Enhancing generalizability of data-driven urban flood models by incorporating contextual information

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Supplementary material

Contents:

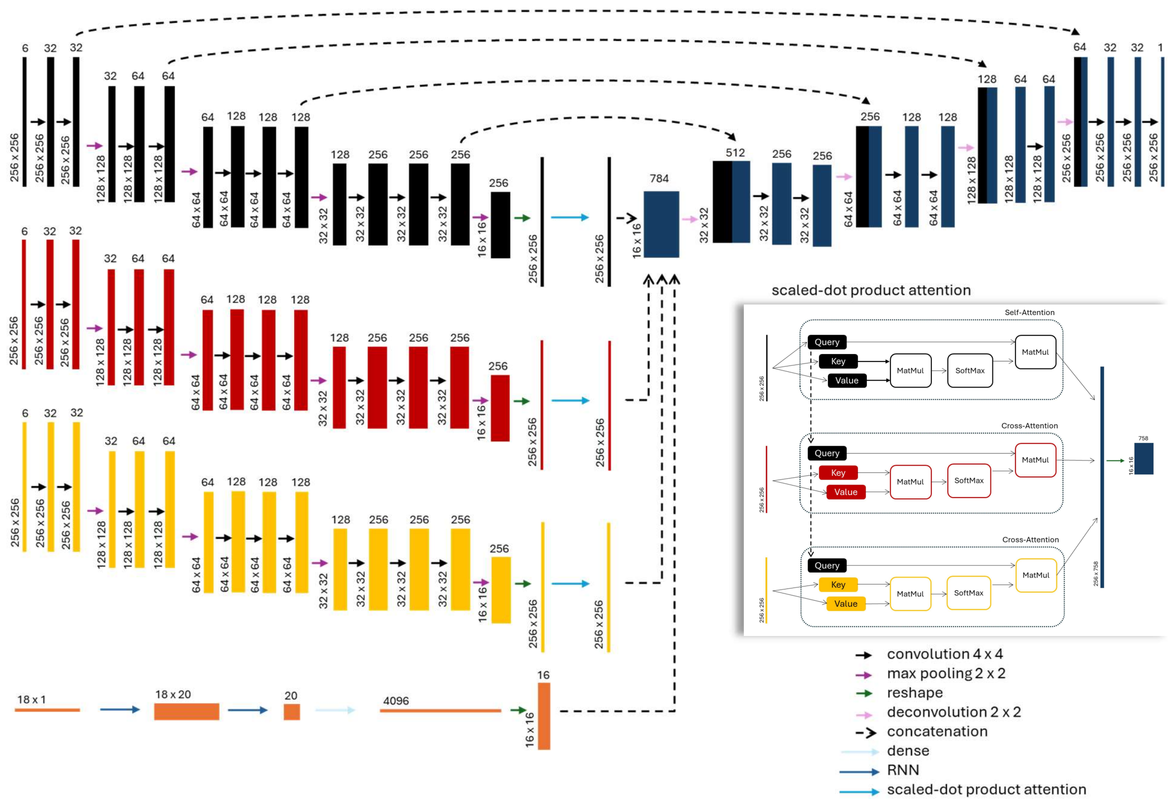

Fig S1. Model's architecture. Each box corresponds to a multi-channel feature map, with the corresponding number of channels denoted on top of the box and its height and width dimensions indicated at the lower left edge of the box. The arrows correspond to different operations and the operations for the scaled-dot product attention are detailed in the figure with shaded contours.

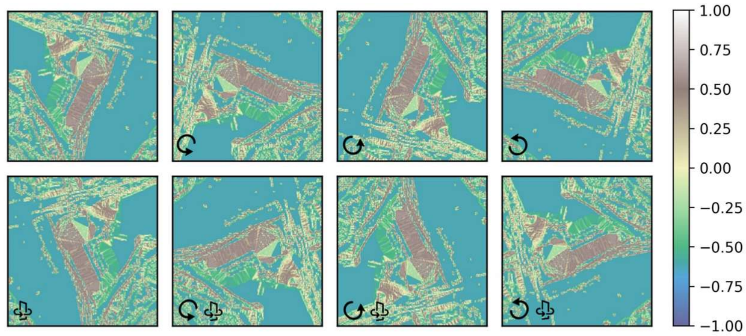

Figure S2. Augmentation techniques that were applied to the patches, consisting of a combination of flips and 90° rotations. The upper left patch is the original patch, without augmentation.

