

1 Quantifying the uncertainty of precipitation forecasting using 2 probabilistic deep learning

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10 Abstract. Precipitation forecasting is an important mission in weather science. In recent years, data-driven precipitation
11 forecasting techniques could complement numerical prediction, such as precipitation nowcasting, monthly precipitation
12 projection and extreme precipitation event identification. In data-driven precipitation forecasting, the predictive uncertainty
13 arises mainly from data and model uncertainties. Current deep learning forecasting methods could model the parametric
14 uncertainty by random sampling from the parameters. However, the data uncertainty is usually ignored in the forecasting
15 process and the derivation of predictive uncertainty is incomplete. In this study, the input data uncertainty, target data
16 uncertainty and model uncertainty are jointly modeled in a deep learning precipitation forecasting framework to estimate the
17 predictive uncertainty. Specifically, the data uncertainty is estimated a priori and the input uncertainty is propagated forward
18 through model weights according to the law of error propagation. The model uncertainty is considered by sampling from the
19 parameters and is coupled with input and target data uncertainties in the objective function during the training process. Finally,
20 the predictive uncertainty is produced by propagating the input uncertainty in the testing process. The experimental results
21 indicate that the proposed joint uncertainty modeling framework for precipitation forecasting exhibits better forecasting
22 accuracy (improve RMSE by 1-2% and R-square by 1-7% on average) relative to several existing methods, and could reduce
23 the predictive uncertainty by ~28% relative to Loquercio et al. (2020)'s approach. The incorporation of data uncertainty in the
24 objective function changes the distributions of model weights of the forecasting model and the proposed method can slightly
25 smooth the model weights, leading to the reduction of predictive uncertainty relative to Loquercio et al. (2020)'s method. The
26 predictive accuracy is improved in the proposed method by incorporating the target data uncertainty and reducing the
27 forecasting error of extreme precipitation. The developed joint uncertainty modeling method can be regarded as a general
28 uncertainty modeling approach to estimate predictive uncertainty from data and model in forecasting applications.

29 **1 Introduction**

30 Precipitation is a key hydrometeorological variable in earth system science, and is the main driving factor of floods and

31 droughts (Xu et al., 2019). In the year of 2019, the flood disaster driven by extreme precipitation caused a direct economic loss
32 of 29.6 billion dollars in China, and the drought disaster led to a crop production loss of 23.6 billion kilograms
33 (<http://www.mwr.gov.cn/sj/#tjgb>). Accurate precipitation forecasting is vital for the early warning of flood and drought, smart
34 city management and agricultural water resources allocation (Van Den Hurk et al., 2012; Pozzi et al., 2013). However, the
35 precipitation forecasting problem suffers from uncertainties from data, algorithms and random factors (Reeves et al., 2014;
36 Kobold and Sušelj, 2005; Xu et al., 2020b). The predictive uncertainty is a measurement of the spread of precipitation
37 forecasting and could indicate how much the forecasted precipitation values fluctuate around the mean (Papacharalampous et
38 al., 2020). Therefore, the uncertainty range should be given when generating precipitation forecasting results.

39 The precipitation forecasting methods can be divided into two categories: numerical weather forecasting and statistical
40 machine learning. Numerical models consider the physical process of earth system and could simulate the interactions between
41 atmospheres, oceans and lands (Sikder and Hossain, 2016; Molinari and Dudek, 1992). Numerical models have strong physical
42 meaning and are the dominant ways of operational precipitation forecasting. However, the forecasting ability of numerical
43 models is limited due to the uncertainty in initial and boundary conditions, the imperfection of parameterization schemes and
44 the uncertainty in parameters (Reeves et al., 2014; Xu et al., 2021a). With the development of computer technology and
45 machine learning algorithms, using random data-driven techniques for precipitation forecasting is becoming popular in recent
46 years (Shi et al., 2015; Trebing et al., 2021; Sønderby et al., 2020). The accuracy of data-driven methods is comparable to
47 currently advanced numerical models in short-term (e.g. from hours to weeks) precipitation forecasting. For example, the
48 convolutional long-short term memory network is shown to outperform the physical optical flow method in precipitation
49 nowcasting based on radar images (Shi et al., 2015). Another deep learning model called MetNet showed advantages over
50 traditional numerical models in terms of the forecasting accuracy and running time for hourly precipitation prediction
51 (Sønderby et al., 2020). The data-driven methods also exhibit appealing results in subseasonal to seasonal precipitation
52 forecasting relative to numerical models (Boukabara et al., 2019; Chantry et al., 2021; Hwang et al., 2019). A key drawback
53 of data-driven precipitation forecasting method is the lack of physical meaning, also known as black-box model. Despite this
54 feature, data-driven statistical machine learning methods have been widely used for parameter calibration, data processing,
55 submodel replacement and process understanding among physical simulations (Ardabili et al., 2019; Sahoo et al., 2017;
56 Reichstein et al., 2019). The data-driven learning techniques are strong complements to numerical models for the improvement
57 of precipitation forecasting accuracy.

58 The predictive uncertainty in precipitation forecasting arises mainly from data and models (Gal, 2016). The data
59 uncertainty comes from external observation conditions, instruments and processing algorithms. The data uncertainty is usually
60 examined by perturbing initial conditions in numerical models and producing a perturbed multi-model ensemble, which is
61 widely seen in hydrometeorological ensemble forecasting (Xu et al., 2019; Gneiting and Raftery, 2005; Duan et al., 2019;

62 Vitart et al., 2017). The data uncertainty is rarely investigated in data-driven precipitation forecasting and is often assumed to
63 be accurate without error. The model uncertainty is often represented by an ensemble of perturbed model physics and
64 parameters in numerical weather forecasting (Vitart et al., 2017; Kirtman et al., 2014; Taylor et al., 2012). In data-driven
65 models, the model uncertainty is generally modeled by random regularization of parameters (Gal, 2016; Kendall and Gal,
66 2017). For linear regression, the parametric uncertainty is indicated by the standard deviation of trained parameters. In deep
67 learning, the network layers could be randomly abandoned to prevent overfitting and generate a forecasted ensemble by Monte
68 Carlo sampling (Kendall and Gal, 2017; Srivastava et al., 2014; Loquercio et al., 2020; Ghahramani, 2015).

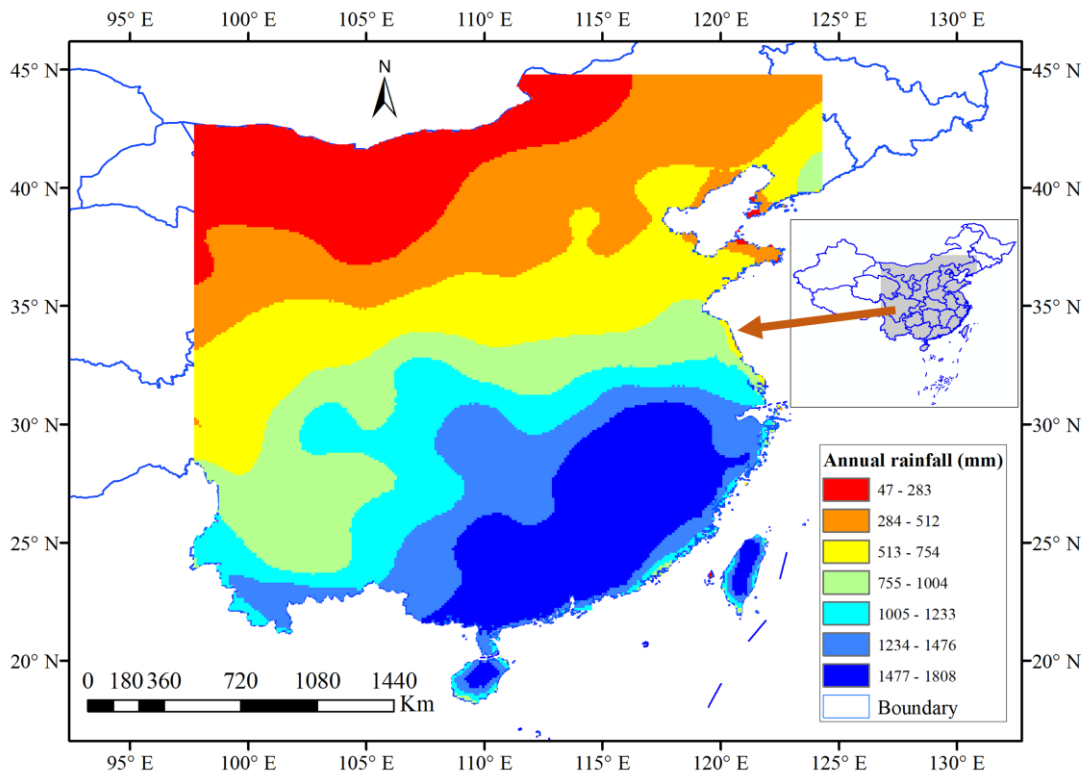
69 The data and model uncertainties should be considered jointly in an integrated modeling framework to get the predictive
70 uncertainty, as the data and model uncertainties could both inflate the predictive spread considerably (Gal, 2016; Kendall and
71 Gal, 2017). It is expected that, the forecasting result would be more or less different if the used data and parameters are
72 randomly sampled from the population. Data uncertainty is usually assumed as a constant or Gaussian distribution and could
73 be propagated into final forecasting through error forward propagation (Loquercio et al., 2020; Xu et al., 2020a). If the data
74 uncertainty is unknown, it can be learned from the training process by considering the data uncertainty as a trainable parameter
75 (Kendall and Gal, 2017). However, the joint learning of data errors and model weights will increase the number of training
76 parameters and may mix the error flow from data and parameters. A prior estimation of data uncertainty could help unravel the
77 data error and facilitate the training process. On the other hand, previous forecasting studies usually model the input data
78 uncertainty and ignore the uncertainty in the target (predictand) data (Kendall and Gal, 2017; Loquercio et al., 2020). The
79 uncertainty in the target dataset also plays an important role in the parameter training process and could influence the
80 forecasting accuracy.

