Determining the Optimal Spatial Distribution of Weather Station Networks for Hydrological Modeling Purposes Using RCM Datasets: An Experimental Approach

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ABSTRACT

In many hydrological studies, the main limiting factor in model performance is the low meteorological data quality. In some cases, no meteorological records even exist. Installing weather stations becomes a necessity in these areas when water resource management becomes an issue. The objective of this study is to propose a new experimental and exploratory method for determining the optimal density of a weather station network when being used for long-term hydrological modeling. Data from the Canadian Regional Climate Model at 15-km resolution (CRCM15) were used to create a virtual network of stations with long and complete series of meteorological data over the Toulnustouc River basin in central Québec, Canada. The weather stations to be fed to HSAMI, Hydro-Québec’s lumped rainfall–runoff hydrological model, were selected in order to minimize the number of stations while maintaining the best hydrological performance possible using a multi-objective optimization algorithm. It was shown that the number of stations making up the network on the Toulnustouc River basin should be at least two but not higher than four. If the stations are positioned optimally, there is little to no gain to be made with a denser network. The optimization algorithm clearly identified that combinations of two or three stations can result in better hydrological performance than if a high-density network was fed to the model. Thus, the major conclusion of this study is that if weather stations are positioned at optimal locations, a very few number of them are required to model runoff with as good as or better performance than when a high-density network is used.

1. Introduction

Weather station network design has been the subject of great interest in the past. Many applications depend on reliable and precise measurements of temperature, precipitation, and other meteorological phenomena. For example, from an engineering point of view, long-term hydrological modeling is a necessary step to optimize reservoir management procedures and predict flood and drought frequency and intensity. This modeling requires inputs of sufficient quality to reduce uncertainty in the prediction chain. One way to increase hydrological model performance is to add stations in the catchment area. The World Meteorological Organization (WMO) claims the density of rain gauges should be in the 250–575 km² per station range for mountainous and hill-and-valley-type terrains, but it does not propose a method to identify ideal locations for stations. For the most part, weather stations are installed in locations that are easy to reach and where installation costs are lower. However, this can lead to a bias in the homogeneity of the network. It is imperative that the location of the new stations be chosen wisely to get the most efficient network possible.

Many studies have focused on this problem. The most common methods consist of using geostatistic methods such as kriging to find areas of high-variance estimation of rainfall on the catchment. By placing stations in the higher-variance areas as defined through the kriging process, the overall variance in precipitation, for example, is reduced (Bastin et al. 1984; Creutin et al. 1988; Amani and Lebel 1997; Pardo-Iguzquiza 1998; St-Hilaire et al. 2003). By minimizing the overall variance in rainfall estimation, these methods are able to considerably improve an existing network. It has also been proven...
that using variance-reducing techniques contributes to improving hydrological forecasting of short, intense rainfall events (Cheng et al. 2008). They have also been used in long-term forecasting, such as in St-Hilaire et al. (2003). However, these methods have two drawbacks. First, parameters must be estimated when variograms and correlograms are used, and second, the methods require that a network of stations already exist on the catchment. In sparsely populated areas such as northern Canada, this condition is often not met.

Other methods have been proposed to evaluate the performance of an existing network and to decide which stations should be removed during a rationalization effort. Methods using a “leave one out” approach to isolate superfluous stations are common, and geostatistics are used to find the areas where the variance is reduced as much as possible in this scenario. These methods also require that a network already be in place (Burn and Goulter 1991; Ouarda et al. 1996).

A reverse of this method has been proposed by Schneebeli and Laternser (2004). Their approach was to build an atlas of all recorded snow precipitation from 107 manual snow measurements in a catchment in Switzerland. They calculated the probability of snowfall by location and assigned a ranking order to each region. While this method is promising for areas with long time series of recorded data, it is impossible to use on basins with low spatial coverage of meteorological events.

An interesting approach to the problem has been to use experimental watersheds to conduct hydrological studies (Osborn and Keppel 1965; Osborn et al. 1972). These watersheds, usually of small size (generally less than 1000 km²), are peppered with many stations to capture a maximum amount of meteorological information (Amatya and Trettin 2007). However, experimental watersheds are seldom used to determine optimal network design; rather, they are used to gain insight on hydrological processes on a catchment scale. These usually very costly experimental watersheds are used, for example, to study the effects of urbanization on surface runoff and agriculture on soil erosion (Burns 1965; Schneider-Vieira 1993; Cafferata and Spittler 1998). This method could provide very useful information on optimal meteorological network design under certain conditions. However, the information would only be useful for the particular basin. For other basins, temporary stations would have to be used to find the optimal design, which implies other financial drawbacks.