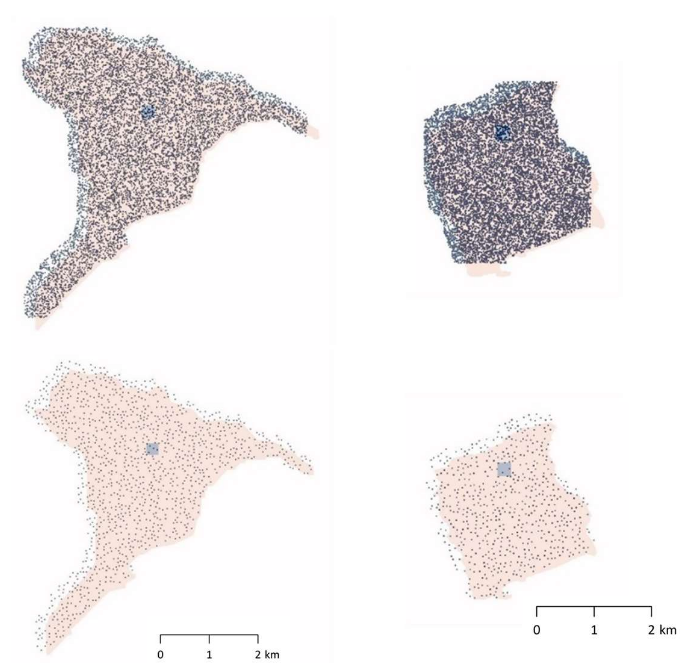

Figure S3. Patch locations in the study areas; the dots indicate the upper left corner of the patches. From left to right: Zürich, Luzern. From top to bottom: number of patches used in a similar study (Guo et al., 2021) and in this study (1250 and 620 respectively for Zürich and Luzern). The light blue square is an example of a patch to help visualize the sampling density.

Section S1: Normalized accumulated rainfall scaling

The output of the RNN was scaled by the normalized accumulated rainfall which is defined as follows for rainfall event i:

$$S_i = \frac{P_{i,acc}}{P_{norm}}, \text{ with } P_{i,acc} = \sum_t P_{i,t} \text{ and } P_{norm} = \sum_t P_{min,t}$$

where t is the time step and P_{min} refers to the rainfall event with minimum accumulated rainfall.

We normalized the scaling in order to avoid vanishing or exploding gradients issues.

Section S2: Splitting data into test/validation/test sets

The data were divided according to the following workflow (respective proportions indicated in brackets):

1. Splitting rainfall events into training (67%), validation (11%) or testing (22%).
2. Splitting the patch characteristics (i.e., patch location and patch augmentation combinations) into training (90%) and validation (10%) sets.
3. Allocating some of the training data, consisting of the combination of both patch characteristics and rainfall events, to the validation datasets (Section S2).

Following this workflow, the data in the training and validation sets are allocated in an 80%-20% ratio. This workflow allows to have the following combinations of data in the validation set:

1. Unseen rain + unseen terrain patch
2. Seen rain + unseen terrain patch
3. Unseen rain + seen terrain patch

Table S1. Residual error in downstream areas (defined as lowest 33% terrain elevation), upstream areas (defined as highest 33% terrain elevation), and depressions.

