Value of accurate urban weather prediction in the day-ahead energy market

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ABSTRACT: Hot temperatures drive excessive energy use for space-cooling in built environments. In a building, a system operator could save costs by making better decisions under the uncertainties associated with urban temperature and future energy demands. In this paper, we assess the impact of urban weather modeling on energy cost, using a value of information (VoI) analysis, in a day-ahead (DA) electricity market. To do that, we combine two probabilistic models: (a) a model for forecasting urban temperature and (b) a model for forecasting hourly net electric load of a building given ambient urban temperature. We then quantify the impact of better urban weather modeling by propagating the uncertainty from the temperature model to the load forecasting model. We perform a numerical case study on residential building prototypes located in the city of Pittsburgh. The result indicates that using a better weather model could save 4.34-8.22% of the electricity costs for space-cooling.

1. INTRODUCTION

According to the annual report of the U.S. Energy Information Administration (EIA), in 2021 cooling of residential and commercial buildings used approximately 10% of the entire national electricity consumption of the US (U.S. Energy Information Administration). As a building interacts with ambient environments, better modeling of ambient environments, specifically of urban temperature, could save energy costs in built environments. For example, the authors of Chen et al. (2019) showed that a model predictive control scheme could help saving energy use when they consider ambient weather information as a predictor for the thermostatic status of a building. In the work of Chen et al. (2020), a machine learning model used weather variables to estimate energy demands and renewable energy generation to better control the thermostatic behavior of buildings in response to power grid conditions. Using information about future weather, therefore, could help saving energy costs and making better decisions.

In 1960, Nelson and Winter Jr (1960) conducted case studies illustrating that the quality of economic decisions could be improved by enhancing the quality of weather forecasts. After that work, several others quantified the value of weather information, related to economic decision-making (Steinker et al. (2017); Badorf and Hoberg (2020); Turner et al. (2021)).

In this paper, we propose an analysis method that quantifies the impact of accurate urban temperature modeling on decision-making, related to building energy systems, based on the Value of Information (VoI). The Value of Information (VoI) assesses the economic benefit of information in decision-making under uncertainty (Pozzi and Der Kiureghian (2011); Li and Pozzi (2019)). Based on information theory (Howard (1966)), the framework has been used in a variety of fields, such as finance (Poh (2000)), industrial management (Keisler and Brodfuehrer (2009)), manufacturing (Yokota and Thompson (2004)), structural health monitoring (Pozzi and Der Kiureghian (2011); Straub (2014); Zonta et al. (2014); Memarzadeh and Pozzi (2016); Li and Pozzi (2019)), sensor placement (Malings et al. (2018)), and information prioritization (Lin et al. (2022)).

This paper applies the VoI analysis to a day-ahead (DA) market for a single building. The case study exploits two forecasting models: one for ambient air temperature forecasts in an urban area and another for forecasts of electricity demand in a single building under a given temperature scenario. We consider urban temperature as a representative weather variable to estimate the electricity demand of a building (Singh et al. (2012); Yang et al. (2018); Burillo et al. (2019)). By coupling the models, the method propagates the uncertainty in urban temperature to electricity use of a building. Then, we derive an optimal solution for the given stochastic optimization to minimize electricity cost of a building in the energy-purchasing market.

This paper presents the VoI analysis for urban temperature modeling in the following sections. In Section 2, we provide a background and important assumptions on the DA market, which we use for the case study. Then, Section 3 introduces a probabilistic spatio-temporal model (PSTM) for forecasting near-surface temperature, of Choi et al. (2021); Choi (2023), and a probabilistic short-term load forecasting model (PSTLF) for a building, of Choi (2023). Section 4 provides a background about the value of information metric for the analysis. Then, Section 5 conducts a case study of the VoI analysis, for residential buildings in a region around the city of Pittsburgh, Pennsylvania. Section 6 provides concluding remarks.

2. THE DAY-AHEAD MARKET

In the DA market, customers voluntarily purchase electricity one day in advance at locked prices, based on their projection of the future energy use of the next day. Alternatively, customers also can buy energy from the real-time (RT) market that sells electricity at changing prices (usually higher than DA prices). Thus, to minimize costs, system operators make economic decisions in the market, as described in Parvania et al. (2014); Ayón et al. (2017); Di Somma et al. (2018). This paper focuses on the demand side of the market to emphasize the value of accurate temperature modeling at a single building scale. Also, we assume that the DA market is open to individual building owners (or operators). We neglect the price-sensitive demands in the market so that the market only allows a customer to decide the amount of energy the next day.

