XVI International Conference on Durability of Building Materials and Components
DBMC 2023, China
K.F. Li and D.P. Fang (Eds)

Prediction and Ranking of Moisture Severity of Climate Years Using Supervised Projection to Latent Structures Applied to Tall Wood Buildings

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Abstract. *Hygrothermal simulation tools are commonly used to assess the moisture performance of building envelope components. Owing to the computational costs required to complete simulations over the long-term, one approach to reduce simulation time when undertaking hygrothermal design analysis is to select representative year(s) amongst sets of long-term climate data. To properly select these moisture reference year(s), a method is required to rank or predict the moisture severity of climate years for sets of long-term climate data. Several methods are used in the literature for this purpose, but none seems to be sufficiently accurate. In this study, the supervised projection to latent structures, also known as partial least squares regression, was trained and validated on data obtained from hygrothermal simulations of tall wood building wall assemblies for several cities across Canada. Models developed at the city level, for a given greenhouse gas emission scenario or time period, or encompassing historical and future time periods, showed comparable scores for ranking. In respect to prediction of the moisture severity of climate year sets, models developed at the city level were shown to be more accurate.*

Keywords: *Tall wood building envelope; Climate years*; *Moisture severity; Prediction and ranking; Projection to latent structures*

1 Introduction

Hygrothermal simulation tools provide a ready means of assessing the moisture performance of building envelope (BE) components and materials when the assembly is subjected to outdoor and indoor climatic loads. However, the year-to-year variation in climate data requires, in principle, that simulations be performed for longer terms, *i.e.*, over 10 to 30 consecutive years. This necessitates longer computing times, especially when considering 2-D or 3-D simulations. This problem is exacerbated when uncertainties in future climate data, simulation parameters and material properties are to be considered using, for example, a stochastic approach.

One approach to reduce the computing costs of completing long-term simulations is to select representative year(s) among the climate data series to perform simulations. These are called Moisture Reference Year (s) (MRYs). The expectation is that they would either give results similar to that which would be obtained using the entire climate data series or otherwise impose a severe stress on BE to achieve the desired level of safety regarding the risk to the occurrence of moisture damage. To properly select the MRYs, a method is required to predict and/or rank the climate years of a climate series in terms of their moisture severity. To this end, several methods have been developed that can be categorized in two groups: climatic-based and response-based methods. The climatic-based methods, also known as construction-independent methods, are based exclusively on climate variables, *e.g.*, PI-factor (Hagentoft and Harderup

1996), Moisture Index (Cornick and Dalgliesh 2003), Wind-driven rain, Temperature, Freeze-thaw cycles, Frost Decay Exposure, and similar. The response-based or construction-dependent methods, require a parameter that can only be obtained by performing hygrothermal simulations for a given wall type, *e.g.*, Moisture content, Climatic index (Zhou et al. 2016), Severity index (Salonvaara 2011), and similar.

The applicability and limits of existing methods have been addressed elsewhere (Cornick and Dalgliesh 2003, Aggarwal et al. 2020, Salonvaara et al. 2011, Singh 2017, Vandemeulebroucke et al. 2021, 2023). The response-based methods seem to be more reliable (Aggarwal et al. 2000, Vandemeulebroucke et al. 2021, 2023). In particular, the Severity index (Salonvaara 2011) appears to be the most consistent and accurate method. It is a statistical model that was calibrated using multiple regression analysis and included several climatic and structural variables. Some unnecessary variables were removed from the final model using stepwise selection but the final model still included some predictors correlated with each other. This multicollinearity may reduce the accuracy of the estimates of the regression coefficients (James et al. 2021). One way to handle the situation where the predictors are numerous and collinear is to use the so-called projection to latent structures or partial least squares (PLS) regression (Tobias 1995).

The idea for the method of PLS regression, a dimension reduction method, is that among all the featured variables, there may be only a few underlying or latent factors that account for most of the variation in the response (Tobias 1995, James et al. 2021). The PLS's algorithm thus extracts these latent factors, that are orthogonal (*i.e.*, independent), to predict the target variable. Further details on the method as well as the various different algorithms as can be used, can be found in Martins et al. (2010). Aggarwal et al. (2022) showed that this method can be successfully applied to the prediction of moisture performance of the BE. The aim of this study is to move ahead and explore different modelling options that would permit, efficiently predicting and ranking the moisture severity of climate years for a long-term climate data series. The large ensemble climate data developed by Gaur et al. (2019) for conducting building energy and hygrothermal simulations comprises data for several greenhouse gas (GHG) emission scenarios for various locations in Canada. For each scenario, there are 15 subsets that account for different initial conditions used to model future climate. The specific questions that were addressed included: (i) for a given GHG emission scenario, how do the results derived from a model developed using data for all cities (GHG model or time period model) compare to results from models developed for each individual city (city-level model)? (ii) Will a model developed for a given GHG emission scenario (or time period model) be more efficient than the model developed using data for all scenarios (global model)?

