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Bare-earth DEM Generation in Urban Areas Based on a Machine Learning Method

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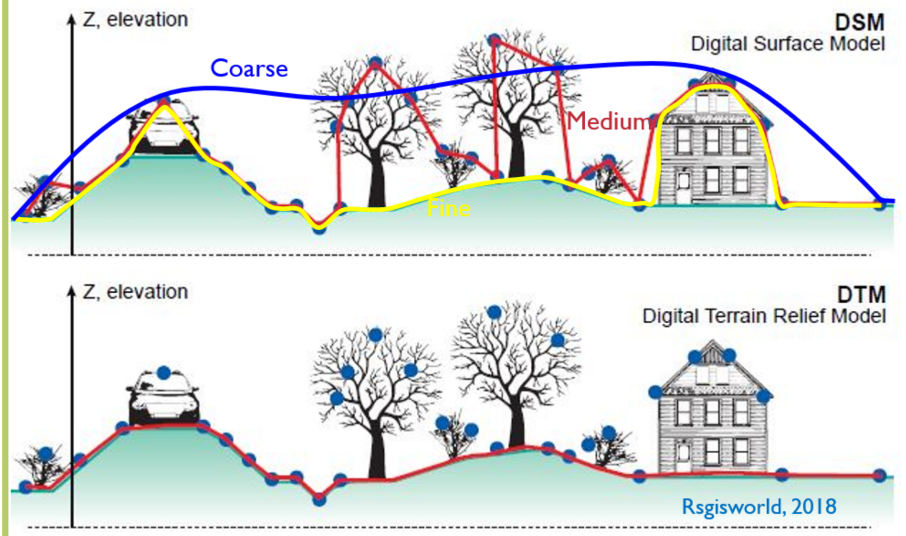
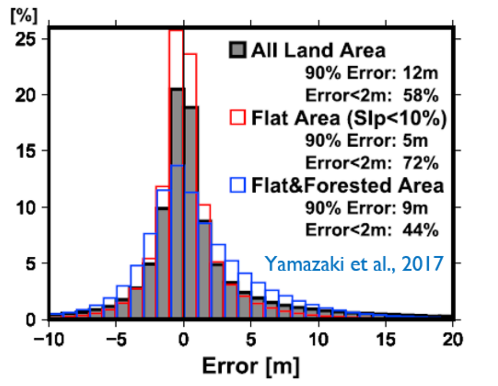
1. Background



SRTM DEM
Shuttle Radar Topography Mission
- 1" void-filled version released

TanDEM-X DEM
TerraSAR-X add-on for Digital Elevation Measurements
- Unprecedented resolution at 0.4"
- 3" (TDM90) released at 2017

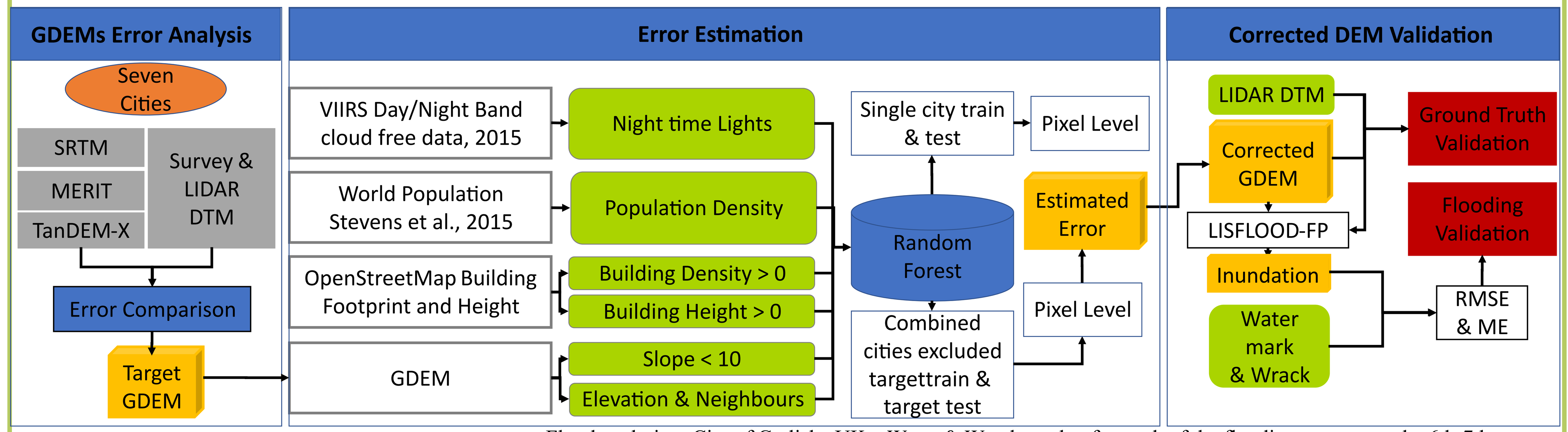
MERIT DEM
Multi-Error-Removed Improved-Terrain DEM
- within ±2 m were increased from 39% to 58%.



