RC1

Prediction of basin-scale river channel migration based on landscape evolution numerical simulation

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We sincerely thank the reviewer for their insightful and constructive comments. We have carefully addressed each point below and will incorporate the corresponding revisions into the manuscript. We hope that the revised manuscript has met the quality standards for publication in HESS.

Note:

(1) In this response, the text in *italic type* is the original comments from the reviewers, and the text in blue, headed with "Reply", is the response from the authors.

(2) In the manuscript, the words in blue indicate the sentence is improved or revised. Some of them are mentioned in this response via the page and line number.

Response to Reviewers

Comments:

(1) *The parameter uncertainty is performed by using Markov Chain Monte Carlo method, and a modified Gaussian likelihood function is used. It is interesting in Bayesian uncertainty analysis. However, the statistical assumptions behind Equation (10) are still somewhat unclear, and further explanation is recommended. What is the physical meaning of Σ in Equation (10)? Could non-Gaussian likelihood functions or different error model specifications further improve results?*

Reply: Reply: Thank you to the reviewer for pointing out these two issues.

① In this study, Eq. (10) is formulated as a modification of the classical Gaussian likelihood in Eq. (6). The key assumption is that the average Hausdorff distance (H) between the simulated and observed channel planforms follows a zero-mean, independent and identically distributed Gaussian error model, i.e., $H \sim \mathrm{N}(0, \sigma^2)$. Under this setting, H_{obs} represents the distance between the true channel and itself (thus H_{obs}= 0), whereas H denotes the distance between the model-simulated channel planform and the true channel.

$$L(\theta^i \mid \mathrm{D}) = \frac{1}{2\pi^{n/2} |\Sigma|^{1/2}} \exp\left[-\frac{[\mathrm{D} - f(\theta^i)]^{\mathrm{T}} \Sigma^{-1} [\mathrm{D} - f(\theta^i)]}{2} \right] \quad (6)$$

$$\ln L = -\frac{1}{2}[\frac{H^2}{\Sigma^2} + \ln(2\pi\Sigma^2)] \quad (10)$$

In Eq. (6), Σ denotes the covariance matrix of the residual errors. Meanwhile,

$$\mathrm{D} - f(\theta^i) = H - H_{obs} = H - 0 = H$$

Therefore, in Eq. (10), Σ is no longer the covariance matrix used in the conventional Gaussian likelihood; instead, it represents the variance of *H*.

$$\ln L = -\frac{1}{2}\left[\frac{H^2}{\sigma^2} + \ln(2\pi\sigma^2)\right]$$

In addition, we have revised Eq. (10) accordingly in the revised manuscript.

② We sincerely appreciate the reviewer's insightful comments regarding the choice of likelihood function. We agree that incorporating non-Gaussian likelihoods or more complex residual structures could potentially enhance predictive performance, such as the correlated, heteroscedastic, and non-Gaussian functions. However, adopting a non-Gaussian likelihood generally entails additional hyperparameters, which increases parameter uncertainty and renders the convergence of MCMC algorithms more challenging, thereby substantially raising computational cost. Given the limited amount of data available for parameter estimation and the absence of clear evidence of heteroscedasticity in the residual diagnostics, the Gaussian likelihood provides a reasonable balance between model reliability and computational feasibility.

(2) *The manuscript mentioned that since 2012, there has been significant agricultural development in the downstream river reaches, and human activities may have altered land cover, soil properties, and river channel constraints. However, in the model, the*

settings for land cover and soil parameters do not seem to be influenced by time. This is an important limitation and should be more clearly emphasized. Currently, it is briefly mentioned only as a qualitative explanation for local mismatches.

Reply: Thank you to the reviewer for providing this important suggestion. We agree that the rapid intensification of agricultural activities in the downstream reach since 2012 may have influenced channel evolution by altering land-cover types and associated soil physical properties. However, in this study, the relevant landscape-evolution parameters were not parameterized as time-varying, for the following reasons.

First, although remote-sensing imagery allows a qualitative identification of cropland expansion in the downstream area after 2012, continuous and reliable land-cover and soil-property datasets at the study-basin scale are not available. Under such data limitations, introducing time-varying landscape-evolution parameters would likely increase parameter uncertainty and consequently reduce the robustness of the model predictions.