2 Methods

2.1 Cities Selected for the Study

Twelve (12) Canadian cities belonging to several climate regions were selected for this study. Their geographic location and current climatic design data, as can be found in the 2020 National Energy Code for Buildings (NEBC 2020) in respect to the climatic zone, and in the 2020 National Building Code (NBCC 2020) for values of moisture index (MI), heating-degree-days below 18 °C (HDD), rain and driving rain wind pressure (DRWP), are given in Table 1. Climate zones 4, 5, 6, 7A and 7B correspond to zones with heating degree-days ranging from 2000 to 2999, 3000 to 3999, 4000 to 4999, 5000 to 5999, and 6000 to 6999, respectively. Latitude and longitude indicated for each city are that of the nearby airport station except for the city of Toronto, for which the weather station is located in the city centre. The definition of MI can be found in Cornick and Dalgliesh (2003).

Table 1. Geographic location and climate design data for selected cities.

City (Province)	Lat. (°)	Long. (°)	Time zone	CZ[1]	HDD[2]	RSI[3] (m^2 K/W)	MI[4]	Rain (mm)	DRWP[5] (Pa, 1/5)
Whitehorse (Yukon)	60.71	-135.07	-8.0	7B	6580	5.26	0.50	170	40
Vancouver (Btitish Columbia)	49.19	-123.18	-8.0	4	2800	3.45	1.20	1070	160
Calgary (Alberta)	51.11	-114.02	-7.0	7A	5000	4.65	0.40	325	220
Saskatoon (Saskatchewan)	52.17	-106.70	-6.0	7A	5700	4.65	0.40	265	160
Winnipeg (Manitoba)	49.91	-97.24	-6.0	7A	5670	4.65	0.60	415	180
Toronto (Ontario)[6]	43.63	-79.39	-5.0	5	3520	3.77	0.90	720	160
Ottawa (Ontario)	45.32	-75.67	-5.0	6	4500	4.17	0.80	750	160
Montreal (Quebec)[7]	45.47	-73.74	-5.0	6	4400	4.17	0.90	760	180
Moncton (New Brunswick)	46.11	-64.68	-4.0	6	4680	4.17	1.00	850	220
Charlottetown (Price Edward Island)	46.29	-63.12	-4.0	6	4460	4.17	1.10	900	350
Halifax (Nova Scotia)	44.88	-63.51	-4.0	6	4000	4.17	1.50	1350	280
St. John's (Newfoundland and Labrador)	47.62	-52.75	-4.0	6	4800	4.17	1.40	1200	400

[1]CZ: climate zone; [2]HDD: Heating Degree-Days; [3]RSI: thermal resistance (m^2K/W); [4]MI: moisture index; [5]DRWP: driving rain wind pressure; [6]City center; [7]Dorval airport.

2.2 Climate Data

The climate datasets used in this study were retrieved from a large ensemble of modelled data developed by Gaur et al. (2019). They comprised hourly time-series of climatic variables necessary to undertake hygrothermal simulations for a baseline period spanning 1986–2016, and future periods when global warming levels of 2 ºC and 3.5 ºC (with reference to the baseline period) are expected in the future. The datasets were generated in such a way as to capture the effects of the internal variability of the climate model for future projections in fifteen hourly realizations (also referred to as “runs”) that are part of the datasets derived from the large ensemble of climates simulated by the Canadian Regional Climate Model (CanRCM4) – version 4. Each of the fifteen hourly realizations was initialized under a different set of initial conditions in the Canadian Earth System Model (CanESM2) under historical and Representative Concentration Pathway 8.5 (RCP8.5) greenhouse gas emission scenario. The RCP8.5 is a high GHG emission scenario with a radiative forcing of 8.5 W/m^2 by the end of the 21st century, compared to the pre-industrial level, and is accepted as an appropriate scenario for business-as-usual and non-climate policy conditions (IPCC 2014). Under this condition, a global warming of 2.0 ºC is expected to occur between 2034 and 2064 whereas a global warming of 3.5 ºC is expected between 2062 and 2092. A detailed description of the procedure used to generate modelled historical and projected future climate data can be found in Gaur et al. (2019).