This study proposes a method for finding the optimal density of meteorological stations in a long-term hydrological modeling perspective when no prior information is available, which has not been looked into as of now. To do so, the Canadian Regional Climate Model with a 15-km resolution (CRCM15) driven by 40-yr European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA-40) data at its boundaries was used to simulate meteorological stations on an experimental watershed. While regional climate model (RCM) data have oftentimes been fed directly into hydrological models for impact studies, they have never been used to study the impact of network density. The main reason for this is that the RCM resolution was too coarse until now. At 15- km resolution, however, the RCM grid points are close enough to allow for good representation of hydrological processes at the catchment scale (Tramblay et al. 2013). The approach discussed in this paper uses this new information to observe the impacts of meteorological station network density on hydrological modeling performance.

2. Data and methodology

The experiment was performed on the Toulnoustouc River basin in central Québec, Canada, shown in Fig. 1. The basin has an area of 8109 km² and its landscape is hilly to mountainous. It has very few inhabitants and a very sparse meteorological record. Only five stations have ever existed, and they were all short lived (two recorded for 4 yr, one for 2 yr, and the remaining two for less than 1 yr). In addition, they only recorded during the summer. The network is therefore inadequate in a timely and spatial manner. The Toulnoustouc River basin is now used for hydropower generation, and a better understanding of the hydrometeorological processes would be an added benefit for the reservoir management rule optimization processes. The discharge is measured by a single gauging station near the basin outlet.

The main problem encountered in this study was the need for a reference knowledge base to which the different hydrological simulations could be compared. Since this is impossible in practice, a virtual world was built using the CRCCM15. Each of the grid points inside the basin boundary was considered to be a meteorological station, for a total of 39 stations. Since the CRCCM simulates all meteorological variables with physical laws of energy and mass conservation, every meteorological process could be monitored through the high density “virtual station network” (Music and Caya 2007; Music et al. 2009). Succinctly, the CRCCM uses energy conservation laws to predict the energy levels in the atmosphere and hydrosphere and then uses mass balance equations to split precipitation into rain or snow to compute how much infiltration and evapotranspiration is generated because of the land cover and how much runoff is produced. Every variable pertaining to any of the physical processes required to run a climate model is
generated and archived, and these variables preserve mass and energy balance throughout the simulation. However, the discharge values simulated by the hydrological model when using the CRCM climate datasets cannot be compared to real-world observed discharge. Biases in the climate model and boundary layer forcing make it impossible to directly correlate CRCM precipitation to observed discharge. For instance, the boundary forcing is based on reanalysis data (which should reflect real-world data quite well) but only at the boundary. The climate model then resolves its numerical equations to fill in the grid over the entire simulation domain. This acts as a filter that removes any day-to-day similarity with the real world over the same region. In addition, while the CRCM is deemed a high-resolution model in the world of climate models, this resolution is nevertheless inadequate at representing the detailed spatial variability of elevation and physiographic reality of the watershed. To counteract this caveat, the methodology made use of the CRCM15’s ability to generate runoff values for the simulation tiles for surface and subsurface water budgets through the Canadian Land Surface Scheme (CLASS), version 2.7 (Verseghy 1991). These runoffs are limited to each tile, and CLASS simply removes them from the model after each time step instead of routing them to a river or outlet. Therefore, a routing scheme based on surface and subsurface unit hydrographs was used to produce river flows at the basin exit. Three unit hydrographs for surface runoff as well as three other unit hydrographs for subsurface runoff were created. The parameters controlling the peak times and shape of the hydrographs were calibrated so the average yearly reconstructed hydrograph would resemble, as closely as possible, the observed hydrograph. This routing was necessary to produce a river discharge time series to use as a reference flow. Therefore, the newly created CRCM flow was used as the now-coherent historic observed discharge.

The hydrological simulations were performed through the HSAMI model (Bisson and Roberge 1983; Fortin 2000; Minville et al. 2008; Arsenault et al. 2013). HSAMI is a lumped conceptual rainfall–runoff model used operationally by Hydro-Québec. It requires only daily maximum and minimum temperature as well as precipitation data. It has 23 parameters that are calibrated internally when observed discharge is fed to the model. Its internal structure is reservoir based, and it simulates the main steps related to water balance, such as evapotranspiration, snowmelt, infiltration, soil freezing, and runoff. The HSAMI model was preferred because of its very short execution time, performing a full 25,000-simulation calibration in just under 40 s on our computers.