Residual [10^{-3} m]	Q25	Median	Q75
Downstream	-3.8	0.4	3.4
Downstream (Guo et al., 2021)	-7	5	20
Upstream	-2.7	0.4	5.6
Upstream (Guo et al., 2021)	-2	0	3
Depressions	-16	1.2	10.2
Depressions (Guo et al., 2021)	-60	1	30

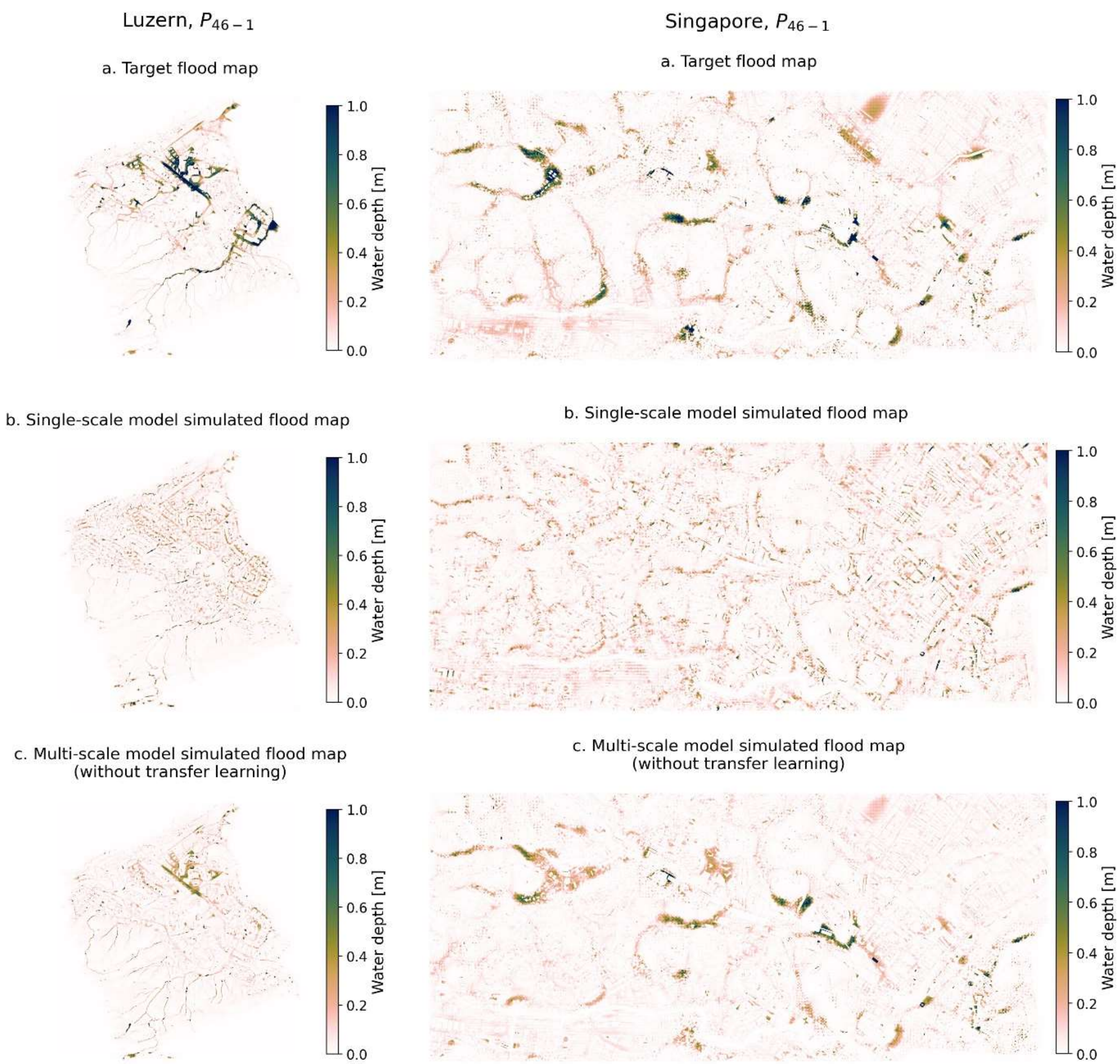

Figure S4. Flood maps for a 100-yr rainfall event in Luzern (left) and Singapore (right) emulated by the single-scale urban flood model presented by Guo et al. (2020) and by the presented multi-scale urban flood model.