Second, while the landscape-evolution model does not explicitly account for temporal changes in parameters driven by human activities, we conducted a Bayesian parameter uncertainty analysis that effectively enables key model parameters to adjust adaptively within physically plausible ranges through parameter identification. By comparing the simulated and observed channel planform distributions, we verified that the identified parameter set can reasonably represent the dominant landscape-evolution characteristics of the study area.

(3) *In section 3.2, the datasets from NASA (Leaf Area Index, Surface Roughness, Air Temperature) are referenced. The resolution of these input raster datasets is relatively coarse. Could this impact the accuracy of the simulations?*

Reply: Thanks for this comment. The objective of this study is to simulate basin-scale, long-term channel migration, rather than short-term, reach-scale hydrodynamic evolution. At these spatial and temporal scales, the response of LE-PIHM to meteorological and hydrological forcing is primarily reflected in the basin-wide water balance and the cumulative effects of long-term erosion–deposition, rather than in a detailed representation of high-frequency processes and fine-scale spatial heterogeneity (Tucker and Hancock, 2010; Coulthard and Skinner, 2016; Zhang et al., 2016). Therefore, using relatively coarse-resolution datasets for basin-scale landscape-evolution simulations, together with a parameter-uncertainty analysis, can achieve an acceptable level of accuracy. Moreover, such datasets have been widely adopted in large-scale watershed hydrologic modeling studies (Asong et al., 2020; Gelaro et al., 2017; Qi et al., 2015; Rodell et al., 2004).

(4) *The simulation technique for basin-scale river channels proposed in the manuscript has been successfully applied to the Kumalake River Basin. A broader discussion of the generalizability of this method would help improve its applicability.*

Reply: Thank you to the reviewer for this important suggestion. We agree that it is necessary to discuss the generalizability of the proposed basin-scale channel-migration modeling framework, and we have added the corresponding discussion in the revised manuscript. Specifically, we address the generalizability of the approach from the following perspectives:

(1) Generality of the modeling framework. The proposed technique is built upon LE-PIHM and a DEM-driven channel-extraction procedure. Because it does not rely on basin-specific assumptions or a particular basin type, it can be transferred to other basins provided that basic topographic, climatic, and geological datasets are available.

(2) Adaptability to different dominant controls. The framework explicitly couples hydrological processes, landscape evolution, and tectonic uplift. Key parameters (e.g., erodibility coefficients, uplift rates, and hydrologic parameters) can be adjusted according to local conditions, enabling application to basins primarily controlled by climate forcing or by tectonic activity.

(3) Transferability of the uncertainty analysis and surrogate modeling components. The LSTM surrogate model and the Hausdorff distance-based modified likelihood are not basin-specific. Their training workflow and the associated parameter-uncertainty analysis framework can be directly transferred to other basin-scale channel-migration studies, indicating strong methodological portability.

Meanwhile, we also clarify in the manuscript the potential limitations of the approach in basins that are strongly regulated by human engineering interventions (e.g., channelization projects or large-reservoir operations). We further discuss possible future extensions, such as introducing parameterizations of human activities, to broaden its applicability. We believe these additions more comprehensively demonstrate the transfer potential and application prospects of the proposed framework across diverse basin settings.

(5) *A marked disparity in the extent of river channel migration is evident between the upstream and downstream reaches of the basin (Figure 11). The mechanisms underlying this phenomenon require further explanation.*

Reply: We thank the reviewer for pointing out this issue. In our study basin, the upstream area is mountainous, whereas the downstream area is a lowland plain. The relatively narrow migration envelope (i.e., lower uncertainty) in the upstream reach is primarily because this segment is confined within a canyon setting where the valley is topographically narrow and comparatively stable. As a result, the channel is strongly constrained laterally, and the channel-migration model exhibits lower predictive uncertainty in this reach, leading to a narrower simulated distribution of channel positions.

In contrast, parts of the downstream reach located on the plain show substantially larger predictive uncertainty. This is because the low-relief terrain provides fewer topographic constraints on lateral migration, and channel behavior is more strongly influenced by the combined effects of deposition, changes in flow hydraulics, and human activities. Consequently, the basin-scale river channel migration model is associated with greater uncertainty in the downstream plain, yielding a wider predicted channel distribution, indicating higher predictive uncertainty.