We adopt the market design of Philpott and Pettersen (2006) and modify the design for a tractable solution to the problem. Under the hypothetical market design, the DA market requests a customer to submit a bid that specifies the amounts of energy one day in advance, and the market also assumes that they have enough supply capacity for the DA purchasing. A customer buys shortfalls at a higher price from the RT market if the actual load of the running day is higher than the DA purchasing (up-regulation case). On the other hand, if the actual load is lower than the DA purchasing, the customer resells the excessive purchase at the lower RT price (down-regulation case); see Philpott and Pettersen (2006) for more details. Although the electricity prices is determined by the total demand in either the DA or the RT market, this paper deals with the DA and RT prices as random variables, assuming the demand of an individual customer is negligible, compared to that of the whole market.

For a single customer, we minimize the expected cost, as follows:

$$\begin{aligned} &\min_{L_t^{\mathrm{DA}}\geq 0} \left[\mathbb{E}\left[\bar{\pi}_t^{\mathrm{DA}}\right] L_t^{\mathrm{DA}} + \mathbb{E}\left[\pi_t^{\mathrm{RT}}\left(L_t - L_t^{\mathrm{DA}}\right)\right]\right] \\ &\pi_t^{\mathrm{RT}} = \begin{cases} \bar{\pi}_t^{\mathrm{UP}}, & \text{if } L_t \geq L_t^{\mathrm{DA}} \\ \bar{\pi}_t^{\mathrm{DN}}, & \text{otherwise} \end{cases} \end{aligned} \tag{1}$$

where $\bar{\pi}_t^{\mathrm{DA}}$ is the price in the DA market that is a random variable, and $\bar{\pi}_t^{\mathrm{UP}}$ is the up-regulation (UP) price in the RT market (when a customer uses more energy than their previously purchased energy from the DA market). $\bar{\pi}_t^{\mathrm{DN}}$ is the down-regulation (DN) price of the opposite case (when the down-regulation works). L_t^{DA} is the DA purchasing of a customer for an assigned time t of the running day. L_t is the actual use that is a random variable to forecast its future value. $\mathbb{E}[\cdot]$ denotes expectation.

We also assume that the electricity prices are independent of the energy use of a single building, as the decision of a customer has a negligible influence on other customers. Then, we derive the optimal solution of Eq.(1) in a closed form. We take a derivative of the objective function in Eq.(1) with respect to the DA purchase L_t^{DA}. Then, one can find an optimal purchase $L_t^{\mathrm{DA*}}$ as follows:

$$\begin{aligned} L_t^{\mathrm{DA*}} &= P_{L_t}^{-1}\left[r_t^*\right] \\ \text{where } r_t^* &= \frac{\mathbb{E}\left[\bar{\pi}_t^{\mathrm{UP}}\right] - \mathbb{E}\left[\bar{\pi}_t^{\mathrm{DA}}\right]}{\mathbb{E}\left[\bar{\pi}_t^{\mathrm{UP}}\right] - \mathbb{E}\left[\bar{\pi}_t^{\mathrm{DN}}\right]}. \end{aligned} \tag{2}$$

$P_{L_t}(\cdot)$ is the cumulative density function (CDF) of L_t, $\mathbb{E}\left[\bar{\pi}_t^{\mathrm{DA}}\right]$ is the expected DA price, $\mathbb{E}\left[\bar{\pi}_t^{\mathrm{UP}}\right]$ is the expected UP price, and $\mathbb{E}\left[\bar{\pi}_t^{\mathrm{DN}}\right]$ is expected DN price. Under perfect knowledge of future energy use, the optimal decision will buy the actual load L_t from the DA market.

The energy market designs the three prices, as follows:

$$\mathbb{E}\left[\bar{\pi}_t^{\mathrm{DN}}\right] \leq \mathbb{E}\left[\bar{\pi}_t^{\mathrm{DA}}\right] \leq \mathbb{E}\left[\bar{\pi}_t^{\mathrm{UP}}\right] \tag{3}$$

See Choi (2023) for the details.