Urban areas

Precise representation of global terrain is of great significance for estimating global flood risk (Schumann and Bates, 2018). However, current **Global Digital Elevation Models (GDEMs)** are all **Digital Surface Models (DSMs) in urban areas**, which will cause substantial **blockage in flood inundation**. As t**he most vulnerable areas** in flooding, urban areas have been **neglected** about their GDEMs accuracy.

2. Method



Vertical: converted to EGM96, same grid as MERIT DEM. LISFLOOD-FP (Bate et al., 2010), specially a subgrid version (Neal et al, 2012) was used for GDEMs modeling.

Flood evalution: City of Carlisle, UK. Water & Wrack mark: aftermath of the flooding event over the 6th-7th January, 2005 (around 1 in 150 years return period) yielded 263 inundation data collection (Neal et al., 2009).
A wide range of friction numbers were used to bracket the best fit results. LIDAR model was calibrated with smallest RMSE, whereas GDEMs models were calibrated with best fit extent benchmarking LIDAR model inundation extent.

3. GDEMs Error Analysis

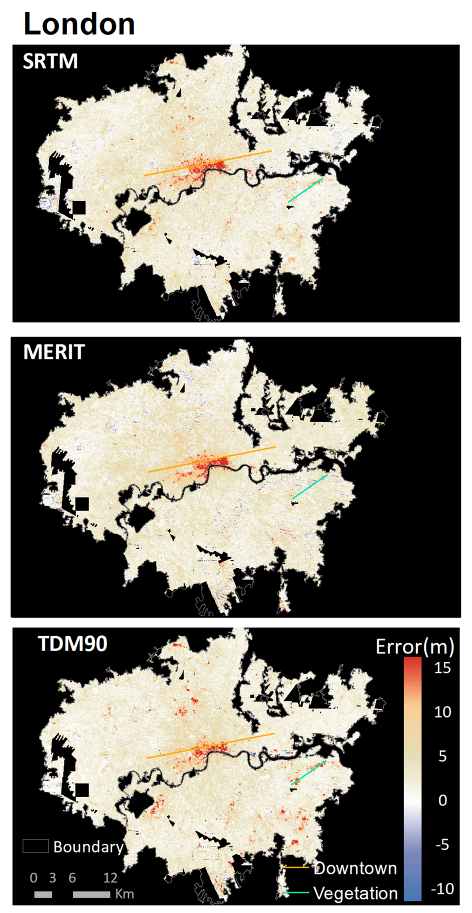


Fig. 1 Error of GDEMs in London.

GDEMs display **negative values** in water coverage, land without current use, and flat and smooth surface like stadiums even some roads and building roofs (Fig. 1).

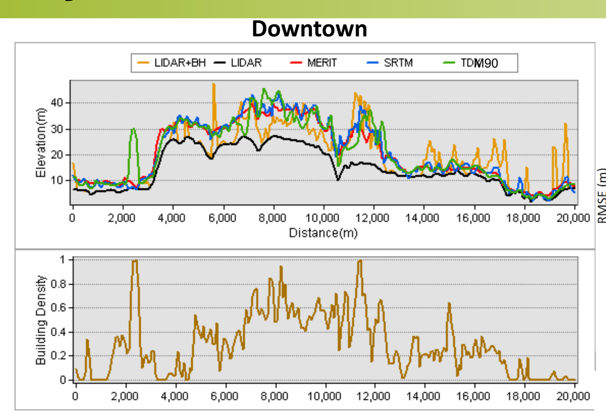


Fig. 2 Profiles of downtown in London.