For this study, only the 31-year historical (H: 1986-2016) and future period corresponding to a global warming of 3.5 °C (F: 2062-2092) were considered for developing and validating the PLS model for a tall wood building wall assembly. Figure 1 shows the distribution of the 15 x 31 annual averages or sums of some of the climate variables for both historical and future periods in the 12 cities considered.

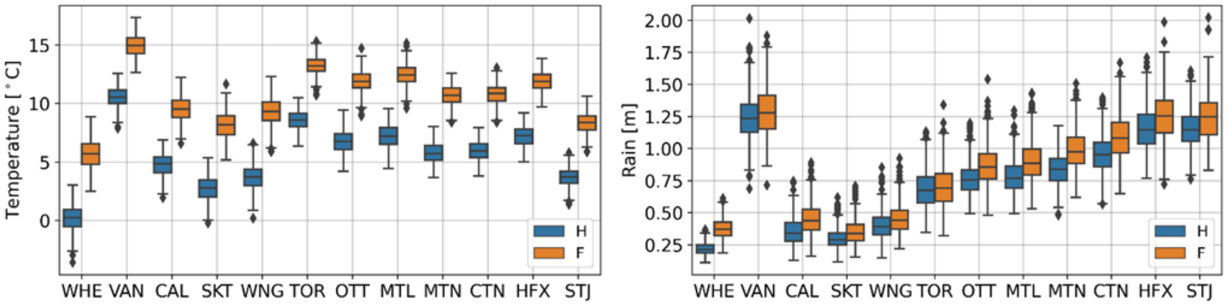

Figure 1. Boxplots of the yearly averages of temperature and yearly sums of horizontal rain for historical (H) and future (F) time-periods in the 12 cities studied, where WHE, VAN, CAL, SKT, WNG, TOR, OTT, MTL, MTN, CTN, HFX, and STJ correspond to Whitehorse, Vancouver, Calgary, Saskatoon, Winnipeg, Toronto, Ottawa, Montreal, Moncton, Charlottetown, Halifax and St. John's.

2.3 Building and Wall Assembly

A 13-story (~41 m) tall wood building assumed located in the city center and having a flat roof was considered for this study. The mass timber wall assembly was supposed to be a non-load-bearing wall, composed of, from exterior to interior: (1) 7.9-mm fibre cement board cladding, (2) 19-mm wood furring/drainage cavity, (3) mineral fibre insulation, (4) sheathing membrane (spun bonded polyolefin, 0.15 mm), (5) 3-layer cross-laminated timber (CLT) made of spruce, (6) air cavity (50 mm) and (7) 15.9-mm type X interior grade gypsum board with latex primer and one coat of latex paint. The insulation thickness varied in respect to climate zone in which the building was located. For climate zones 4 (Vancouver), 5 (Toronto), 6 (Ottawa, Montreal, Moncton, Charlottetown, Halifax and St. John's), (Calgary, Saskatoon and Winnipeg) and 7B (Whitehorse), the minimum thermal resistance value (RSI), as recommended by the National Energy Code for Buildings (NEBC 2020) for above-grade opaque walls is 3.45, 3.77, 4.17, 4.65 and 5.26 m^2K/W, respectively. To meet this minimum requirement, a 2.5-in. (64 mm), 3.0-in. (76 mm), 3.5-in. (89 mm) and 4.5-in. (114 mm) layer of mineral fibre was used as insulation for climate zones 4, 5, 6, and 7A and 7B, respectively.

2.4 Hygrothermal Simulations

Data used to train and validate the PLS models were generated using hygrothermal simulations. They were performed using DELPHIN (https://bauklimatik-dresden.de/delphin/index.php) v5.9 in a one-dimensional configuration on a portion of the vertical cross-section of the opaque wall passing through the middle of the drainage cavity, *i.e.*, not including the furring. In this position in the wall, the heat and mass flows are almost unidirectional and can be represented by a one-dimensional model configuration.

To achieve the objectives of this study, two climate realizations were randomly selected from each of the two selected scenarios for each city considered in this study. Hygrothermal simulations were then performed separately for each of the 31 years of each climate realization for a total of 1448 simulations, assuming a water penetration rate of 1%; the infiltrated water was deposited on the outer layer of the sheathing membrane within the wall assembly. The wall orientation in each case was that receiving the highest amount of wind-driven rain. The simulation for each year was repeated 5 times: the first four repeats were considered as conditioning years and the last repeat was used for analysis.