3. Electricity demand forecasts under stochastic temperature

In Section 3.1 and 3.2, we revisit the probabilistic temperature forecasting model of Choi et al. (2021) and the probabilistic electric load forecasting model of Choi (2023) for the building energy use[1]. Then, Section 3.3 briefly describes model coupling and uncertainty quantification method.

3.1. *Probabilistic spatio-temporal model for temperature forecasts*

The temperatures of multiple locations within a region are listed in vector $\mathbf{y}_t$ $[P\times 1]$, which consists of the sum of three terms: a mean temperature field $\mu_{\tau(t)}$, a linear combination of the embedding matrix Φ $[P\times R]$ and the low-dimensional latent states $\mathbf{x}_t$ ($R \ll P$), and an error term ν_t $[P\times 1]$. The relationship between the variables is expressed as:

$$\mathbf{y}_t = \mu_\tau + \Phi \mathbf{x}_t + \nu_t \tag{4}$$

The mean temperature field μ_τ depends on the time of the day τ, discretized into h steps from 00:00 to 24:00. In this paper, we discretize a day into $h = 24$ steps, then $\tau \in \{00{:}00, 01{:}00, 02{:}00, ..., 23{:}00\}$ (hours of the day). τ can also be computed as $\tau = \mathrm{HoD}(t)$ where $\mathrm{HoD}(\cdot)$ is a function that returns the hour of the day τ for input of timestamp t. ν_t is a zero-mean Gaussian noise.

The dynamic process follows a linear Markov model whose transition matrix $\mathbf{F}_\tau$ also depends on the hour of the day τ.

$$\mathbf{x}_t = \mathbf{F}_\tau \mathbf{x}_{t-1} + \varepsilon_t \tag{5}$$

where ε_t is the process noise that follows a zero-mean Gaussian distribution. The random variables $\mathbf{x}_t$ and $\mathbf{y}_t$ follow Gaussian distributions. See Choi et al. (2021) for details.

We introduce the observation vector $\mathbf{z}_t$ to enable probabilistic temperature forecasts.

$$\mathbf{z}_t = \mathbf{H}_t \mathbf{y}_t + \eta_t \tag{6}$$

where $\mathbf{H}_t$ is an observation matrix that linearly relates the full temperature field $\mathbf{y}_t$ to the observation vector $\mathbf{z}_t$ with a zero-mean Gaussian noise η_t. The elements of $\mathbf{z}_t$ are either local measurements (of past/present temperature) or outputs of another coarse-resolution forecasting model. Next, the local temperature y_t^{loc} of interest is expressed as follows:

$$y_t^{\mathrm{loc}} = \mathbf{e}^{\mathrm{T}} \mathbf{y}_t. \tag{7}$$

[1]Hereafter, the probabilistic spatio-temporal model (PSTM) refers to the probabilistic temperature forecasting model of Choi et al. (2021), and the probabilistic short-term load forecasting model (PSTLF) refers to the probabilistic electric load forecasting model of Choi (2023)

where $\mathbf{e}$ is a vector whose element takes one if the element associates with a location of interest, or zero, otherwise. The probabilistic forecast then estimates the posterior distributions of the state vector $\mathbf{x}_t$ and local temperature y_t^{loc} from the observation vector $\mathbf{z}_t$. Using the Kalman Filter/Smoother scheme, following the procedures of Barber (2012), the probabilistic temperature forecast estimates the posterior distribution of local temperature, $p(y_t^{\text{loc}}|\mathbf{z}_{1:T})$, conditional to a time series of observation vectors $\mathbf{z}_{1:T} = \{\mathbf{z}_1, \mathbf{z}_2, ..., \mathbf{z}_T\}$ for $t = 1, 2, ..., T$; where $p(\cdot)$ represents the probabilistic density function of interest.

3.2. *Probabilistic short-term load forecasting model*

We use a benchmark-class model, based on multivariate polynomial regression, to forecast a time series of electrical loads of a building. The model predicts future hourly loads, given the inputs of past/present loads and ambient air temperature. The logarithm of hourly electrical load, $\log(L_t)$, consists of two additive terms: $\mu_L^{\tau,\omega}$ and l_t.

$$\log(L_t) = \mu_L^{\tau,\omega} + l_t \tag{8}$$

where $\mu_L^{\tau,\omega}$ is the mean of the logarithm load, by the hour of the day τ and the type of day ω, i.e., $\tau = HoD(t)$ and $\omega = ToD(t)$; $ToD(\cdot)$ returns an index that denotes the type of day. For example, ω indexes the entries of a set {Off-day, Work-day}, or alternatively {Sunday-or-Holiday, Saturday, Workday}. Different sets of day types can be adopted, depending on the energy use patterns of a building. We use local temperature y_t^{loc} as a predictor for the perturbation l_t.