Fig 2. indicated that **building bias** relates to **building height and building density.**

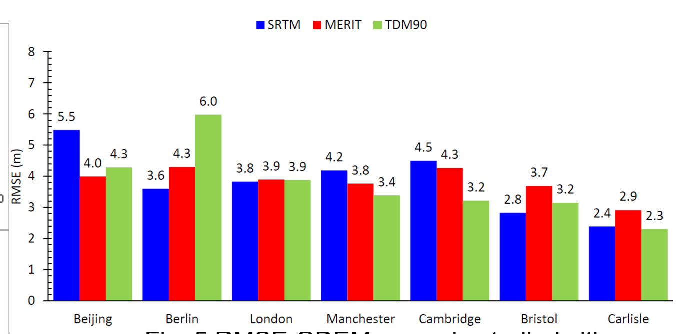


Fig. 5 RMSE GDEMs error in studied cities.

Fig. 5 showed the **RMSE** of GDEMs error is at range of **2.3 – 6.0 m** in studied cities.

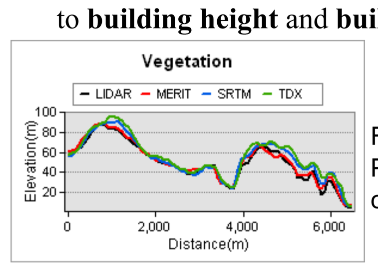


Fig. 3 Profiles of vegetation coverage in London.

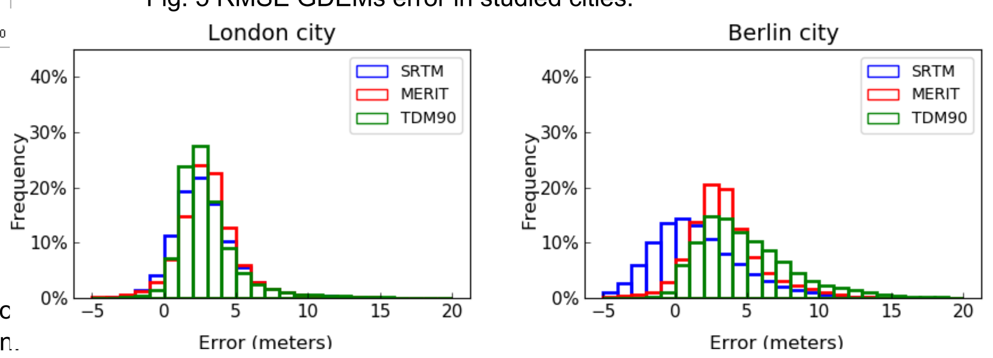


Fig. 4 Error histogram of GDEMs in London, Berlin.

The elimination of tree bias and absolute bias in MERIT was evidenced (Fig. 1, Fig. 3, Fig. 4).

4. Error Estimation

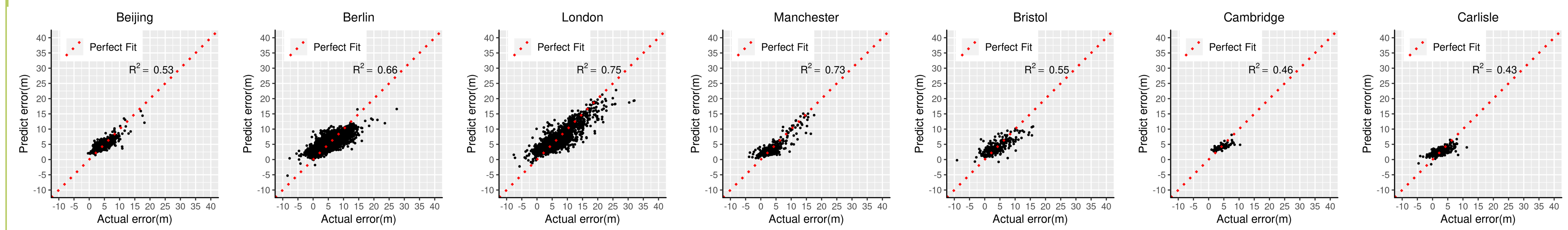


Fig. 6 Regression results of single city.