81 There are two ways to estimate the data uncertainty. One is to use in-situ ground stations to calculate the systematic and
82 random errors within the data and the other is to use multisource datasets to compute random error by intercomparison (Xu et
83 al., 2021b; Gruber et al., 2016; Sun et al., 2018). The in-situ validation method is limited to the number and density of ground
84 stations and are suitable for small areas with enough station coverage. The second method is independent of the in-situ stations
85 and requires multisource datasets with independent error distribution (Gruber et al., 2016). There are numerous precipitation
86 datasets from various sensors and models and could be used to calculate precipitation data error at a large spatial scale (Xu et
87 al., 2020b; Sun et al., 2018). Three-cornered hat (TCH) and triple collocation (TC) are two commonly used methods to evaluate
88 the random error among multisource datasets, which do not require ground measurements as references (Premoli and Tavella,
89 1993; Mccoll et al., 2014; Stoffelen, 1998). The basic assumption of TCH and TC methods is the stationarity of both the raw
90 dataset and its error, which may not be always satisfied for real-world data. Most of the existing studies assume that the used
91 multisource datasets obey the stationarity condition when using TCH or TC methods (Xu et al., 2020b; Gruber et al., 2016;
92 Gruber et al., 2017), which is useful for the determination of relative prior random error.

93 In this study, we aim to quantify the predictive uncertainty of data-driven precipitation forecasting by fully considering
94 the uncertainty from data and models. The data uncertainty is estimated by the TCH method a priori and is assumed as Gaussian
95 distribution. The data uncertainty is propagated within model training by the law of error propagation. The parametric
96 uncertainty is modeled by randomly abandoning some network layers during the training process. The data and model
97 uncertainties are jointly considered in the objective function within a deep learning encoder-decoder framework. The
98 forecasting experiments are conducted to see whether the accuracy of precipitation forecasting can be improved by joint data-
99 model uncertainty modeling relative to several uncertainty processing strategies from the existing studies.

100 2 Study area and data

101 The study area is located at southern and northern China, East Asia (Figure 1). The annual rainfall decreases from the
102 southeast to the northwest, with an approximately average rainfall of 1500 mm in the southeast regions and 300 mm in the
103 northwest areas. Most of the southern areas feature a subtropical monsoon climate and the rainfall is relatively larger in summer
104 and smaller in winter. From June to July in 2020, extreme precipitation hit the southern China (Wei et al., 2020) and caused a
105 direct economic loss of 13.2 billion dollars. The precipitation forecasting in southern area of China is very challenging and
106 meaningful. Previous studies use numerical models for precipitation forecasting in this area and show some values (Yuan et
107 al., 2012; Luo et al., 2017). The northern area of China features the temperate monsoon and continental climates, with an annual
108 rainfall of 400 to 800 mm and the main rainy season of July and August. Here we would like to explore the possibility of
109 weekly precipitation forecasting by a data-driven deep learning method.



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Figure 1: The study area for short-term precipitation forecasting.

Multisource precipitation datasets are used here to obtain the data error and to measure the precipitation forecasting ability of different uncertainty processing strategies, including the Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2) (Gelaro et al., 2017), the National Centers for Environmental Prediction Reanalysis version 2 (NCEP R2) (Saha et al., 2014) and the European Centre for Medium-Range Weather Forecasts Reanalysis version 5 (ERA-5) (Hersbach et al., 2020) datasets from 1980 to 2020. The surface 2-meter temperature and the geopotential height at 500 hPa datasets are collected from the three datasets accordingly as predictors. All these daily datasets are converted to weekly data and are bilinearly interpolated into 0.25° resolution. In the forecasting process, the temperature and geopotential height predictors in the historical three consecutive weeks are used to forecast the precipitation in the target week. For example, the predictors in the first week, the second week and the third week (P1, P2, P3) are used to forecast the total precipitation in the fourth week.

3 Methods

3.1. Estimation of data uncertainty

The TCH method (Xu et al., 2020b; Premoli and Tavella, 1993) is used to estimate the uncertainty in temperature, geopotential height and precipitation datasets. The collected three datasets are all reanalysis data, which is generated from different physical models and data assimilation algorithms. The different reanalysis datasets and their errors are generally not closely correlated and are regarded as collocated datasets for the uncertainty estimation, similar with existing studies (Xu et al., 2021b; Mccoll et al., 2014; Gruber et al., 2017). In the TCH algorithm, one arbitrary dataset is chosen as the reference among the three datasets, and then the differencing operation is conducted between the reference and the other two datasets to get the differencing series. The covariance of the differencing series is connected to the variance-covariance matrix of precipitation datasets through matrix transformation. The parameters of the variance-covariance matrix are iteratively resolved by minimizing the global correlation of the covariance of the differencing series. A detailed introduction of TCH method could refer to Premoli and Tavella (1993) and Xu et al. (2020b).

Consider the data series $\{P_i, i=1, 2, \dots, N\}$, they can be generally expressed as

$$P_i = P_{true} + \varepsilon_i \quad (1)$$

where P_{true} denotes the true predictor or predictand data in a specific area and is unknown; ε_i is the measurement error. Choosing an arbitrary dataset as the reference, the differences of $N-1$ data and the reference data are calculated.

$$D_{iN} = P_i - P_N = \varepsilon_i - \varepsilon_N, \quad i = 1, \dots, N - 1 \quad (2)$$

where P_N is the reference series and the TCH result is independent of the selection of reference data. These $N-1$ differences are

140 concatenated into an $M \times (N-1)$ matrix

$$141 \quad D = [D_{1N} \ D_{2N} \ \cdots \ D_{(N-1)N}] \quad (3)$$

142 where the rows of D denote the differenced time series with M length. The variance/covariance of D is then obtained by

$$143 \quad S = \left[\frac{1}{M-1} \right] [(D - \bar{D})^T (D - \bar{D})] \quad (4)$$

144 where \bar{D} represents the average of D . The covariance of D can be related to S by

$$145 \quad S = K^T \cdot R \cdot K, \quad K = \begin{bmatrix} I \\ -u^T \end{bmatrix} \quad (5)$$

146 where R is the $N \times N$ covariance matrix of $\{\epsilon_i, i=1,2,\dots,N\}$ and u represents the vector $[1 \ \cdots \ 1]^T$. The covariance matrix of D
 147 is regarded as the Allan covariance when TCH was initially proposed to evaluate the instability of clocks, which requires a
 148 filtering operation on the original time series before differencing. However, the covariance can also be the commonly
 149 mentioned sample variance. The Equation (5) can be reformatted as

$$150 \quad S = [I - u] \begin{bmatrix} \hat{R} & r \\ r^T & r_{NN} \end{bmatrix} \begin{bmatrix} I \\ -u^T \end{bmatrix} \quad (6)$$

151 where \hat{R} is the $(N-1) \times (N-1)$ matrix and r is the $(N-1)$ vector $[r_{1N} \ r_{2N} \ \cdots \ r_{N-1,N}]$ grouping covariance estimates with the N th
 152 time series and r_{NN} denotes the variance of N th time series. This partitioning can help solve the underdetermined problem in
 153 Equation (5) by isolating the N free parameters (r and r_{NN}). When the free parameters are determined, the unknown elements
 154 in \hat{R} is obtained by

$$155 \quad \hat{R} = S - r_{NN} [uu^T] + ur^T + ru^T \quad (7)$$

156 A suitable objective function is suggested by Galindo and Palacio (1999) based on the Kuhn-Tucker theorem to minimize
 157 the quadratic mean of covariances

$$158 \quad F(r, r_{NN}) = \sum_{i < j} \frac{r_{ij}^2}{L^2} \quad (8)$$

159 subjecting to a constraint

$$160 \quad G(r, r_{NN}) = -\frac{r_{NN} - [r - r_{NN}u]^T \cdot S^{-1} \cdot [r - r_{NN}u]}{L} < 0 \quad (9)$$

161 where $L = N^{-1} \sqrt{\det(S)}$. The initial conditions are selected as follows to meet the constraint (Torcaso et al., 1998).

$$162 \quad r_{iN}^{(0)} = 0, i < N \quad \text{and} \quad r_{NN}^{(0)} = (2 \cdot u^T \cdot S^{-1} \cdot u)^{-1} \quad (10)$$

163 Once the free parameters are determined, the unknown elements in R can be solved using Equation (7).

164 The uncertainties of the predictors and predictands are estimated weekly by the TCH method. The weekly datasets are
 165 grouped according to the weekly climatology and then used to estimate the uncertainty. For example, all the precipitation
 166 datasets which belongs to the first week of each year are concatenated to apply the TCH method in order to get the uncertainty
 167 of the datasets on the first week of each year. Similarly, the data uncertainty on the second week, third week and until the fifty-
 168 two week is evaluated sequentially. This strategy enables a time-variant uncertainty estimation, which is more reasonable as
 169 the precipitation climatology is different for different seasons. The NCEP R2 and ERA-5 data are used to assist the uncertainty

170 estimation of MERRA-2 data by the TCH method, and the precipitation forecasting experiments are conducted based on
171 MERRA-2 data to evaluate the proposed forecasting framework.

172 **3.2. Variational Bayesian inference**

173 Here we introduce the variational inference theory (Hoffman et al., 2013), which is a standard Bayesian modeling
174 technique for the estimation of model uncertainty. Given the input data $X=\{x_1, \dots, x_N\}$ and the output data $Y=\{y_1, \dots, y_N\}$, the
175 Bayesian regression is to find suitable parameters within the function $y=f^w(x)$ which could generate the output Y according to
176 the input X . The parameters w is assumed to obey a prior distribution $p(w)$ before the observations are known. When the
177 observed data is obtained, it is possible to determine which parameters are more suitable for the function according to the data.
178 A likelihood distribution $p(y|x, w)$ is defined to describe the probability of y generated by x and w . For example, a Gaussian
179 likelihood function is defined as

$$180 \quad p(y|x, w) = \mathcal{N}(y; f^w(x), \tau^{-1}I) \quad (11)$$

181 where τ^{-1} is the observation noise and I is the identity matrix.