Then, the PSTLF model predicts the electrical load at time $t + \delta_t$, based on a multivariate polynomial regression model:

$$l_{t+\delta_t} = f_{\delta_t}^{\tau,\omega}(\mathbf{v}_{e,\delta_t}) + \zeta_{t+\delta_t} \tag{9}$$

where $f_{\delta_t}^{\tau,\omega}(\cdot)$ is a polynomial function whose coefficients depend on the forecasting ahead time δ_t, the hour of the day τ, and the type of day ω of the forecasting generation time t, e.g., the present. $\zeta_{t+\delta_t}$ is a forecasting residual, which follows zero-mean Gaussian distribution that depends on τ and ω. The input vector $\mathbf{v}_{e,\delta_t}$ is assembled by two sub-vectors, $\mathbf{l}_{e,\delta_t}$ and $\tilde{\mathbf{y}}_{e,\delta_t}$, i.e., $\mathbf{v}_{e,\delta_t} = \left[\mathbf{l}_{e,\delta_t}^{\text{T}}, \tilde{\mathbf{y}}_{e,\delta_t}^{\text{T}}\right]^{\text{T}}$. $\mathbf{l}_{e,\tau}$ consists of several past to present perturbations:

$$\mathbf{l}_{e,\delta_t} = \left[l_{t+\delta_t-24}, l_{t-N_p}, ..., l_{t-2}, l_{t-1}\right]^{\text{T}} \tag{10}$$

where $l_{t+\delta_t-24}$ denotes the 24 hours ago perturbed load from $t + \delta_t$, and N_l is the number of consecutive past hourly loads to the present t. This paper uses $N_p = 3$. Similarly, $\tilde{\mathbf{y}}_{e,\delta_t}$ is a time series of local temperatures, from $t + \delta_t - N_y$ to $t + \delta_t$:

$$\tilde{\mathbf{y}}_{e,\delta_t} = \left[y_{t+\delta_t-N_y}^{\text{loc}}, ..., y_{t+\delta_t-1}^{\text{loc}}, y_{t+\delta_t}^{\text{loc}}\right]^{\text{T}} \tag{11}$$

where $N_y < 24$ represents the number of consecutive temperatures in consideration. This paper sets $N_y = 3$.

3.3. *Quantile estimation: inverse reliability problem*

As shown in Eq.(2), the optimal purchase is related to a quantile value. We compute the quantile value by adopting an approximation method for the inverse reliability problem, as discussed in Der Kiureghian et al. (1994), Wu (1994), and Youn et al. (2003). This paper uses the algorithm of Wu (1994) to estimate quantile values with a first-order approximation method.

4. VALUE OF INFORMATION

Let $\mathscr{A}$ be a set of possible actions in consideration. $\mathscr{C}(\mathbf{s}, \mathbf{a})$ be the cost function that is a function of state $\mathbf{s}$ and action $\mathbf{a}$. The prior loss $\mathscr{L}_{\text{pri}}$ is the minimum of expected cost when the decisions are made solely based on the prior distribution of the state, assuming less informative models or no use of sensors. The prior loss is formulated as follows:

$$\mathscr{L}_{\text{pri}} = \min_{\mathbf{a}\in\mathscr{A}} \mathbb{E}_{\mathbf{s}}\left[\mathscr{C}(\mathbf{s}, \mathbf{a})\right] \tag{12}$$

where $\mathbb{E}_{\mathbf{s}}[\cdot]$ is the expectation with respect to the state $\mathbf{s}$.