(6) *In the future scenario of SSP2-4.5 (Figure 14), significant river channel reorganization occurs, and the elevation changes in the river segments under this scenario are also noticeable, which is very interesting. What are the underlying mechanisms causing this phenomenon?*

Reply: Thanks for this insightful comment. We argue that the pronounced channel migration and the large reach-scale elevation changes under SSP2-4.5 are not solely driven by the magnitude of climate change itself, but rather reflect a nonlinear, threshold-like response of the fully coupled hydro–geomorphic system under specific climatic forcing.

Within the LE-PIHM landscape evolution framework, channel planform dynamics and elevation changes are jointly controlled by the following processes:

(1) Precipitation–runoff mechanisms, including rainfall, infiltration and runoff generation, and surface–groundwater exchange;

(2) Sediment supply and transport capacity, including hillslope diffusion, weathering-driven sediment production, and river sediment transport;

(3) Landscape–flow-routing feedbacks, whereby landscape evolution and the associated adjustment of D8-based flow paths modify local slope and discharge concentration.

Under the SSP2-4.5 scenario, the combined effects of these mechanisms drive downstream lowland reaches toward a critical geomorphic threshold, thereby triggering obvious channel migration.

(7) *It would be beneficial to add information on the variability (such as the standard deviation) of precipitation and temperature across the different scenarios in Table 5.*

Reply: We have added the variances and ranges of precipitation and temperature in Table 6 of the revised manuscript. The results show that the different scenarios exhibit not only substantial differences in the mean values of precipitation and temperature, but also clear scenario-dependent variability. In general, higher-emission scenarios are associated with larger fluctuations, reflected by greater variances and wider ranges in both temperature and precipitation.

(8) *To help readers distinguish the variables for the four climate scenarios, the line colours in Figure 13 should be redesigned.*

Reply: Thanks for pointing out this issue. As shown in Fig. 13, we have adjusted the line colors accordingly in the revised manuscript.

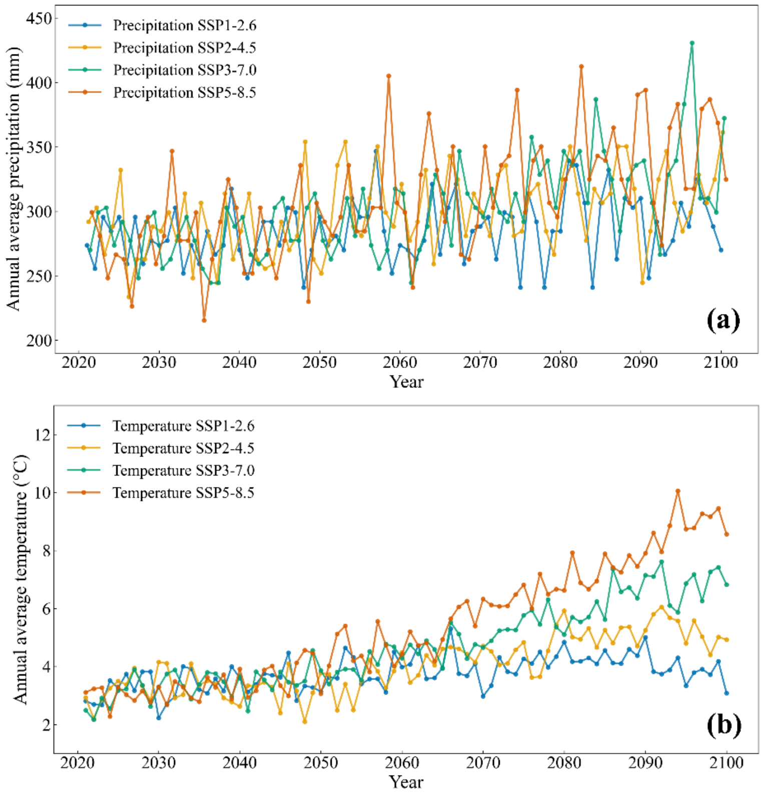

Figure 13. Annual mean precipitation and temperature for the four climate scenarios.

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