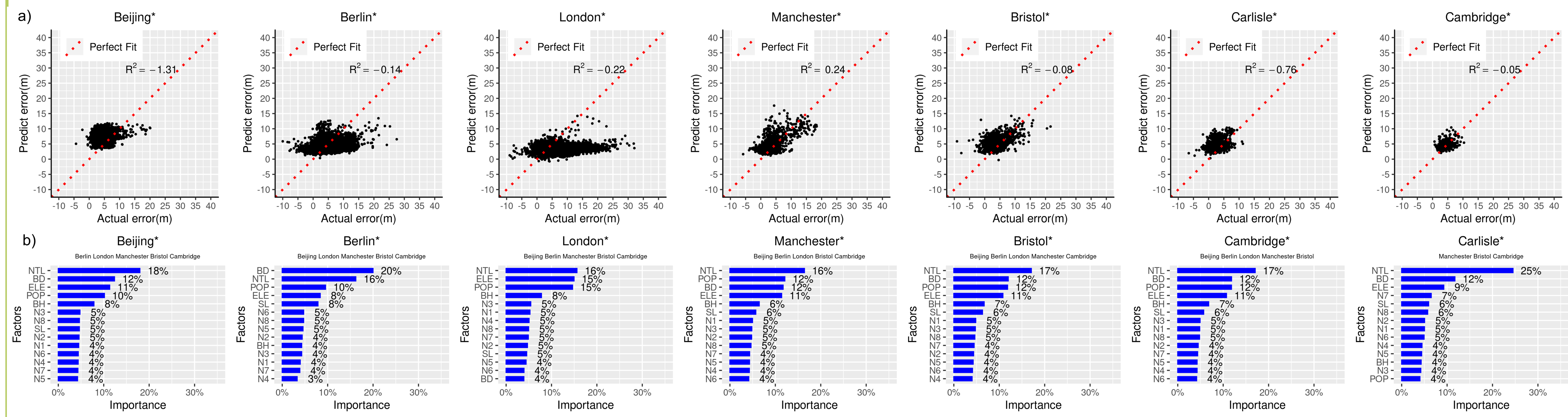


Fig. 7 Regression results and factor importance score of combined model by every five cities. *NTL: night time light; POP: population density; BD: building density; BH: building height; SL: slope; ELE: elevation; N1-N8: neighbor elevation values of target pixel in 3×3 windows.

Target city train and test model showed R-squared values vary in the range of **0.43 – 0.75** in six cities (Fig 6.). This indicated that most of the variations (except two cities) of the predicted MERIT error can be explained by target city's training data.

Target city excluded training model showed that small error was overestimated and large error (more than 10 m) was underestimated. **Predicted error was concentrated between 0-10 m**, though actual error has a larger range up to 30 m in some cities (Fig. 7a).

Importance score indicated that **Night time light and building density** are significant factors (Fig. 7b).

5. Corrected DEM Validation

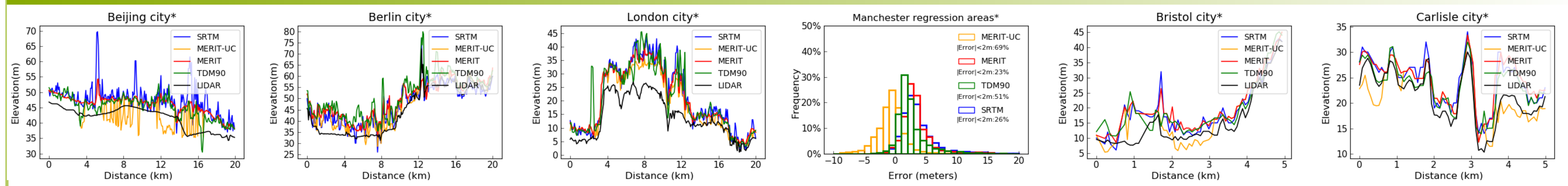


Fig. 8 Downtown areas transect profile (MERIT-UC corrected by target cities excluded model).

The MERIT-UC (MERIT, Urban Corrected) showed a lower value than the original MERIT DEM, **moving towards DTM**. However, overestimated of MERIT error was presented in some cities, especially in Beijing (Fig. 8).

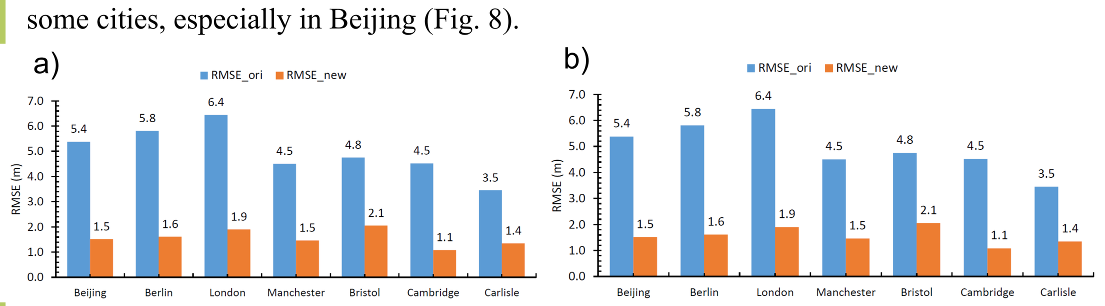


Fig. 9 RMSE (meter) of original and corrected MERIT (a) target city train and test, b) target city excluded).