The internal calibration process is based on maximizing the Nash–Sutcliffe efficiency (NSE) value, which
is arguably the most used efficiency measure in hydrology. It is computed as

\[
\text{NSE} = \left\{ \frac{\sum_{t=1}^{T} (Q_o^t - Q_m^t)^2}{\sum_{t=1}^{T} (Q_o^t - \bar{Q}_o)^2} \right\}^{1/2},
\]

where \( T \) is the number of time steps, \( Q_o^t \) is observed discharge at time \( t \), and \( Q_m^t \) is simulated discharge at time \( t \). The NSE can hold values between \(-\infty \) and 1 inclusively, where 1 is a perfect match between both flow time series. A value of 0 would be found if the simulated flow were set as a constant equal to the mean of the observed discharge. Many more objective functions exist, such as RMSE and \( R^2 \), but the fact that the model is used operationally with NSE as the objective function warrants its use in this study. The high computational cost of this project did not allow redoing the entire project with other calibration metrics.

The HSAMI model was calibrated independently using all 39 stations, giving a benchmark NSE to which to compare the results. This step allows a better understanding of the effect of network density on hydrological performance.

A multi-objective genetic algorithm approach was utilized to determine the optimal number of stations to be used on the Toulmoustouc River basin using the Nondominated Sorting Genetic Algorithm II (NSGA-II; Deb 2001). The first objective was to minimize the number of stations used during the calibration of HSAMI, and the second objective was to minimize the error between the flow simulated by the hydrological model and the CRCM flow. The output of the multi-objective optimization algorithm is a series of parameter sets that minimize both objectives simultaneously. These solutions cannot be improved upon in either objective without worsening the other objective. For a detailed description of the Pareto front concept, readers are encouraged to see Deb (2001). In this study, each solution in the Pareto front consists of weather station combinations forming the network used to generate the average climate data fed to the HSAMI model for calibration. By repeatedly calibrating HSAMI with different virtual weather station combinations using the NSGA-II, it was possible to determine which ones were most often present on the Pareto front and in the next few following fronts. To verify the convergence of the algorithm, these Pareto-optimal station sets were then compared to randomly selected sets with the same number of stations. The comparison was made in both calibration and validation. A Wilcoxon rank sum test (Wilcoxon 1945) was used to statistically measure significance between the two groups.

3. Results

This section discusses the results obtained during the various experiments undertaken in this study. The routing scheme, model calibration, and multi-objective optimization results are presented here.

a. Routing and model calibration

The CRCM flows were calibrated over the observed flows for the entire available period, which was 1966–2000. However, since the meteorology is not the same in the real world as it is in the CRCM world, there is no chance that both hydrographs would ever have the same day-to-day behavior. This is not a problem for this study: all that is required is a flow that resembles the general pattern of what is observed in reality. For this reason, the routing schemes’ seven parameters (three for the surface unit hydrographs’ peak times, three for the subsurface hydrographs’ peak times, and a unique and common shape factor) were calibrated on the mean interannual daily flow (Fig. 2). Furthermore, this flow is based on the CRCM meteorology, which limits the discrepancies between observed meteorology and observed discharge.

The CRCM flow was validated with HSAMI to determine if the model could handle the reconstructed discharge. The simulated hydrograph and the CRCM flows are shown in Fig. 3.

During calibration (1961–75), the NSE was computed at 0.9223. As for validation (1976–2000), the NSE dropped slightly to 0.9122. This small drop between calibration and validation NSE shows that the model was adequately calibrated, and as a result, that the CRCM flows are usable by HSAMI. Furthermore, when

![Observed and CRCM reconstructed yearly average discharge](image-url)
the model was calibrated with real data (meteorological and hydrometric) for the years 1976–2000, the NSE value was significantly lower at 0.847. This is still a good NSE value, but it is still much lower than the 0.9122 obtained in validation using the CRCM data during that same period. This shows that the reconstructed discharge is extremely consistent with the CRCM precipitation and temperature data.

b. Multi-objective optimization approach

The use of the multi-objective optimization method to determine the optimal density of the weather network could only be performed with the HSAMI model or another very fast model. In fact, two other models were enlisted for this study but the sheer number of calibrations required quickly eliminated all but the fastest model. This aspect will be discussed later, but for illustrative purposes, literally billions of model evaluations were made during the multiobjective calibration process.