182 Given the input data X and the output data Y , the Bayesian theorem is to find the posterior distribution of parameters in
183 the parameter space.

$$184 \quad p(w|X, Y) = \frac{p(Y|x, w)p(w)}{p(Y|X)} \quad (12)$$

185 where the numerator $p(Y|X)$ is the normalization factor, also named as model evidence.

$$186 \quad p(Y|X) = \int p(Y|X, w)p(w)dw \quad (13)$$

187 The solution of Equation (13) needs to marginalize the likelihood over w , which is tractable analytically for some simple
188 models such as Bayesian regression, while is intractable for complex models such as deep learning methods (Gal, 2016).

189 Given the new input data x' , the forecasted value is generated by the integral of probability over the parameter space,
190 which is called the inference process.

$$191 \quad p(y'|x', X, Y) = \int p(y'|x', w)p(w|X, Y)dw \quad (14)$$

192 Since the posterior distribution of parameters $p(w|X, Y)$ cannot be obtained analytically, an approximate analytical
193 distribution $q_\theta(w)$ could be defined, with θ as the parameter to be estimated, to be as close as the posterior distribution. The
194 Kullback-Leibler (K-L) divergence (Kullback and Leibler, 1951) is an indicator to measure the similarity of two distributions,

195 also known as relative entropy. The objective function is to minimize the K-L divergence between the two distributions.

$$196 \quad KL(q_\theta(w)||p(w|X, Y)) = \int q_\theta(w) \log \frac{q_\theta(w)}{p(w|X, Y)} dw \quad (15)$$

197 The optimal variational distribution $q'_\theta(w)$ is obtained when the K-L divergence is minimized. The estimated variational
198 distribution could be regarded as the posterior distribution of parameters and then the predictive distribution could be generated.

$$199 \quad p(y'|x', X, Y) \approx \int p(y'|x', w) q'_\theta(w) dw =: q'_\theta(y'|x') \quad (16)$$

200 The above inference process is the variational Bayesian inference. Variational inference replaces the integral of the
201 likelihood with optimization, which simplifies the estimation of posterior distribution.

202 3.3. Monte Carlo sampling

203 Monte Carlo method is a kind of stochastic simulation technology, proposed by Stanislaw Ulam and John von Neumann
204 during the second world war (Von Neumann and Ulam, 1951). Monte Carlo methods are used to estimate unknown parameters
205 by random sampling and are widely applied in mathematics, physics, game theory and finance (Brooks, 1998; Jacoboni and
206 Lugli, 2012; Metropolis and Ulam, 1949; Rubinstein and Kroese, 2016).

207 In Equation (14), the posterior distribution $p(w|X, Y)$ cannot be solved analytically. Assume U_i as the weight matrix $K_i \times K_i$,
208 U_i from $i-1$ layer to i layer, i.e. $w = \{U_i\}_{i=1, \dots, L}$, a variational weight distribution $q(w)$ is defined to randomly replace the columns
209 with zero (dropout process).

$$210 \quad U_i = H_i \cdot \text{diag}([z_{i,j}]_{j=1}^{K_i}) \quad (17)$$

$$211 \quad [z_{i,j}] \sim \text{Bernoulli}(p_i), i = 1, \dots, L, j = 1, \dots, K_{i-1} \quad (18)$$

212 where p_i and H_i are variational parameters; $z_{i,j}$ is a binary variable, with a value of zero representing the abandoning of j th unit
213 in $i-1$ layer and a value of one the keeping, based on the *Bernoulli* distribution at the probability p_i .

214 The predictive distribution is estimated after minimizing the K-L divergence.

$$215 \quad q(y'|x') = \int p(y'|x', w) q(w) dw \quad (19)$$

216 The predictive mean and variance can be obtained after repeating the dropout process multiple times.

$$217 \quad \mathbb{E}_{q(y'|x')}(y') = \int y' q(y'|x') dy' = \int y' \mathcal{N}(y'; \hat{y}'(x', U_1, \dots, U_L), \tau^{-1}I) \text{Bern}(U_1) \cdots \text{Bern}(U_L) dU_1 \cdots dU_L dy' =$$

$$218 \quad \int \hat{y}'(x', U_1, \dots, U_L) \text{Bern}(U_1) \cdots \text{Bern}(U_L) dU_1 \cdots dU_L \approx \frac{1}{T} \sum_{t=1}^T \hat{y}'(x', \hat{U}_{1,t}, \dots, \hat{U}_{L,t}) \quad (20)$$

$$219 \quad \text{Var}_{q(y'|x')}(y') \approx \tau^{-1} I + \frac{1}{T} \sum_{t=1}^T \hat{y}'(x', \hat{U}_{1,t}, \dots, \hat{U}_{L,t})^T \hat{y}'(x', \hat{U}_{1,t}, \dots, \hat{U}_{L,t}) - \mathbb{E}_{q(y'|x')}(y')^T \mathbb{E}_{q(y'|x')}(y') \quad (21)$$

220 where $u_{t,i}$ is the forecasted value for i th pixel and t th ensemble. The calculation of predictive variance is based on the standard
 221 deviation of the ensemble, which represents the spread of the forecasted values.

222 The above Monte Carlo sampling and dropout process is the Monte Carlo dropout technique, which is used to obtain the
 223 model uncertainty here.

224 3.4. Joint data and model uncertainties modeling

225 Dropout is a Bayesian method to model the model uncertainty in forecasting (Srivastava et al., 2014). However, the data
 226 uncertainty also needs to be considered. Kendall and Gal (2017) regarded the data uncertainty as a trainable parameter and
 227 jointly considered data and model uncertainties. However, the predictand data uncertainty is ignored and the learning of data
 228 uncertainty increases the number of training parameters. Here we propose an integrated modeling framework to fully
 229 incorporate the data and model uncertainties during the training process (Figure 2). First, the data uncertainties of predictors
 230 and predictands are estimated by the TCH method and are assumed as Gaussian distribution.

$$231 \quad \sigma = TCH(D_i), i = 1, 2, 3 \quad (22)$$

$$232 \quad \sigma_x \sim \mathcal{N}(0, \sigma) \quad (23)$$

$$233 \quad \sigma_y \sim \mathcal{N}(0, \sigma) \quad (24)$$

234 The sampling methods are used to sample from the data distribution to produce ensemble forecasts. The sampling process
 235 is conducted both for predictor data and predictand data. The data uncertainty is randomly sampled T times to generate an
 236 ensemble of predictors and predictands. In the meantime, the parameters are randomly dropped out for T times to construct a
 237 parametric ensemble. The perturbed data and parameter values are jointly used to calculate the training loss. The objective
 238 function is expressed as follows (Kendall and Gal, 2017), which is obtained from the likelihood of a Gaussian process
 239 (Srivastava et al., 2014).

$$240 \quad \mathcal{L}(\theta, p) = -\frac{1}{N} \sum_{i=1}^N \log p(y_{i,\sigma} | f^{\hat{U}_i}(x_{i,\sigma})) + \frac{1-p}{2N} \|\theta\|^2 \quad (25)$$

$$241 \quad \sigma = \sqrt{(\sigma_x^{(l)})^2 + \sigma_y^2} \quad (26)$$

242 where N is the sample size; p is the dropout probability; $\hat{U}_i \sim q'_\theta(U)$; θ is the parameter to be estimated; σ_x and σ_y are the data
 243 uncertainty for predictor and predictand, respectively. σ_x^l represents the propagated data uncertainty for the l th network layer.
 244 The negative log-likelihood function can be deduced according to the objective function.

$$245 \quad -\log p(y_{i,\sigma} | f^{\hat{U}_i}(x_{i,\sigma})) \propto \frac{1}{2\sigma^2} \|y_i - f^{\hat{U}_i}(x_i)\|^2 + \frac{1}{2} \log(\sigma^2) \quad (27)$$

246 where σ is the regression noise, with the mean of zero in a Gaussian distribution.

247 The objective function consists of a mean square error (MSE) term adjusted by data uncertainty and a regularization term,
 248 which is the negative logarithm of the Gaussian likelihood function. The objective function includes an uncertainty parameter
 249 σ^2 , which is determined by the sum of propagated uncertainty and target data uncertainty. The minimization of the negative
 250 log-likelihood function could be reached by differentiating the optimization function and setting to zero.

$$251 \quad \frac{\partial}{\partial \sigma^2} \left[\frac{1}{2\sigma^2} \|y_i - f^{\hat{U}_i}(x_i)\|^2 + \frac{1}{2} \log(\sigma^2) \right] = 0 \quad (28)$$

$$252 \quad \Rightarrow -\frac{1}{2\sigma^4} \|y_i - f^{\hat{U}_i}(x_i)\|^2 + \frac{1}{2\sigma^2} = 0 \quad (29)$$

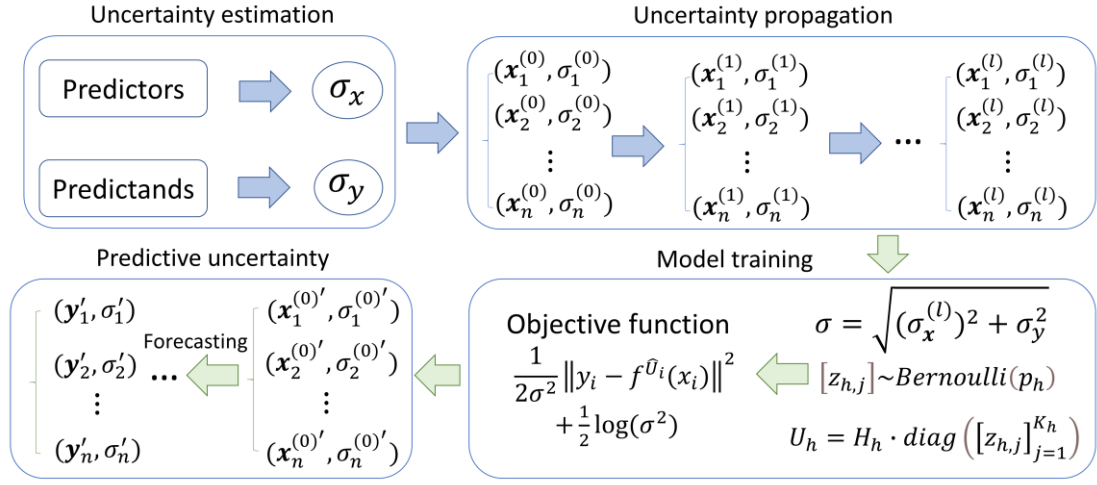
$$253 \quad \Rightarrow \sigma^2 = \|y_i - f^{\hat{U}_i}(x_i)\|^2 \quad (30)$$

254 where the minimum value of the negative log-likelihood function could be reached when the data variance equals to the square
 255 of the difference between the forecasted value and the observation.