Moisture content (MC) was selected as the hygrothermal response to model in this study. The CLT panel is the critical component of the CLT wall assembly in regard to moisture durability. The outer layer of the CLT panel, in contact with the sheathing membrane, is more prone to moisture uptake, and as such, can give rise to the formation of mold or decay in the outer layer. This location (0.5-mm) was selected as the critical location from which to retrieve MC values from simulation results.

2.5 PLS Model Development

2.5.1 Features and target variables

As indicated earlier, simulations were repeated 5 times for each individual year, then the hourly values of the MC (%, dry mass basis) of the outer layer of the CLT panel for the last repeat were averaged and used as the target variable to predict. The potential predictor variables used for this study consisted of the yearly values of the original and derived climate variables. Original climate variables were the annual average values of temperature (T, ºC), relative humidity (RH, %), wind speed (WSPD, m/s), wind direction (WDIR, º from North), Cloudiness (C, %), and the annual sums of horizontal rain (RH, mm) and global solar radiation (GR, W/m^2). Climate-derived variables included the values of moisture index (MI); the annual average vapor pressure (Pv, Pa); and the annual sum of drying index (DI, $kg_{vapor}/kg_{dry\ air}$), wind-driven rain (WDR, kg/m^2), free field wind-driven rain (FWDR, m^2/s) and global solar radiation normal to the wall (GRN, W/m^2).

2.5.2 Model development and evaluation

To address the research questions, several models were developed as shown in Table 2. For each of the models, one realization of climate data was randomly selected and included in the training set whereas another one was included in the test set. It was undertaken in this way because the final intent was to predict and rank moisture severity of individual years for a 31-year series of climate data. Otherwise, the samples for training and validation sets would have been randomly selected.

Table 2. Summary of the number of models developed

Model name	Number of models	Number of cities included in the model	Number of time periods	Climate realization	Number of samples		
					Total	Training set	Test set
Global model	1	12	2	2	1448	744	744
Time-period model	2	12	1	2	744	372	372
City-level model	12	1	1	2	62	31	31

For this study, the Nonlinear Iterative Partial Least Squares (NIPALS) algorithm (Geladi and Kowalski 1986) was used. The package PLS (Mevik and Wehrens 2021) in R (R Core Team 2021) was used to perform the analysis. Martens Uncertainty test (Martens and Martens

2000) implemented in that PLS package was used to select the most contributing variables, based on the percentage of variance explained in the target variable. Before developing each model, data was preprocessed by median centering with interquartile range (IQR) scaling, *i.e.*, for each feature, the median value was removed from each observation, then the resulting value was divided by the IQR. The same parameters for transforming the training data, *i.e.*, the median and IQR values, were used to transform the test set data. Given the relatively small size of the training sets, the leave-one-out cross-validation was used to find the optimal number of PLS components to retain in the model.

All developed models were used to predict MC and rank the individual years of the 31-year series of climate realization of the test set for each city. For evaluating the predictive ability of the models, the metrics used were the coefficient of determination (R^2) and the root mean square error (RMSE) of prediction. For ranking, the Spearman's rank correlation (ρ) was used to compare their ability to rank all 31 years of a series, and the number of similar top 5 and 10 worst years identified by the models and from hygrothermal simulations. It should be noted this last performance metric does not take into account the position of the years amongst the top 5 or 10. The non-parametric Mann-Whitney U test (Mann and Whitney 1947) was used to compare the median values of each score over the 12 cities considered.

3 Results and Discussion

3.1 Comparison of Time-period (Future) Level Model *versus* City-level Models

Table 3 shows prediction and ranking performance scores obtained using the model developed for historical period and those developed for individual cities. R^2 values were generally good (>0.80) for all the cities, to the exception of Charlottetown where the city-level model has a R^2 of 0.40. However, the result of the Mann-Whitney U test showed that the median values of R^2 for the two categories of models over all the cities are not significantly different (*$U = 57.5$, $p = 0.42$, two-tailed*). The RMSE of prediction varied from 0.24 (Saskatoon) to 1.04 (Toronto) for the future model whereas for city-level models, it varied from 0.13 (Whitehorse) to 0.73 (Charlottetown). The Mann-Whitney U test (*$U = 30.5$, $p = 0.02$*, *two-tailed*) showed that the city-level models had significantly lower RMSE (median = 0.26) than future period model (median = 0.54). This indicates that to predict MC with a better accuracy, city-level models could be recommended. The ranking scores (ρ, Top5 and Top10) were generally similar for both categories of models even if the median value of the city-level models (9.0) seems greater than that obtained with the historical period model (8.5). Similar trends were observed when comparing models developed using historical period data to city-level models.