TESTING CALIBRATION PERFORMANCE WITH RANDOM STATION COMBINATIONS

Figure 4 shows the NSE values for calibration when different combinations of stations were used. The Pareto front in Fig. 4 (illustrated by the circles) is the result of the multi-objective optimization process. For each number of stations per combination (y axis), the x symbols in Fig. 4 show the distribution of NSE values obtained from 1000 individual optimization runs. These combinations are selected at random. There are exceptions for combinations of 1, 2, 37, 38, and 39 stations, in which case all possible combinations were selected because the relatively small number of possible combinations allowed it. The square represents the NSE value when all stations are selected and is considered as the baseline in this case. It is important to note that the calibration algorithm was run with a fixed initial seed (random starting point for the stochastic optimization algorithm) for maintaining the problem structure during multi-objective optimization. This was done to make sure that the algorithm would find the same results when running the same parameters. The problem structure is thus fixed. The boxplot superimposed on the 39-station marker shows the NSE distribution when all stations are used and seeds are random during 100 calibration runs.

It can be seen that there are many combinations with considerably less stations that perform just as well as, and sometimes even better, than with all 39 stations, especially when the network is optimized as such. However, it should also be noted that the risk of producing a lower-quality network is higher when fewer stations are used. The multi-objective approach, on the other hand, found both of the optimal combinations for one and two stations and also beat the random combinations of three and four stations. The algorithm found solutions that were consistently better than the random selections for combinations of 5–15 stations, but these were slightly worse than the four-station Pareto-optimal solution.

c. Station locations for varying number of stations in the network

The optimal station sets were plotted on the catchment map for densities ranging from one to five stations, as can be seen in Fig. 5. It can be seen that stations 12 and
34 are found in three optimal sets. Also, stations 3 and 27 appear twice in the optimal sets. The five-station optimal value was slightly inferior to the four-station one; thus, it does not appear in the Pareto front in Fig. 4. It was left in place, however, to show the continuity between the optimal station sets.

d. Validation

Validation of the method was verified by comparing the hydrological models’ performance using the Pareto-optimal stations to randomly generated station sets of the same size. For example, the best 4-station set was compared to randomly generated groups of 4 stations. Calibration was performed on the first 15 yr and validation on the last 25 yr. In each case, the Pareto-optimal station set was used to calibrate the HSAMI model 50 times while leaving the initial seed random. This allowed for testing of the results in a noncontrolled and nonbiased environment. Afterward, 50 randomly generated station sets were calibrated and validated under the same conditions.
conditions. The hypothesis underlined here is that the best stations should outperform the randomly selected stations in calibration and validation.

The validation tests were carried out for station set sizes ranging from one to five stations since the Pareto front ceased at four stations, with the fifth station being very similar to the four-station value. A Wilcoxon rank sum test was used to verify that the groups (best versus random) come from distributions with equal medians. Table 1 shows the validation results.

In all cases, the best station combination outperforms the random station performance. While the actual NSE value differences may seem insignificant, in this particular context, they represent quite an achievement, as will be discussed later.

4. Analysis and discussion

Traditionally, hydrologists have thought that a denser weather observation network would provide more and better information for modeling purposes. This study’s results show that it is not only possible to maintain good model performance for long-term modeling with fewer stations, but in some cases, better performance can be seen as well when the appropriate stations are used. Many important factors can contribute to the results seen in this study. This discussion is about these factors as well as possible ways to render the results useful in the real world.

a. Routing

The routing method was relatively simple. By separating the basin into three areas of approximately the same size, a good distribution was achieved through the routing scheme. Of course, the parameters were calibrated on mean daily discharge to mimic the annual flow regime, which would add uncertainty to the results. However, this is not an important point in this study as the CRCM flows are accepted as being the reference flows. Even if they had been slightly different, the main results still would have reflected the same effects of network density on model performance. Furthermore, the fact that the hydrograph is directly correlated to the CRCM meteorology through its land surface scheme provides a relatively safe base to perform this type of research. Many of the uncertainties related to measuring biases for weather and hydrometric stations are non-existent, compared to up to 25% for real-world hydro-metric stations (Di Baldassarre and Montanari 2009). This was shown by using these data in HSAMI and assessing its much higher performance than when observed data for the same period were fed to the model.

Figure 2 clearly shows the similarities between observed and CRCM flows. The mean daily hydrographs share similar peak times and peak flows, as well as their general aspect, minus the winter base flow, which can be attributed to the differing soil characteristics between the real world and the CRCM. The curves’ amplitudes need not be identical since rainfall and runoff are not necessarily the same.