256 Once the network weights are determined according to the objective function, the new input data uncertainty is propagated
 257 and the weights are randomly sampled to produce the forecasted ensemble. The predictive mean and variance are calculated
 258 from the predictive ensembles.

$$259 \quad \mu_i = \frac{1}{T} \sum_{t=1}^T y_{t,i} \quad (31)$$

$$260 \quad Var_i \approx \frac{1}{T} \sum_{t=1}^T y_{t,i}^2 - \left(\frac{1}{T} \sum_{t=1}^T y_{t,i} \right)^2 + \frac{1}{T} \sum_{t=1}^T \sigma_{t,i}^2 \quad (32)$$



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Figure 2: The proposed integrated data-model uncertainty modeling framework in precipitation forecasting. σ_x and σ_y are the predictor and predictand uncertainty, respectively. x_n^l and σ_n^l represents the propagated data value and uncertainty, respectively, for the l th network layer.

3.5. The deep learning forecasting framework

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In deep learning, encoder-decoder is a commonly used forecasting model (Badrinarayanan et al., 2017; Cho et al., 2014). In the encoder process, an input signal is converted into a one-dimension vector with fixed length. In the decoder process, the one-dimension vector is transformed into the target data with variable length. The available networks used for encoder and decoder processes are arbitrary and depend on the specific problem, such as convolutional neural network (CNN), recurrent neural network (RNN) and long-short term memory (LSTM) network (Hochreiter and Schmidhuber, 1997; Goodfellow et al., 2016). The CNN network is used in this study to construct the encoder-decoder forecasting model. Here we designed a deep learning encoder-decoder model for weekly precipitation forecasting (Figure 3). The temperature and geopotential height data for previous three weeks are regarded as inputs, with an image size of $64 \times 64 \times 7$ (including the land-sea mask). In the encoder process, the input image is down-sampled by a series of convolution, pooling and dropout operations, resulting in a one-dimension vector ($1 \times 1 \times 2048$). In the decoder process, the one-dimension vector is up-sampled by deconvolution, dropout and convolution operations, resulting in a forecasted precipitation image ($64 \times 64 \times 1$). The down-sampling and up-sampling procedures are used to learn the nonlinear mapping relationships between predictors and predictands.

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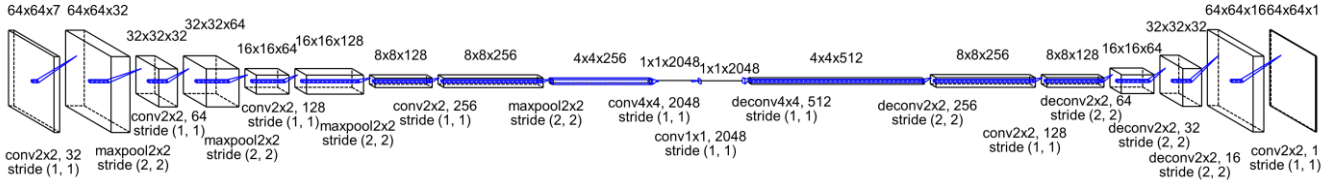
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In the training process, the optimization algorithm is set to Adam (Kingma and Ba, 2014), which is a stochastic learning algorithm based on adaptive moment. The network learning rate is set to 0.001 and the stopping rule of iteration is that the validating error does not decrease for at least 100 times. The data uncertainty is propagated forward according to the law of uncertainty propagation and the dropout process is repeated 10 times with a dropout rate of 0.5. The random seed is set to 1 to enable the reproducibility of the experiment. The experimental data spans from 1980 to 2020 (2139 weeks), of which 60%, 20% and 20% of the data are used for training, validating and testing, respectively. The optimal model parameters are

284 determined based on the minimal validating loss.



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Figure 3: The developed deep learning model for precipitation forecasting.

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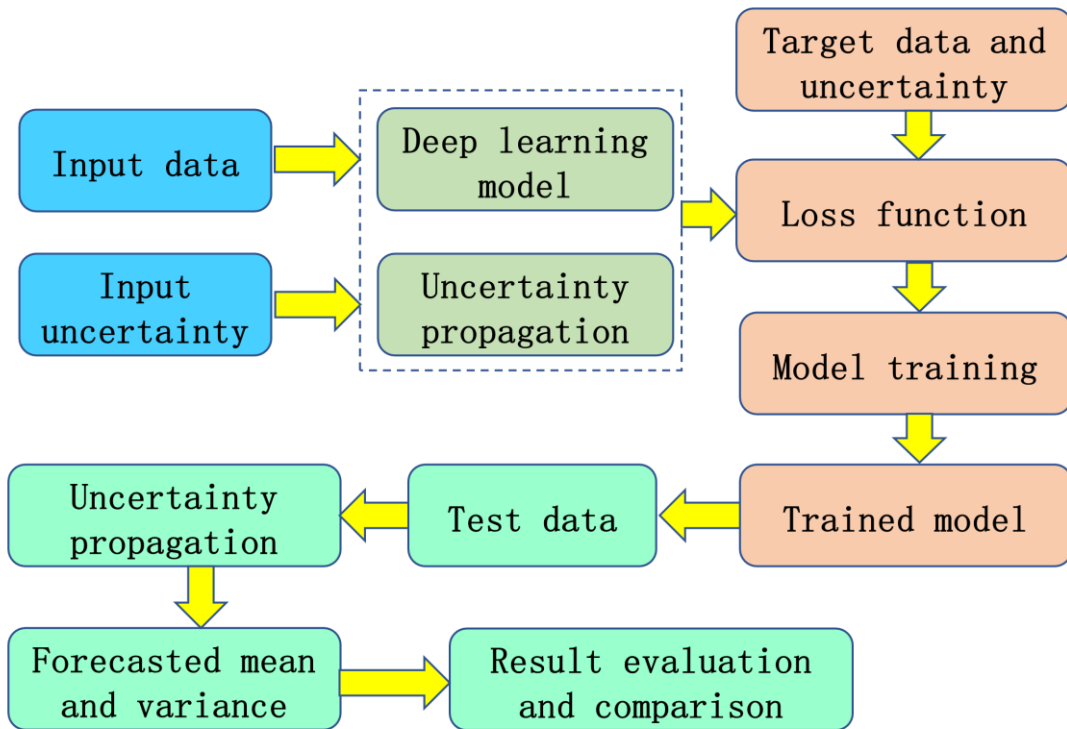
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The proposed deep learning framework for precipitation forecasting is demonstrated in Figure 4. The input data and its uncertainty are prepared and are considered as inputs for the forecasting model. The model weights are initialized and the input uncertainty is propagated forward according to the weights. The loss function value is calculated according to the forecasted value, the propagated uncertainty, target data and its uncertainty. The forecasting model is trained according to the optimization algorithm and then the trained model is obtained. Next the test data is used to produce the forecasted value and variance based on the model weights and uncertainty propagation. Finally, the forecasted value and variance are evaluated and compared with several precipitation forecasting methods.



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Figure 4: The proposed deep learning framework for precipitation forecasting.

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We designed a series of comparison experiments to investigate the effect of different uncertainty processing strategies on the forecasting performance (Table 1). The precipitation forecasting experiment without considering uncertainty is used as the baseline (Experiment 1). The mean square error is used as the loss function and the data and model uncertainties are not considered in Experiment 1. The uncertainty sources are incorporated differently into the experiments, including predictor uncertainty (Experiment 2), predictor and predictand uncertainties (Experiment 3), model uncertainty based on Srivastava et

301 al. (2014)'s method (Experiment 4), data and model uncertainties based on Loquercio et al. (2020)'s method (Experiment 5),
 302 and data and model uncertainties (Experiment 6) based on the proposed framework here. The data uncertainty only includes
 303 the propagated uncertainty from the input data in Equation (26) in Experiment 2, while the propagated uncertainty from the
 304 input data and the target data uncertainty are both included in Experiment 3. In Experiment 4, the data uncertainty is ignored
 305 and the model parameters are randomly sampled for 10 times to get the model spread. In Experiment 5, the input data
 306 uncertainty is propagated and the model uncertainty is modeled by sampling the parameters. In Experiment 6, the input
 307 uncertainty is propagated and the target data uncertainty is included in Equation (26) and the model uncertainty is represented
 308 by multiple sampling process.

309 Table 1. A summary of the experiment setup in this study. The \surd and \times symbol indicates that the specific factor is considered
 310 and omitted, respectively.