The expected posterior loss $\mathscr{L}_{\text{post}}$ is the expectation of the minimum of the conditional expectation of the cost, assuming the adoption of informative models or sensor deployments.

$$\mathscr{L}_{\text{post}} = \mathbb{E}_{\mathbf{Z}} \left[\min_{\mathbf{a} \in \mathscr{A}} \mathbb{E}_{\mathbf{s}|\mathbf{z}} [\mathscr{C}(\mathbf{s}, \mathbf{a})] \right] \tag{13}$$

where $\mathbb{E}_{\mathbf{s}|\mathbf{z}}[\cdot]$ is the conditional expectation of the cost, given $\mathbf{z}$. Then, VoI is the difference between the prior and posterior expected losses.

$$\text{VoI} = \mathscr{L}_{\text{pri}} - \mathscr{L}_{\text{post}} \tag{14}$$

In this paper, the state $\mathbf{s}$ consists of the local temperature $y^{\text{loc}}_{t+\delta_t}$ and the associated electric load of a building $L_{t+\delta_t}$ for $\delta_t = 0, 1, ..., T$, assuming t is the present time. In the energy purchasing market, the action $\mathbf{a}$ is the DA purchasing amount $L^{\text{DA}}_{t+\delta_t}$ for $\delta_t = 0, 1, ..., T$. We can compute the VoI by Monte-Carlo simulation (MCS), but this paper also computes it with an approximation method based on first-order linearization, for computational efficiency. See Choi (2023) for the details.

5. THE VALUE OF TEMPERATURE MODELING

We investigate case studies, performing the VoI analysis, for three types of residential buildings: the Base, High, and Low models. The Base model represents the prediction on the hourly load of 2009 IECC single-family houses, located in Very Cold and Cold climate zones of U.S. Energy Information Administration (2020); see International Code Council Inc. (2009) and Ong and Clark (2014) for details. The High model roughly approximates a large old house with poor insulation and low energy efficiency. The Low model describes a smaller house with excellent insulation and energy-efficient equipment. The dataset of Ong and Clark (2014) includes building energy simulations of these three residential buildings under representative weather conditions, based on the typical meteorological year, at about 1,000 locations (Wilcox and Marion (2008)). The PSTLF of Section 3.2 learns the relations between ambient air temperature and electricity use of each building from the dataset for the three residential building prototypes.

We set up realistic electricity prices in the DA market. We assume that the electricity prices at a building scale present no significant difference

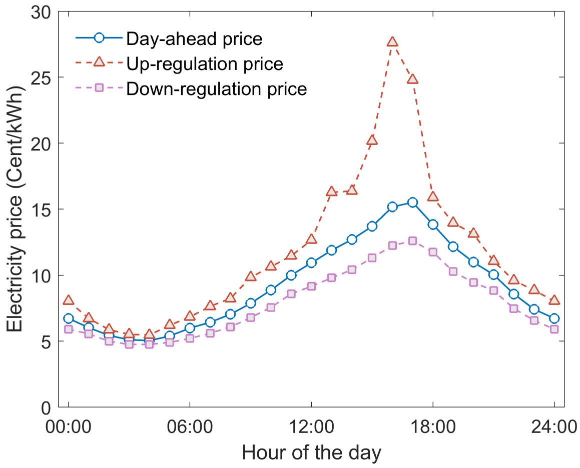

Figure 1: Expected electricity prices by the hour of the day, revisited by Choi (2023)

from the case of a bulk transmission system. We employ the price information of the whole pricing node of PJM interconnection LLC from June 1st to August 31st, 2022, both for the DA and RT markets. The data were used to estimate the expected DA, UP, and DN prices of Eq.(2). We also set the prices to only depend on the hour of the day for simplicity. Figure 1 is adapted from Choi (2023) to represent the estimated expectations on the electricity price by hours of the day.

Using the calibrated model of Section 3.1, we conduct a case study for the VoI analysis in the region around the city of Pittsburgh. We assume that the prior distribution of the probabilistic temperature forecasting model well represents the true temperature distribution of summer in the region. Next, we consider the model use case 3 of Choi et al. (2021), which exploits local temperature measurements (6-km spacings with 30-min intervals for information of past/present temperature) and coarse resolution outputs of external forecasting model (12-km grid zones with 3-hour intervals for future temperature). Then, the PSTLF model predicts the energy use of a building up to the next 25 hours, producing the forecast at 23:00 in local time. Again, the observation vector $\mathbf{z}$ of Eq.(13) is the vector of temperature information (local measurements and coarse resolution outputs of external forecasting system). Table 1 represents the input information for the VoI analysis. With hypotheti-