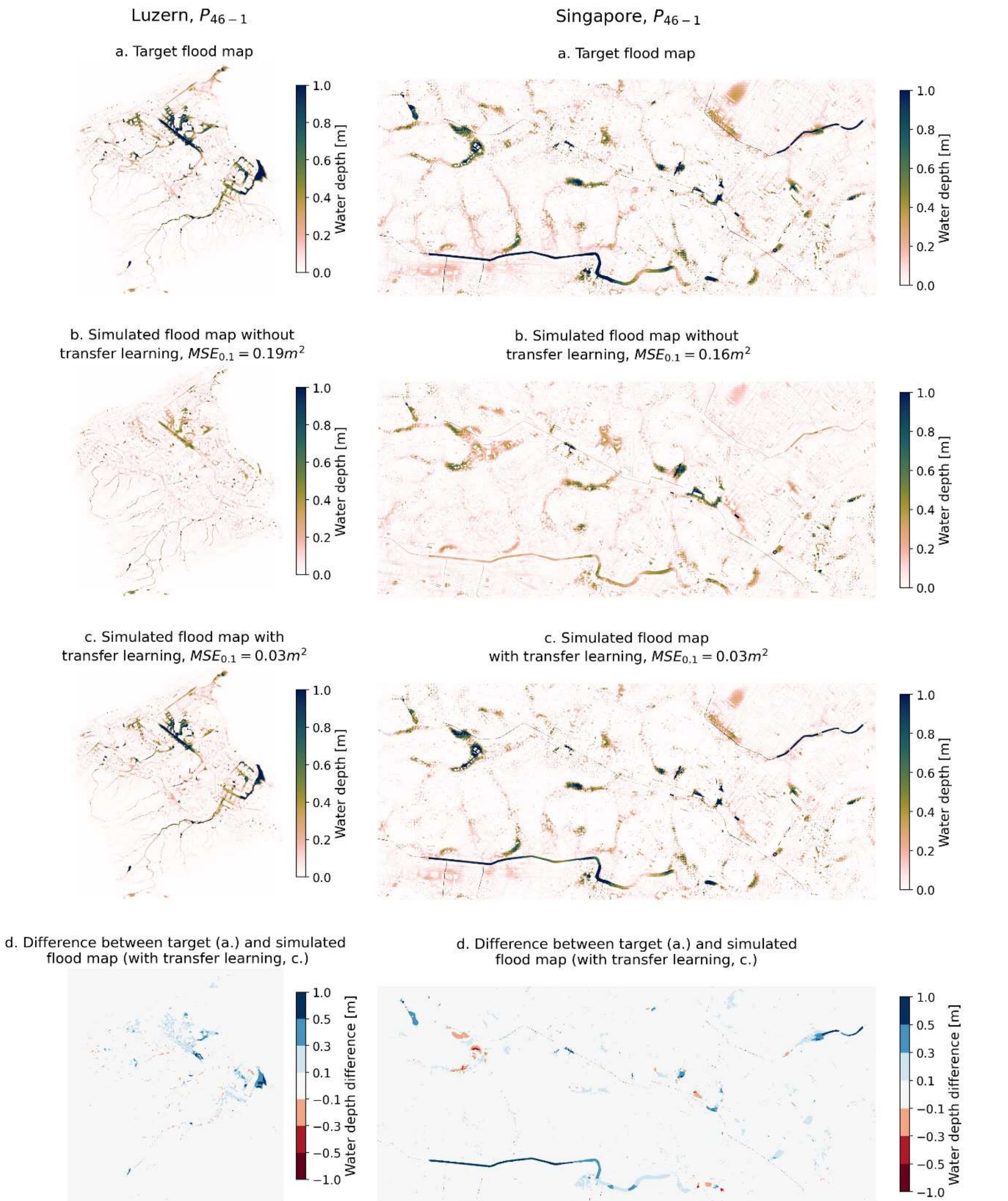

Figure S5. Flood maps and error in Luzern (left) and Singapore (right), without excluding the results in water bodies. Note that the models used to simulate the flood maps 6c were retrained for P_{31-2}.