Experiments	Uncertainty processing		
	Data uncertainty		Model uncertainty
	Input data (predictor) uncertainty	Target data (predictand) uncertainty	
Experiment 1	\times	\times	\times
Experiment 2	\surd	\times	\times
Experiment 3	\surd	\surd	
Experiment 4 (Srivastava et al., 2014)	\times	\times	\surd
Experiment 5 (Loquercio et al., 2020)	\surd	\times	\surd
Experiment 6 (This study)	\surd	\surd	\surd

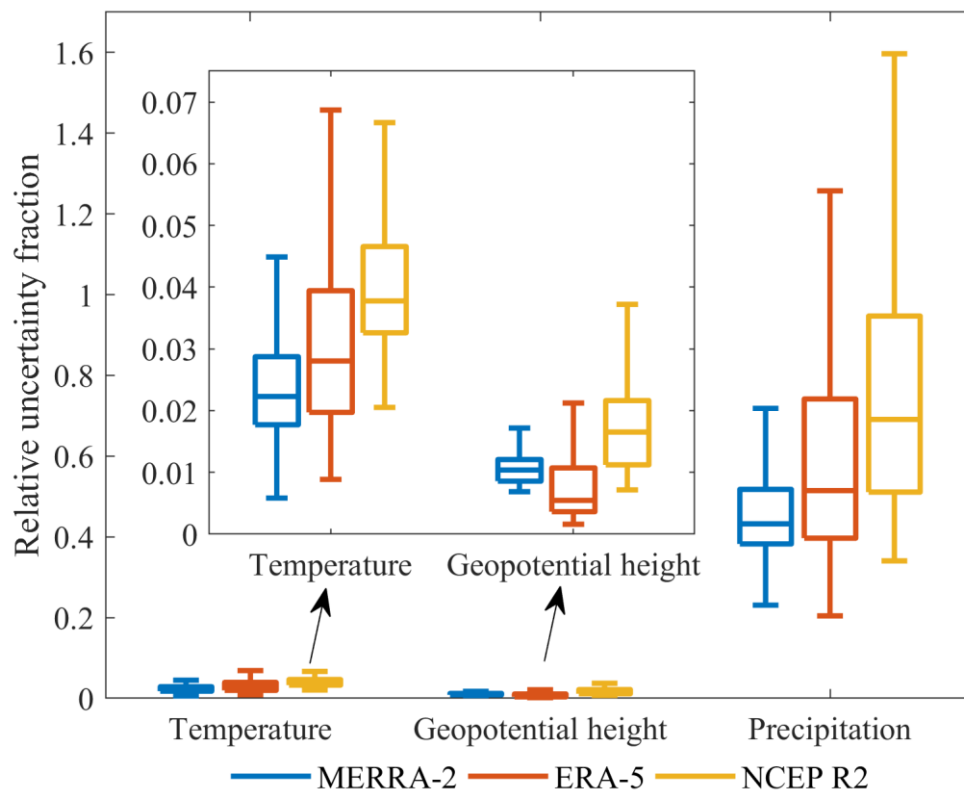
311
 312 The root mean square error (RMSE) statistic is used to measure the difference between forecasted value and true value.

$$313 \text{ RMSE} = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}} \quad (33)$$

314 where y_i is the true value or observation and \hat{y}_i is the forecasted value; n is the sample size.

316 4.1. The uncertainty of input and output datasets

317 The data uncertainty of predictors and predictand is calculated based on the TCH method and is shown in Figure 5. The
 318 precipitation data uncertainty is much higher than the temperature and geopotential height variables, with a median of ~43%
 319 relative uncertainty fraction for precipitation, ~2% for temperature and ~1% for geopotential height in the MERRA-2 data,
 320 and this pattern is also seen in the ERA-5 and NCEP R2 datasets. Therefore, the precipitation data suffer from greater
 321 uncertainty relative to the input data and the predictand uncertainty should not be ignored in the training process. The
 322 combination of the propagated input uncertainty and the predictand uncertainty is used as the adjusted parameter to regularize
 323 the loss function, which is relatively reasonable as the data with larger uncertainty should contribute less to the total training
 324 loss. It should be noted that the predictor and predictand data are normalized to [0,1] before uncertainty estimation to ensure a
 325 fair comparison of uncertainty value. The high uncertainty for precipitation data is related to strong spatiotemporal
 326 heterogeneity of precipitation and the high inconsistency among the reanalysis data (Xu et al., 2020b), while temperature and
 327 geopotential height data are much more homogeneous in space and time.



328

329 Figure 5: The data uncertainty calculated by the TCH method. The uncertainty distribution is plotted according to the
 330 uncertainty over all the pixels of the study area.

331 4.2. Overall precipitation forecasting performance

332 The RMSE and uncertainty in Table 2 are calculated based on the averaged values of all the grid cells. As for the predictive
 333 uncertainty, the forecasting method that only considers model uncertainty (Srivastava et al., 2014) obtains the minimum
 334 predictive uncertainty (Table 2). However, the data uncertainty is not considered when only sampling from the parameters and
 335 thus the impact of data error on forecasting is not evaluated. Loquercio et al. (2020) used the law of uncertainty propagation
 336 to propagate the data uncertainty and sampled the parameters randomly during training. In our proposed method, the input data
 337 uncertainty, target data uncertainty and model uncertainty are jointly coupled by uncertainty propagation and random parameter
 338 sampling. The average predictive uncertainty (10.859) based on the proposed method is smaller than the Loquercio et al.
 339 (2020)'s method (15.232), and the predictive R^2 is higher (0.539) than the latter (0.523). In this regard, the proposed method
 340 could reduce the predictive uncertainty of precipitation forecasting to some extent, when jointly modeling data and model
 341 uncertainties. The proposed method could improve the precipitation forecasting performance and could improve the reliability
 342 of precipitation forecasting by reducing the uncertainty.

343 When only the input uncertainty is modeled in the forecasting model, the predictive uncertainty is 14.729. If the target
 344 data uncertainty is coupled with input uncertainty, the predictive uncertainty is substantially reduced (9.290). In Equation (30),
 345 when the predictive error on the right side of the equation reaches local minimum and remains unchanged basically, the left
 346 side of the equation includes the input uncertainty propagation and the target data uncertainty. When new data is used to make
 347 prediction, the predictive uncertainty is generated by the input uncertainty and the law of error propagation. Thus, when only
 348 the input uncertainty is modeled in Equation (30), the left side of this Equation equals to the propagated uncertainty from the
 349 input data. If the left side of the Equation (30) is replaced from the propagated input uncertainty with the combination of
 350 propagated input uncertainty and target uncertainty, the propagated input uncertainty after replacement will be smaller than
 351 that of no replacement, i.e. $(\sigma_x^{(l)})^2 = \sigma^2 - \sigma_y^2 < \sigma^2 = \|y_i - f^{\hat{U}}_i(x_i)\|^2$.

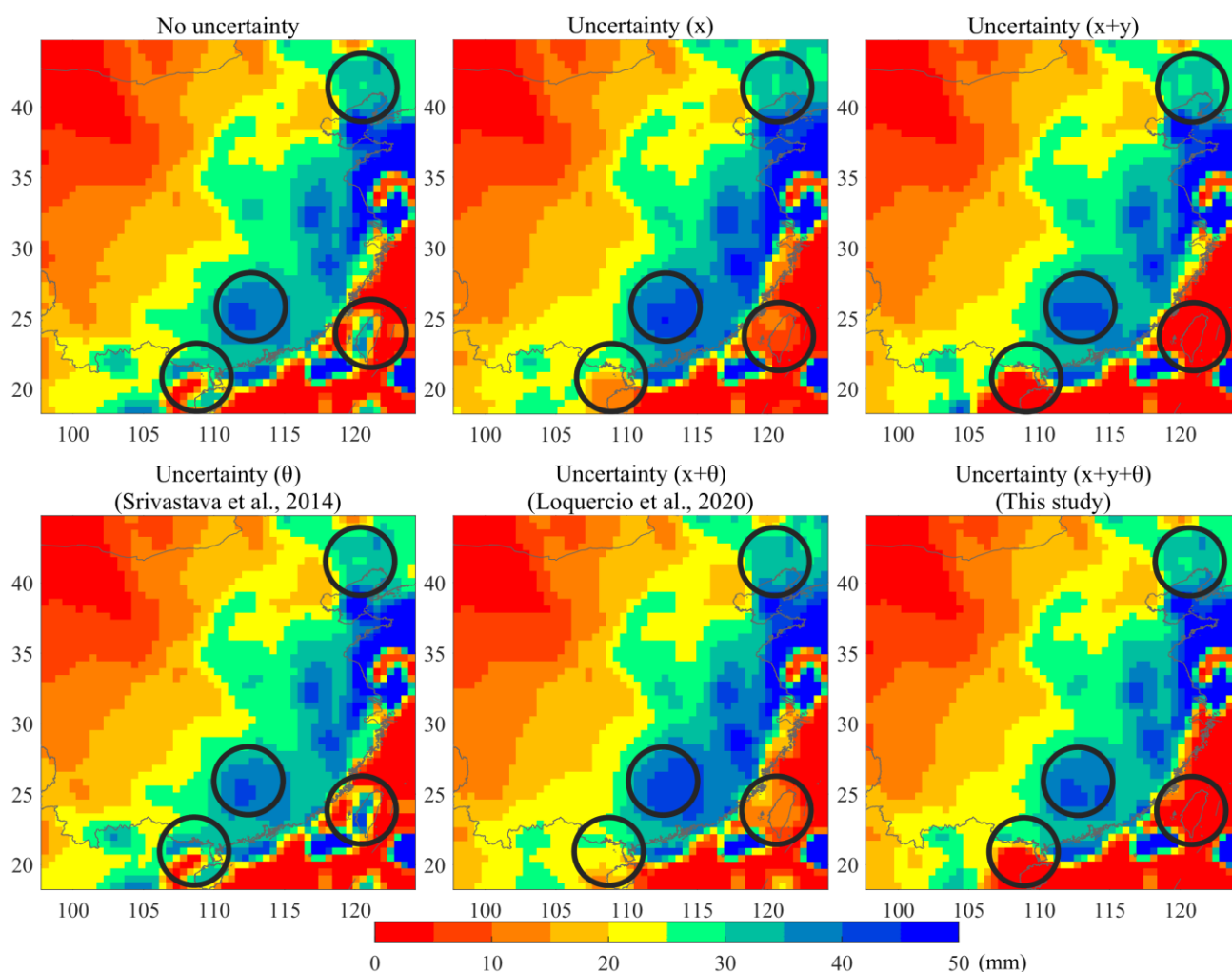
352 The predictive accuracy generally increases with the uncertainty processing procedures. The predictive RMSE decreases
 353 when incorporating the predictor uncertainty processing relative to the prediction without uncertainty handling. Further
 354 improvement is expected when considering the predictor and predictand uncertainties from the data aspect, relative to the sole
 355 predictor treatment. The R-square exhibits slight improvement when incorporating model uncertainty (Srivastava et al., 2014)
 356 relative to the prediction without uncertainty processing. In Loquercio et al. (2020)'s method, the input data uncertainty and
 357 model uncertainty are both considered and the predictive performance increases relative to the no uncertainty and predictor
 358 uncertainty processings. In our method, the input data uncertainty, target data uncertainty and model uncertainty are jointly
 359 considered, reaching the lowest RMSE and the highest R-square relative to the above uncertainty processing methods.