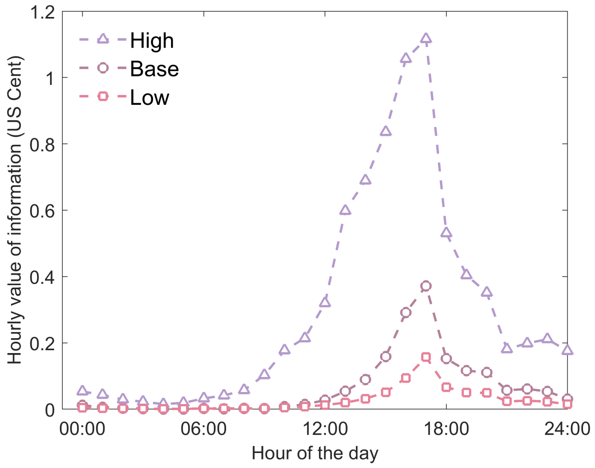

Figure 2: The value of information for the residential building prototypes by hours of the day

cal field measurements, this case provides multiple average temperatures of 12km $\times$12km grid zones, from WRF-PUCM data, with three hourly intervals (00:00, 03:00, ..., 18:00, 21:00 UTC) for the future. The spatial resolution and time intervals are similar to those of the North American Meso-scale Forecast System (NAM).

In the numerical case study, the PSTM of Section 3.1 downscales ambient-air temperature, by processing the information in Table 1. Then, the load forecasting of Section 3.2 forecasts the electricity demand of a building, using the posterior distribution of ambient air temperature. We conduct the VoI analysis to measure the economic benefits of having the uncertainty-aware temperature model in the DA market. In Figure 2, the VoI is calculated for the residential building prototypes by different hours of the day. The VoI integrates hourly price, intensity and variability of temperature, and the energy use pattern of the building. So, the VoI shows a fluctuating pattern over a day.

Figure 3 shows the VoI according to the building prototype in percentage after normalizing the metric by its own nominal cooling cost. In the figure, the nominal cooling cost is computed as the average electricity cost under perfect information. We computed the average minimum cost for each hour of the day, using the data of Ong and Clark (2014) for June/July/August at Pittsburgh International Airport. The heterogeneity of the buildings produces significance, and the weather information reduced 4.34-8.22% of energy costs in the DA market. The variability would come from material characteristics, occupancy schedule, and tightness of set points (a range of allowable indoor temperatures).

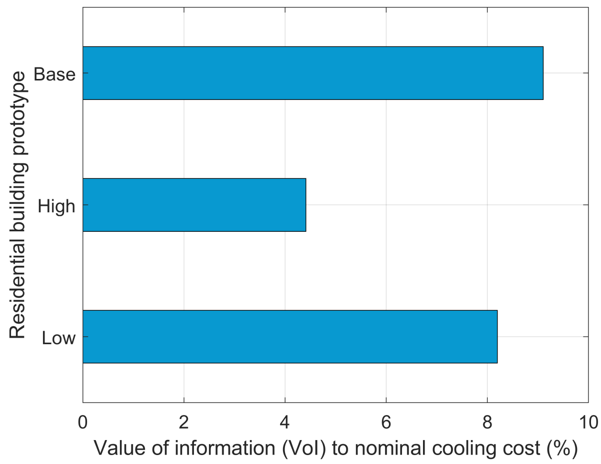

Figure 3: Ratio of VoI by building prototypes

6. Conclusion

In this paper, we have proposed a method to assess the impact of accurate temperature modeling on cost savings in the DA electricity market, open to individual building owners. We coupled two uncertainty-aware models: a probabilistic spatio-temporal model for temperature forecasts and a load forecasting model for the electricity demand of a building, given a temperature scenario. Then, we have assessed the VoI, to measure the economic benefits of better urban temperature modeling in saving energy costs for buildings. Through the numerical case study, we showed that better temperature modeling could help saving electricity costs in the DA market: using the uncertainty-aware temperature model reduces 4.34-8.22% of space cooling costs in residential building prototypes. The numerical examples also demonstrated how the VoI integrates prices, temperature, and energy use pattern, and the heterogeneity of buildings could significantly affect the VoI.

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Table 1: Summary of input information for the case study

	Local measurements (past/present)		External forecasting model (future)	
	Grid spacing	Time interval	Spatial resolution	Time interval
Input resolution	6 km	1 hour	12 km $\times$ 12 km	3 hour

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