An experiment was performed to determine the effect of the routing scheme on overall results. Instead of separating the basin into three zones, it was separated into 10 zones, and 20 unit hydrographs were therefore required: 10 for surface runoff and 10 for subsurface runoff. The resulting flow was calibrated once more on the observed annually averaged daily flow. When the hydrograph was produced for the 1961–2000 period with the three-zone and 10-zone routing scheme, the results were very clear: the parameter calibration process for the routing scheme was able to perform equally well, as the NSE of this simulation is 0.9938, which indicates near perfection. This should not affect the results in such a manner that the final ranking of selected stations would be different.

b. Multi-objective optimization

The multi-objective genetic algorithm (MOGA) was used to find solutions that answered both constraints in this research: minimize the error function and minimize the number of stations. The use of this tool was necessary to speed up the already very time-consuming process of calibrating the HSAMI model repeatedly. The semi-intelligent method coded in the algorithm allows

<table>
<thead>
<tr>
<th>No. of stations</th>
<th>Calibration (NSE)</th>
<th>Validation (NSE)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Optimal</td>
<td>Random</td>
</tr>
<tr>
<td>1</td>
<td>0.8918</td>
<td>0.8759</td>
</tr>
<tr>
<td>2</td>
<td>0.9001</td>
<td>0.8906</td>
</tr>
<tr>
<td>3</td>
<td>0.9048</td>
<td>0.8884</td>
</tr>
<tr>
<td>4</td>
<td>0.9028</td>
<td>0.8918</td>
</tr>
<tr>
<td>5</td>
<td>0.9054</td>
<td>0.8916</td>
</tr>
</tbody>
</table>
converging on the Pareto front without having to test all combinations one by one, which would not be feasible even with modern-day computers. Each optimization run had to calibrate HSAMI at least 24000 times and each HSAMI calibration was limited to 25000 model simulations. Even with HSAMI’s speed and the MOGA’s effectiveness, approximately 10 days of intensive computing were required for each of the 12 optimization runs performed throughout this project. In total, more than 6.5 billion HSAMI simulations were launched during testing. This means time constraints would be an issue with distributed models [Soil and Water Assessment Tool (SWAT; Neitsch et al. 2002) and Hydrotel (Fortin et al. 2001), for example], where each model simulation can be four to five orders of magnitude longer than for HSAMI. The process was initially planned with the Hydrotel distributed model but was dismissed because of the roughly 250000 yr it would have taken to perform the same steps on modern computers.

One of the disadvantages of multi-objective optimization algorithms is that they cannot tolerate randomness inside the objective function. For example, when HSAMI is calibrated with five stations, it may return an NSE of 0.92. If, later on, the optimizer again feeds the same five stations to HSAMI, it must return the same NSE of 0.92. For this to occur, HSAMI’s internal calibration module was modified for it to always start with the same number rather than issue one from a random number generator. This means the study was based on a single seed for calibration. Tests with a different seed for a single period showed the same tendency to converge to smaller networks. The results can therefore be assumed to follow the same pattern for different seeds. Furthermore, the validation aspect discussed in section 3d eliminates any leftover doubt concerning the predictive power of this proposed method.

c. Model performance increase

As will be seen in section 3d, the NSE values are quite similar whether using three or 39 stations or whether using optimal or random station sets. Yet what seems at first as a marginal gain (0.01–0.02) in the NSE metric is actually an impressive gain compared to reference values. The main reason why this is the case is that the model is performing in a controlled environment and is showing very good performance to begin with. To improve on the already excellent model is much more difficult than to improve on a model that performs weakly. In the real world, many uncertainties and biases (station related or not) affect the model results, which results in a larger error during calibration and validation. These types of errors are nonexistent in the current project framework, as the virtual laboratory it is conducted in removes these uncertainties in the first place. Some uncertainty remains in the virtual outflows, but a large part of the possible model improvement due to climate uncertainty is removed in the virtual world.

Consequently, the NSE values obtained in calibration and validation are more difficult to increase than in a real-world model and, given the level of performance obtained, more difficult to improve compared to a model whose performance is poor on a given catchment.

d. General discussion

The results obtained speak largely for themselves. They clearly show that a complete coverage of the basin with weather stations is not necessary for flow modeling and may in fact lead to worse hydrological model performance for lumped models. The multiple Pareto fronts show that this is the case under many different conditions. However, the right stations must be selected for this to occur. Figure 4 clearly shows the phenomenon: there are many combinations of three or four stations that yield the same performance than when all 39 stations are used. On the other hand, from this figure it is also clear that the more stations are present, the more the HSAMI model converges to the reference NSE. This entails that if few stations are selected at random, there are greater chances of them generating worse performance than the reference NSE.