3.2 Comparison of Global Model *versus* Time-period Level Models

Table 4 shows the prediction and ranking scores for each city when using a global model encompassing both historical and future data and the historical model. Prediction and ranking performances were almost the same when using both models even if for depicting the top 5 worse years, the global model tends to depict lower number of years (median = 3.0) than the period-level model (median = 4.0). But, the Mann-Whitney U test for the top 5 years (*$U = 57.5$, $p = 0.38$, two-tailed*) indicated no significant difference for the distribution of the top 5 years from the two models. This trend was confirmed when comparing scores of a global model to those for future period model. Therefore, if time does not permit developing individual city models, a global model would be preferred to period-level models as it requires fewer modelling work.

Table 3. Comparison of prediction and ranking scores of the period-level model (future) to models developed at city level for the future time period (city-level models).

	Period-level model (Future)					City-level models (Future)				
City	R^2	RMSE	ρ	Top5	Top10	R^2	RMSE	ρ	Top5	Top10
Ottawa	0.81	0.83	0.90	4	9	0.96	0.21	0.98	4	10
Vancouver	0.89	0.67	0.94	4	10	0.95	0.27	0.97	4	10
Calgary	0.93	0.28	0.96	4	9	0.88	0.30	0.95	5	9
St. John's	0.84	0.36	0.92	3	8	0.89	0.36	0.94	3	9
Winnipeg	0.88	0.27	0.87	5	6	0.86	0.24	0.87	4	7
Toronto	0.88	1.04	0.94	4	8	0.81	0.37	0.90	3	7
Halifax	0.81	0.78	0.95	4	8	0.81	0.53	0.96	4	9
Montreal	0.90	0.52	0.95	4	9	0.94	0.23	0.97	4	9
Charlottetown	0.80	0.66	0.89	4	8	0.40	0.73	0.63	2	8
Moncton	0.92	0.32	0.90	4	9	0.95	0.25	0.94	5	10
Saskatoon	0.92	0.24	0.95	4	8	0.90	0.23	0.94	4	8
Whitehorse	0.94	0.56	0.97	5	9	0.98	0.13	0.99	5	10
Average	**0.88**	**0.54**	**0.93**	**4.1**	**8.4**	**0.86**	**0.32**	**0.92**	**3.9**	**8.8**
Median	**0.89**	**0.54**	**0.94**	**4.0**	**8.5**	**0.90**	**0.26**	**0.95**	**4.0**	**9.0**

Table 4. Comparison of prediction and ranking scores for each city when using the model developed for both historical and future data (global model) to that developed using data for historical period (period-level model).

	Priod-level model (Historical)					Global model (Historical and future)				
City	R^2	RMSE	ρ	Top5	Top10	R^2	RMSE	ρ	Top5	Top10
Ottawa	0.76	0.51	0.89	4	9	0.56	0.48	0.73	2	7
Vancouver	0.94	0.33	0.96	4	9	0.94	0.38	0.96	4	9
Calgary	0.91	0.65	0.94	5	8	0.9	0.43	0.95	3	8
St. John's	0.74	0.45	0.77	3	7	0.69	0.42	0.85	4	7
Winnipeg	0.65	0.26	0.80	3	7	0.86	0.22	0.90	3	8
Toronto	0.91	0.98	0.96	3	8	0.76	0.70	0.84	3	8
Halifax	0.83	0.60	0.93	4	8	0.73	0.39	0.78	3	6
Montreal	0.81	0.56	0.90	4	7	0.83	0.32	0.83	3	8
Charlottetown	0.83	1.20	0.88	3	7	0.74	0.91	0.85	3	7
Moncton	0.92	0.45	0.97	4	9	0.83	0.29	0.92	5	8
Saskatoon	0.89	0.20	0.91	4	9	0.87	0.26	0.92	4	8
Whitehorse	0.90	0.55	0.92	4	10	0.88	0.47	0.89	5	10
Average	**0.84**	**0.56**	**0.90**	**3.8**	**8.2**	**0.80**	**0.44**	**0.87**	**3.5**	**7.8**
Median	**0.86**	**0.53**	**0.92**	**4.0**	**8.0**	**0.83**	**0.41**	**0.87**	**3.0**	**8.0**

4 Conclusions

Several options for developing PLS models were evaluated in this study. The results suggest that a single PLS model encompassing data for different time periods or GHG emission scenarios could be used for predicting or ranking climate years at the city level without a significant loss of performance when comparing to models developed for each GHG emission scenario. As well, the ranking of climate years using either a period level model or city level models are similar. However, to predict moisture severity with a better accuracy, city-level models would be recommended.

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