360 Table 2. The accuracy of precipitation forecasting based on different uncertainty processing strategies. The best RMSE and the
 361 highest R-square are shown in bold for each column.

Uncertainty processing	RMSE	Uncertainty	R-square
No uncertainty	25.138	-	0.503
Predictor uncertainty	25.065	14.729	0.517
Predictor and predictand uncertainties	24.679	9.290	0.533
Model uncertainty (Srivastava et al., 2014)	25.156	1.570	0.506
Data and model uncertainties (Loquercio et al., 2020)	25.056	15.232	0.523
Data and model uncertainties (This study)	24.531	10.859	0.539

362 **4.3. Spatial patterns of precipitation forecasting**

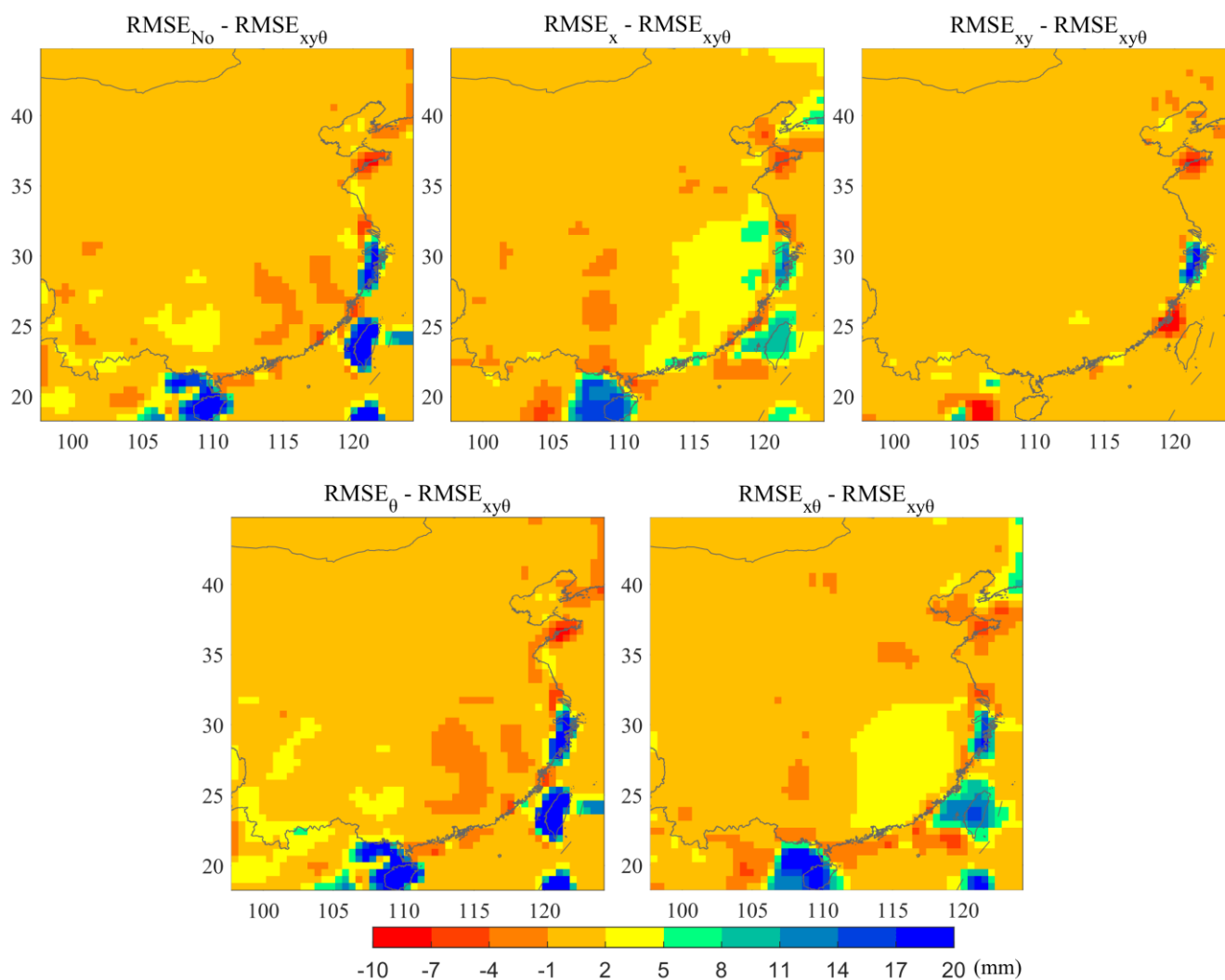
363 In Figure 6, the spatial patterns of the RMSE for precipitation forecasting demonstrate some similarities and differences
 364 between different uncertainty processing strategies. Overall, the spatial distribution of RMSE is similar with each other and is
 365 smaller in the northwest region but larger in the southeast region. In the places where the annual rainfall is abundant, the water
 366 cycle process is accelerated and the precipitation observations may suffer from large uncertainty. The difficulty of forecasting
 367 extreme high precipitation volume also increases the average RMSE in the southeast region relative to the northwest region
 368 (Yuan et al., 2012; Huang et al., 2013). There are some differences of the forecasting error among different forecasting methods
 369 in local areas. For example, the forecasting performance based on our proposed method could outperform the methods in
 370 Experiments 1, 2, 4 and 5 and is comparable with the methods in Experiments 3 for the local areas covered by black circles in
 371 Figure 6.



372
 373 Figure 6: The spatial patterns of RMSE for precipitation forecasting. In this figure, x means the modeling of input uncertainty;
 374 x+y represents the modeling of input and output uncertainty; x+y+θ indicates the modeling of input uncertainty, output
 375 uncertainty and model uncertainty. The black circles represent the highlighted areas.

376 Figure 7 demonstrates the difference of the predictive RMSE between other uncertainty processing approaches and the
 377 proposed method for precipitation forecasting. It can be seen that there is little difference of the predictive RMSE between the

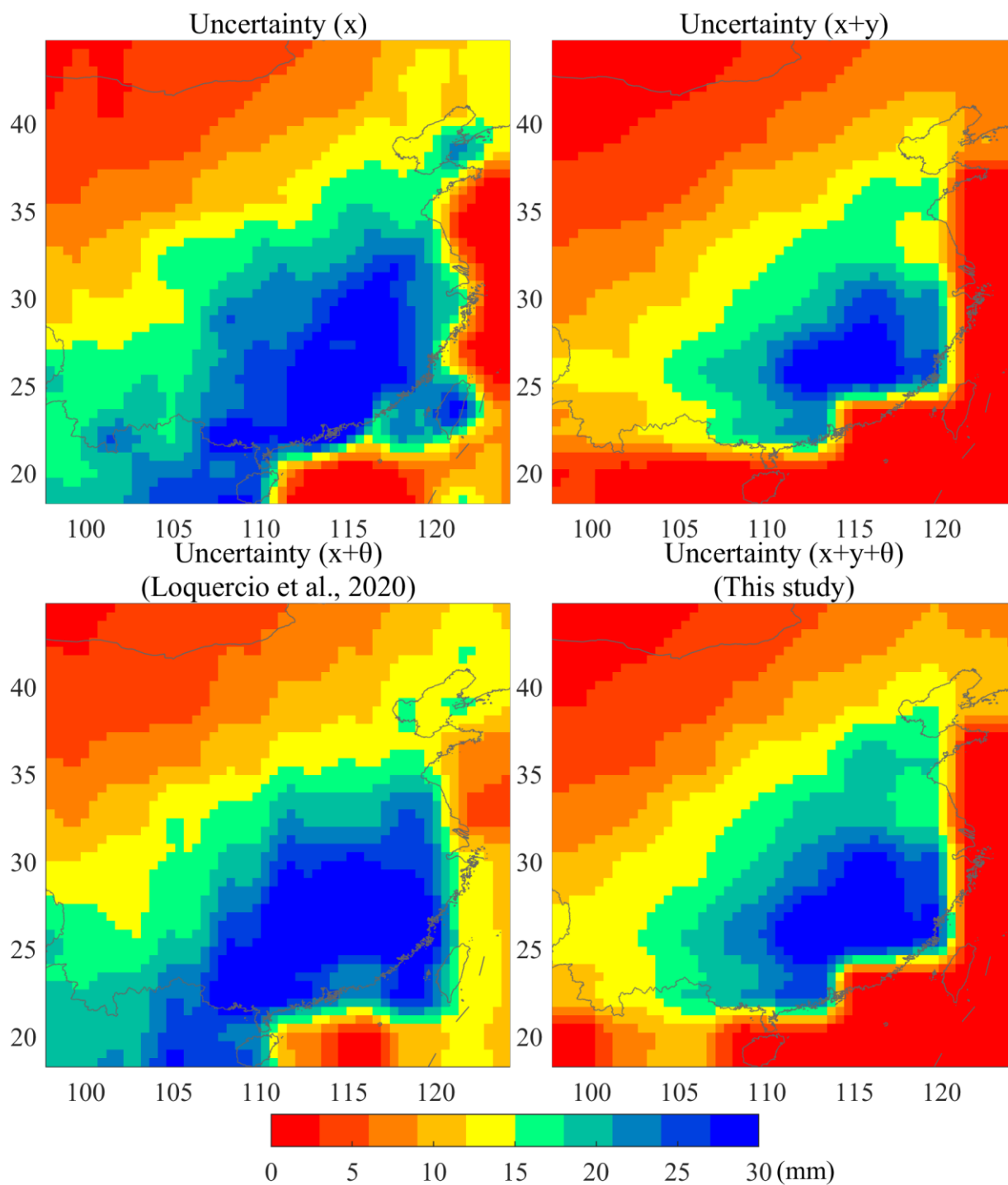
378 proposed method and other uncertainty processing approaches. However, the RMSE is larger for some uncertainty processing
 379 methods relative to the proposed method in some areas, including the Hainan and Taiwan provinces and part of eastern China.
 380 It is likely that the predictive RMSE is reduced in the proposed method by improving the prediction performance in the areas
 381 with accelerated water cycle and abundant rainfall. The target data uncertainty is incorporated into the objective function to
 382 pay different attentions in space during the training process, leading to a different weight distribution of the forecasting model
 383 for the proposed method relative to others. The changing weight distribution improves the forecasting accuracy in the southeast
 384 areas by reducing the forecasting error of extreme precipitation.