Another important aspect of this paper is the temporal scale used. The aim of this study was to determine the optimum network density for long-term model performance. No effort was made to determine the effects of the network on shorter time scales. It could be argued that summer rainfall and thundershowers would be better represented by a very dense network because of their short duration and small areal coverage, but this premise has not been tested. Nevertheless, these storms are simulated by the CRCM and they are present in the weather stations. The associated CRCM runoff is also affected by these storms. Thunderstorms are therefore part of the objective function used and are considered during the calibration processes, granted they do not weigh as much as the spring flood events in the NSE computation.

It is important to restate the fact that the results obtained are valid only inside the virtual world for the moment. For it to be transferable to the real world, the experiment would have to be done on a dense network that has a resolution as fine as the RCM to test the similarity between observations and RCM data. No catchment on the CRCM15 grid has a density high enough to perform this validation. However, the main observation regarding good modeling performance with fewer stations can be transposed in the real world since
the datasets, methodology, and modeling steps are all the similar as to what is normally done in the real world. The validation step showed that the method works well in the virtual world, and so the concept should hold for applications in the real world.

e. What is the optimal network density for hydrological modeling purposes?

The aim of this project was to determine the optimal weather station network density for hydrological modeling purposes. This study shows that it is possible to use a relatively small number of stations while preserving good hydrological performance and even better than what would be expected with the use of all available stations. It was also shown that it would be conceivable to use two or three stations, but that four or five would be optimal on the Toulnustouc River basin. This amounts to a network density of 1600–4000 km² per station. The World Meteorological Organization (2008) suggests a density of 250–575 km² per station, which equates to anywhere between 14 and 33 stations on this particular basin. Depending on their type, size, and characteristics, other catchments could have very different optimal network densities.

As was shown in Fig. 5, some of the stations were part of the optimal set for varying set sizes. The reason why these stations were selected and not others can be explained by a few contextual factors. First, the stations near the mountains in the northern and eastern parts of the catchment are located in the areas with the most day-to-day variability in precipitation. The orographic effects can cause the optimization algorithm to select these sites as they allow the hydrological model to better simulate the hydrologic response to these precipitation events. Second, stations such as numbers 3 and 12 are located in a relatively homogeneous area that is representative of the rest of the catchment. Having these stations included in the optimal set allows the model to make use of the average precipitation they record. Because of their similarity to much of the catchment, there is little gain to be made by adding many stations in similar areas, especially when modeling long-term flows.

It was also shown that new stations should be installed on the catchment because of the lacking spatial and temporal coverage of the existing network. This study shows where these stations could be located, based on Fig. 5, in order to optimize performance instead of installing them randomly, as is the case nowadays. Of course, in the virtual world, there are no constraints on selecting a location for installing a rain gauge, whereas in the real world, important constraints exist, such as easy access for installation and maintenance as well as the presence of transmission lines for both power and data transfer. While it is technically possible to install a station in a totally remote location, this is essentially never done because of budgetary and logistic constraints.

Finally, it was exposed that the NSE variance in calibration becomes increasingly smaller when stations are added (see Fig. 4). This illustrates the already-known fact that increasing the number of stations improves the accuracy of the rainfall estimation. Adding more stations at random will increase performance to a certain extent, but this approach requires adding costly stations to increase performance. The method proposed in this study eliminates the need to install many stations by simply reorganizing the network design. Of course, methods to transpose results from the virtual world to the real world will require further research. The proof of concept made herein, based on a reanalysis-driven RCM, should mimic the behavior of the real basin quite well.

5. Conclusions

This study proposed and tested a method to determine the optimal number and location of weather stations composing an observational network on the Toulnustouc River basin in Québec, Canada, for hydrological modeling purposes. By using CRCM15 datasets, it was possible to create a data-rich world that acted as a perfect, error-free, and dense meteorological observation network. It was shown that the optimal range would be in the area of 1600–4000 km² per station. The location of these stations was linked to the stations that showed the best performance under model calibration.

It was also shown that a denser network is preferable if stations are to be placed randomly. However, because of evident financial drawbacks that this would incur, it would be advisable to install stations in such a way that information loss is minimal and model performance is conserved, all the while reducing the number of actual stations. The method proposed in this study is an experimental approach toward accomplishing this in the real world.

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