under RCP8.5. Lotfi et al. (2020) used outputs of the CanESM2 model under RCP2.6, 4.5, and 8.5 to find the effect of climate variability on the ET_0 in the West of Iran by calculating the ET_0 by Hargreaves and Priestley-Taylor methods and observed the highest rate of change of ET_0 was under RCP8.5 scenarios.

3.4 Deep learning algorithms based evaluations

All the models were run at the selected combination for all the baseline and future periods and found out the validation r , and RMSE (Table 4). The changes in r values were observed at western part which were 0.96 to 0.98 (CNN), 0.96 to 0.97 (LSTM), and 0.96 to 0.98 (MLP) while at central part r values were changed from 0.96-0.97, 0.96, and 0.96 to 0.97 for CNN, LSTM, and MLP, respectively. The values of r in the eastern part were also changed, irrespective of the RCPs and periods, from 0.95 to 0.98, 0.95 to 0.97, and 0.95 to 0.98%. The CNN, LSTM, and MLP validation RMSE were recorded in the range of 0.28-0.30, 0.29-0.31, and 0.28-0.29 mm/day respectively in the western part. The validation RMSE values for the central part were recorded in the range of 0.30-0.36, 0.30-0.38, and 0.30-0.34 mm/day, while for the eastern part it was recorded in the range of 0.26-0.27, 0.28-0.31, and 0.26-0.27 mm/day for CNN, LSTM, and MLP, respectively. The

results of r and RMSE showed that all these neural networks performed well in calculating the ET_0 but CNN and MLP both showed slightly higher accuracy at all the parts of the island as compared to the LSTM. The validation r and RMSE at all the parts of the island showed slightly higher accuracy (r) in the 2080s scenario under RCP8.5 (Figure 5).

Table 4 The RMSE and r for the validation periods of artificial neural networks (CNN, LSTM, and MLP) for western, central, and eastern parts of the island.

Parts of the island	RCPs	Future Scenarios	CNN		LSTM		MLP	
			Valid_ r	Valid_ RMSE	Valid_ r	Valid_ RMSE	Valid_ r	Valid_ RMSE
Western	Baseline	1989-2005	0.96	0.29	0.96	0.30	0.96	0.29
		2020s	0.97	0.28	0.97	0.29	0.97	0.28
		2050s	0.97	0.29	0.97	0.3	0.97	0.28
	RCP2.6	2080s	0.97	0.28	0.97	0.29	0.97	0.29
		2020s	0.97	0.29	0.96	0.3	0.97	0.28
		2050s	0.97	0.29	0.97	0.3	0.97	0.28
		2080s	0.97	0.29	0.97	0.3	0.97	0.28
	RCP8.5	2020s	0.97	0.28	0.96	0.3	0.97	0.28
		2050s	0.97	0.29	0.97	0.31	0.97	0.28
		2080s	0.98	0.3	0.97	0.32	0.98	0.29
Central	Baseline	1989-2005	0.96	0.30	0.96	0.30	0.96	0.30
		2020s	0.97	0.3	0.96	0.32	0.96	0.31
		2050s	0.96	0.32	0.96	0.33	0.96	0.31
	RCP2.6	2080s	0.96	0.31	0.96	0.32	0.96	0.32
		2020s	0.96	0.32	0.96	0.33	0.96	0.23
		2050s	0.96	0.32	0.96	0.34	0.96	0.32
		2080s	0.96	0.32	0.96	0.34	0.96	0.32
	RCP8.5	2020s	0.96	0.3	0.96	0.32	0.96	0.3
		2050s	0.97	0.34	0.96	0.35	0.97	0.33
		2080s	0.97	0.36	0.96	0.38	0.97	0.34
Eastern	Baseline	1989-2005	0.95	0.27	0.95	0.28	0.95	0.27
		2020s	0.97	0.26	0.96	0.28	0.97	0.26
		2050s	0.97	0.27	0.96	0.28	0.97	0.26
	RCP2.6	2080s	0.97	0.26	0.96	0.28	0.97	0.27
		2020s	0.97	0.27	0.96	0.29	0.96	0.26
		2050s	0.97	0.26	0.96	0.29	0.97	0.26

	2080s	0.97	0.26	0.96	0.29	0.97	0.27
	2020s	0.96	0.27	0.96	0.29	0.96	0.26
RCP8.5	2050s	0.97	0.27	0.97	0.29	0.97	0.27
	2080s	0.98	0.27	0.97	0.31	0.98	0.27

CNN: convolutional neural network; LSTM: long-short term memory; MLP: multilayer perceptron; r: coefficient of correlation; RMSE: root means square error

The lower peaks in figures 5a, b, c indicate the ET_0 in the winter season of the year while higher peaks reflect the values of ET_0 for the summer season. The results of this study corroborate with other studies in which MLP, and CNN performed well as compared to other deep learning models. Ferreira and da Cunha (2020) used deep learning algorithms (combination of CNN and LSTM, and LSTM, 1D CNN), and outdated machine learning models (artificial neural network and random forest) for forecasting (seven days) of the daily ET_0 . They found that the deep learning algorithms showed slightly better performance as compared to the traditional machine learning models and can be used for forecasting the ET_0 . Tabari and Hosseinzadeh Talaei (2013) used four MLP models for estimating the ET_0 in the semi-arid region of Iran. They used a different combination of meteorological variables in these models and concluded that the MLP model can be used for calculating the ET_0 . The results also showed that all these neural networks that have a non-linear structure can be used for predicting the ET_0 by using minimal meteorological data.

Fig. 5 Validation phase of 2080s time span under RCP8.5 for CNN, LSTM, and MLP at (a) western part, (b) central part, (c) eastern part of Prince Edward Island.

4 Conclusion

This study deals with the change in the patterns of climatic parameters (T_{max} , T_{min} , and ET_0) in the baseline (1989-2005) and future (2006-2100) periods. These projected results were compared with the baseline period. The comparison results showed that the projection of T_{max} ,

Tmin, and ET_0 for all the parts of the island were different in magnitude but similar in the pattern under all the three RCPs. The temporal variation showed that changes in Tmax, Tmin, and ET_0 were exceeded over time under all the RCPs. Overall, it was noticed that, in all the cases of this study, the highest and the worst changes in the considered climate variables were found in the 2080s under RCP8.5, as also reported in various studies.

All the models showed higher accuracy (>95%) in estimating the ET_0 for the three future periods under all the RCPs in all the parts of the island. No major difference was observed in the performance of the neural networks. The use of the new architecture of neural networks (LSTM and CNN) did not show any better performance as compared to the older one (MLP). It was observed that CNN and MLP performed quite similarly and have almost the same accuracy, while LSTM showed slightly lower accuracy as compared to them for estimating ET_0 for all the scenarios. This study showed that all the models, SDSM (for downscaling of Tmax and Tmin), Hargreaves method (for calculating the ET_0 with limited input parameters), and ANNs (CNN, LSTM, and MLP) for highly accurate estimation of the ET_0 were applicable in this study area (Prince Edward Island) of Canada. This study will also help in future management relating to water resources, irrigation scheduling, supplement irrigation, and eco-environment management practices.

The literature reviewed indicated that no work has been done so far for the generation of future ET_0 from statistically downscaled meteorological data (Tmax, Tmin, and Tmean) by using the Hargreaves method and ANNs (1D-CNN, LSTM, and MLP) in Prince Edward Island, Canada. This might be due to the inaccessibility to the meteorological stations, nonavailability of meteorological data, and inadequate resources. This study may be a valuable benchmark for others

who wants to apply these models and methods for accessing the variations in future Tmax, Tmin, and ET₀.

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Declarations

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