385
 386 Figure 7: The difference of the predictive RMSE between the proposed method and other uncertainty processing approaches
 387 for precipitation forecasting.

388 Figure 8 demonstrates the impact of different uncertainty processing methods on the predictive uncertainty of
 389 precipitation. The spatial patterns of predictive uncertainty indicate larger uncertainty in the southern China relative to northern
 390 China, which is consistent with the knowledge that the water cycle in southern China is accelerated and precipitation
 391 forecasting may suffer from large uncertainty. If only the input uncertainty is considered in the forecasting model, the predictive
 392 uncertainty is large in the central and southeast regions. The predictive uncertainty could be substantially reduced when

393 incorporating the target data uncertainty besides the input uncertainty. In Loquercio et al. (2020)'s method, the predictive
 394 uncertainty is slightly higher than that of input uncertainty modeling in space, because the input and model uncertainties are
 395 jointly modeled. Our proposed method could include the input, target and model uncertainties jointly and could help reduce
 396 the predictive uncertainty to a large extent, relative to the Loquercio et al. (2020)'s method.



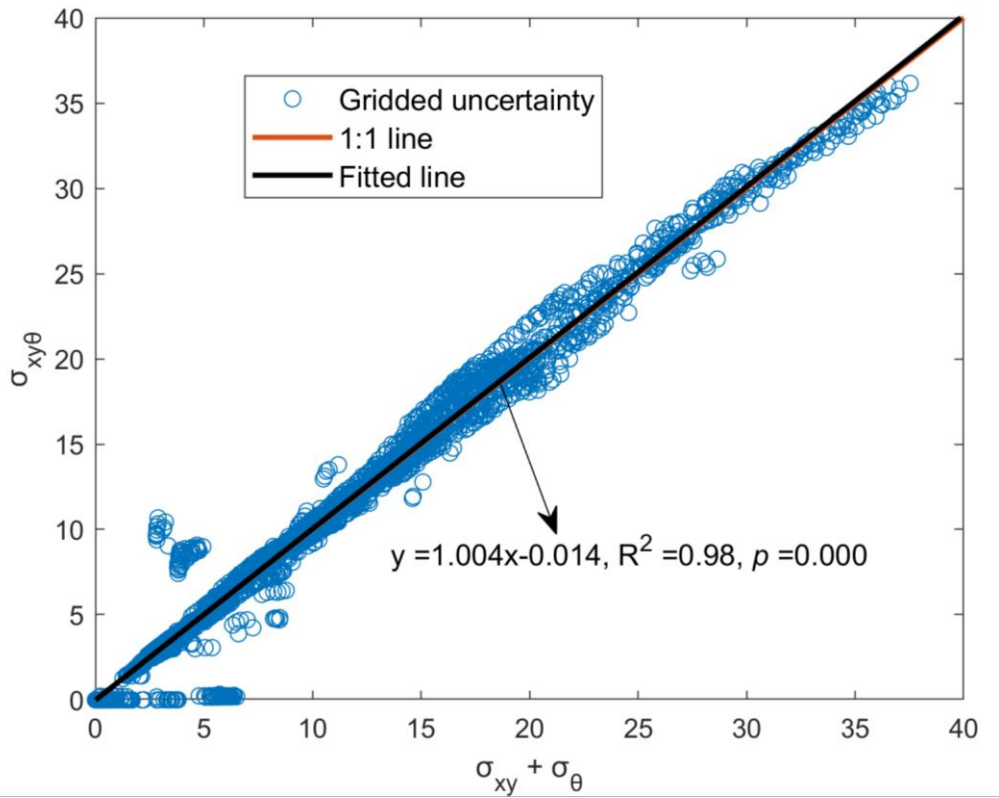
397
 398 **Figure 8:** The spatial patterns of uncertainty for precipitation forecasting.

399 **4.4. Uncertainty analysis and discussion**

400 In precipitation forecasting, data and model uncertainties both bring uncertainty to the forecasting result. The higher the

401 data and model uncertainties, the more divergent and less reliable the forecasting. Therefore, the data and model uncertainties
402 should be jointly considered in the forecasting process (Gal, 2016; Kendall and Gal, 2017; Loquercio et al., 2020; Parrish et
403 al., 2012). Although the predictive error is close to each other among different forecasting methods in Figure 6 and Table 2,
404 the predictive uncertainty has some discrepancies. The modeling of input uncertainty only in the forecasting model would
405 bring high predictive uncertainty and the target data uncertainty is ignored. The joint modeling of input and target uncertainties
406 could reduce the predictive uncertainty substantially, which is related to the change of the variance in Equations (26) and (30)
407 corresponding to the minimum value of the forecasting error term. The propagation of input uncertainty is constrained by
408 refining the uncertainty representation in Equation (26) after incorporating the target uncertainty term and thus changing the
409 weight training process.

410 Figure 9 demonstrates the relationship between the predictive uncertainty by the proposed method and the summation of
411 the predictive uncertainty from data and model. The predictive uncertainty by the proposed method ($\sigma_{xy\theta}$) agrees well with the
412 summation of the predictive uncertainty from data and model, with a regressed slope of 1.004 and a R^2 of 0.98, indicating the
413 good consistency of the predictive uncertainty between joint and separate uncertainty modeling. The median predictive
414 uncertainty is 8.04, 1.40 and 9.49 mm for data, model and joint data-model uncertainty modeling, respectively in the
415 precipitation forecasting experiments (Figure 10). The data and model uncertainty account for ~85% and ~15% of the total
416 predictive uncertainty by the proposed method respectively. The model structure is fixed in this study and thus the model
417 uncertainty comes from mainly the parameters. The dropout method enables the random abandoning of network parameters
418 over the specific layer and prevents the overfitting of the forecasting model. The distributions of model weights are changed
419 when incorporating the data uncertainty into the objective function (Figure 11). The model weights become larger and more
420 dispersive relative to the prediction without uncertainty processing or with model uncertainty consideration. The data
421 uncertainty is propagated into the prediction through model weights and thus the data uncertainty contributes more to the
422 predictive uncertainty than model uncertainty. Although the model weights appear more scattered, the predictive accuracy
423 exhibits small improvement due to the uncertainty consideration in the objective function.

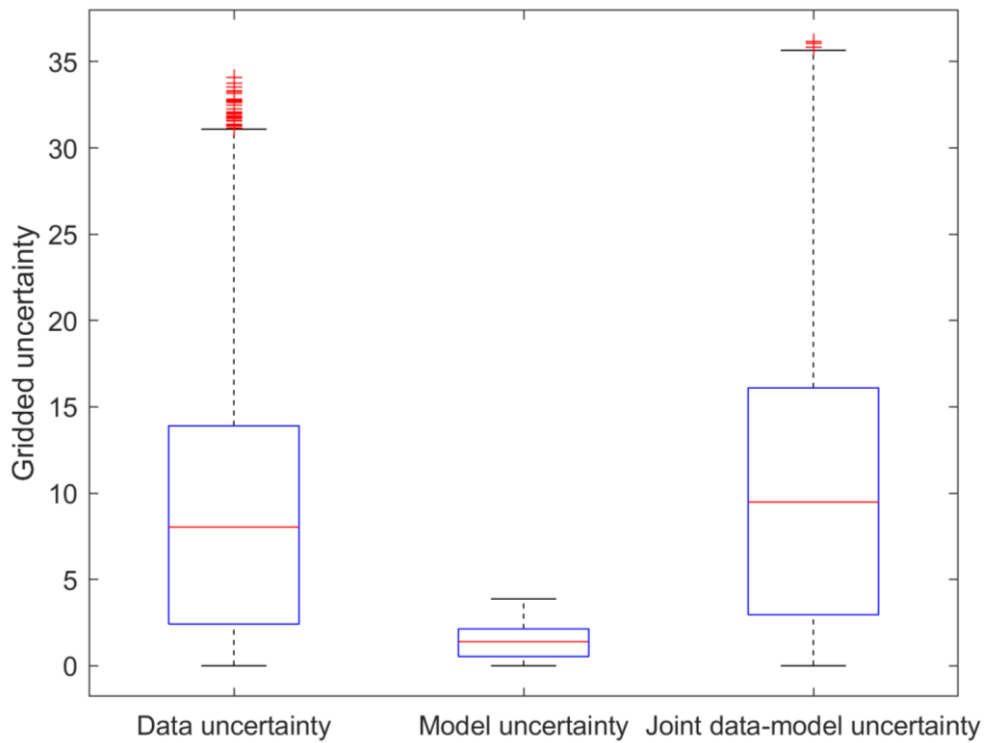


424

425 Figure 9: The relationship between the summation of predictive uncertainty from data (input and target data) and model and

426

the predictive uncertainty from joint consideration of data (input and target data) and model.

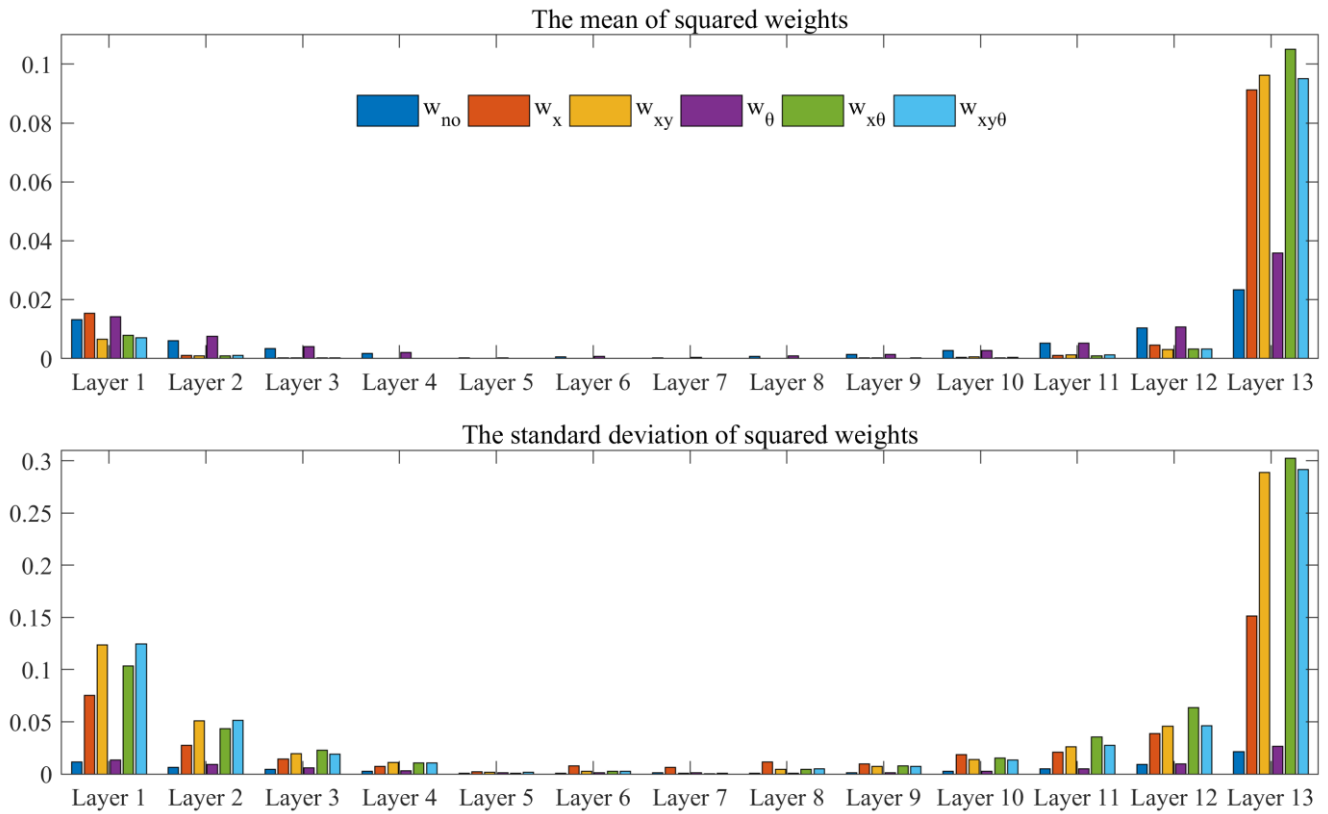


427

428 Figure 10: The distributions of the predictive uncertainty from data, model and joint data-model modeling methods for

429

precipitation forecasting.



430
431 Figure 11: The mean and standard deviation of squared weights of the precipitation forecasting model.

432 The predictive uncertainty is closely related to the input data uncertainty and model weights. In Figure 2, the input data
 433 uncertainty is propagated into predictive uncertainty through model parameters, while the target data uncertainty is
 434 incorporated into the training process by the objective function. The incorporation of uncertainty processing changes the
 435 training process and the distributions of model weights (Figure 11). The last CNN layer (Layer 13) weights of the precipitation
 436 forecasting model are generally higher than the other layers, which may contribute largely to the predictive uncertainty by
 437 propagating the data uncertainty. The mean and the standard deviation of the squared weights of the last CNN layer for the
 438 Loquercio et al. (2020)'s method are higher than other uncertainty processing methods, suggesting an overall larger and more
 439 dispersive weight distribution for Loquercio et al. (2020)'s method than the others, which could partly explain the high
 440 uncertainty of the Loquercio et al. (2020)'s method in Table 2.

441 The proposed method in this study could model the input uncertainty, target uncertainty and model uncertainty jointly
 442 and could reduce the predictive uncertainty relative to Loquercio et al. (2020)'s method. The developed method does not
 443 increase the training parameter and is a general forecasting uncertainty method for geophysical applications such as
 444 temperature forecasting, runoff forecasting and wind speed forecasting, especially for data-driven forecasting models (Ham et
 445 al., 2019; Zheng et al., 2020; Hossain et al., 2015).

446 In numerical precipitation forecasting systems, ensemble forecasting is commonly used to quantify the predictive
 447 uncertainty (Duan et al., 2019). In ensemble forecasting, the model parameters and data are perturbed to produce a forecasted
 448 ensemble and thus the data and model uncertainties are both considered. However, it would be time-consuming and cost-

449 expensive to conduct large-sample sampling for complex physical models. In our developed method, the law of error
450 propagation is used to propagate the data uncertainty. The uncertainty propagation of convolution, max-pooling and
451 deconvolution in the deep learning forecasting model is tractable in an analytical form. However, the uncertainty propagation
452 process is generally intractable analytically for complex statistical or physical models. Therefore, the theory and
453 implementation technology for uncertainty modeling require further development, such as surrogate modeling, Monte Carlo
454 methods, polynomial chaos expansions and Bayesian approaches (Linde et al., 2017; Sudret et al., 2017; Zhu and Zabarar,
455 2018; Schiavazzi et al., 2017; Nitzler et al., 2020).

456 **5 Conclusion**

457 In this study, we proposed a data-model uncertainty coupling framework to estimate the predictive uncertainty of
458 precipitation forecasting. In this framework, the predictor and predictand uncertainties are estimated a priori by the TCH method
459 and are assumed as Gaussian distribution. The predictor uncertainty is propagated forward during training and testing processes
460 by the law of error propagation. The model uncertainty is represented by randomly abandoning model weights from deep
461 learning layers. The data and model uncertainties are jointly modeled in the objective function during training and are also
462 used during the testing process. The loss function is constructed by the MSE statistic adjusted by data uncertainty and a
463 regularization term based on logarithmic data uncertainty. In the loss function, the adjusting parameter is determined by the
464 combination of the square of predictor and predictand uncertainties. The forecasted ensembles are used to calculate the
465 predictive mean and variance to estimate the predictive uncertainty of precipitation.

466 The weekly precipitation forecasting in southern and northern China is used as an example to examine the effectiveness
467 of the proposed joint uncertainty modeling framework. Temperature and geopotential height data in previous three weeks are
468 used to forecast the precipitation in the target week. The forecasting model is developed based on an encoder-decoder CNN
469 deep neural network, with multivariate spatiotemporal predictor data as inputs and spatiotemporal precipitation data as output.
470 The experimental results indicate that the proposed joint uncertainty modeling framework for precipitation forecasting exhibits
471 better forecasting accuracy (improve RMSE by 1-2% and R-square by 1-7% on average) relative to several existing methods,
472 and could reduce the predictive uncertainty by ~28% relative to Loquercio et al. (2020)'s approach. The reduction of predictive
473 uncertainty is significant for quantitative precipitation forecasting from a data-driven view. The predictive performance is
474 improved in the proposed method by incorporating the target data uncertainty and reducing the forecasting error of extreme
475 precipitation.

476 The data-driven precipitation forecasting method has limitations in the interpretation part relative to numerical weather
477 prediction. The precipitation forecasting accuracy for numerical models could still be improved by improving the
478 parameterization schemes and resolving the uncertainties in observations, parameters and models. The proposed uncertainty

479 modeling framework may also provide some insights for the uncertainty quantification in numerical prediction models. For
480 example, the uncertainty propagation for the input data and the coupling with target data uncertainty could be used in a data
481 assimilation scheme to estimate the propagated uncertainty in weather forecasting.

482 Data-driven precipitation forecasting could be used as a tool to assist regional prediction and warning of extreme weather
483 events together with numerical models. The proposed joint data-model uncertainty modeling framework could help estimate
484 the forecasting spread and is a general approach to derive predictive uncertainty for geophysical forecasting applications.
485 Further research should focus on the non-Gaussian uncertainty modeling for complex integrated statistical-physical models.

486 **Data availability**

487 The meteorological data are publicly available and can be obtained via the website [https://gmao.gsfc.nasa.gov/reanal](https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/)
488 [ysis/MERRA-2/](https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/) for MERRA-2, <https://psl.noaa.gov/data/gridded/data.ncep.reanalysis2.html> for NCEP R2 and [https://cl](https://climate.copernicus.eu/climate-reanalysis)
489 [imate.copernicus.eu/climate-reanalysis](https://climate.copernicus.eu/climate-reanalysis) for ERA-5.

490 **Author contributions**

491 LX conceptualized and wrote the paper. CY provided supervision of this study. NC gave support in developing the
492 manuscript. HY and ZC reviewed and revised the manuscript.

493 **Competing interests**

494 The authors declare that they have no conflict of interest.

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