RMSE of MERIT-UC DEM **decreased by up to 76%**, which gave a much lower RMSE at 1.1 – 2.1. For new MERIT corrected based on target city excluded model, its **RMSE decreased by 15%-67%.** The reduced percentage is smaller than the model trained by target cities' own data.

In Carlisle, RMSE of MERIT-UC DEM is 2.38, reduced from the original 3.35.

The LIDAR model was calibrated with the smallest RMSE which is 0.25m, while mean error is 0.0m. It is small, fitting in the water & wrack collection uncertainty, qualified to be used as the benchmark for GDEMs flood model calibration. The channel friction is 0.055 and floodplain friction is 0.06. (Fig. 11). In the calibrard GDEMs flood models, channel friction is 0.08 for both MERIT and MERIT-UC, whereas 0.07 achieved the smallest RMSE for TDX. Floodplain friction are 0.04 for MERIT, 0.02 for both MERIT-UC and TDM90.

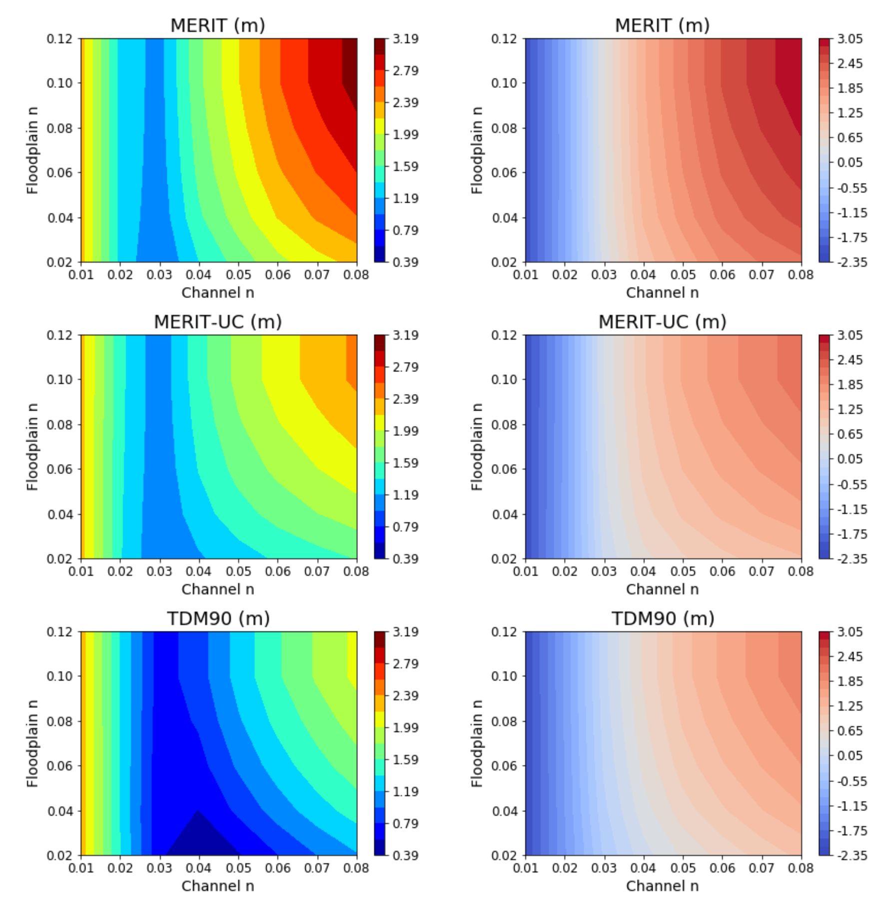


Fig. 10 RMSE (left column) and Mean error (right column) of water depth for GDEMs.

The MERIT-UC DEM can **reduce the RMSE from 2.58 m to 1.59 m, Mean error from 2.53 m to 1.22 m**. However, **TanDEM-X DEM** achieved an even better result than corrected MERIT DEM, with **a RMSE of 0.99 m and 0.92 m Mean error** (Fig. 10).

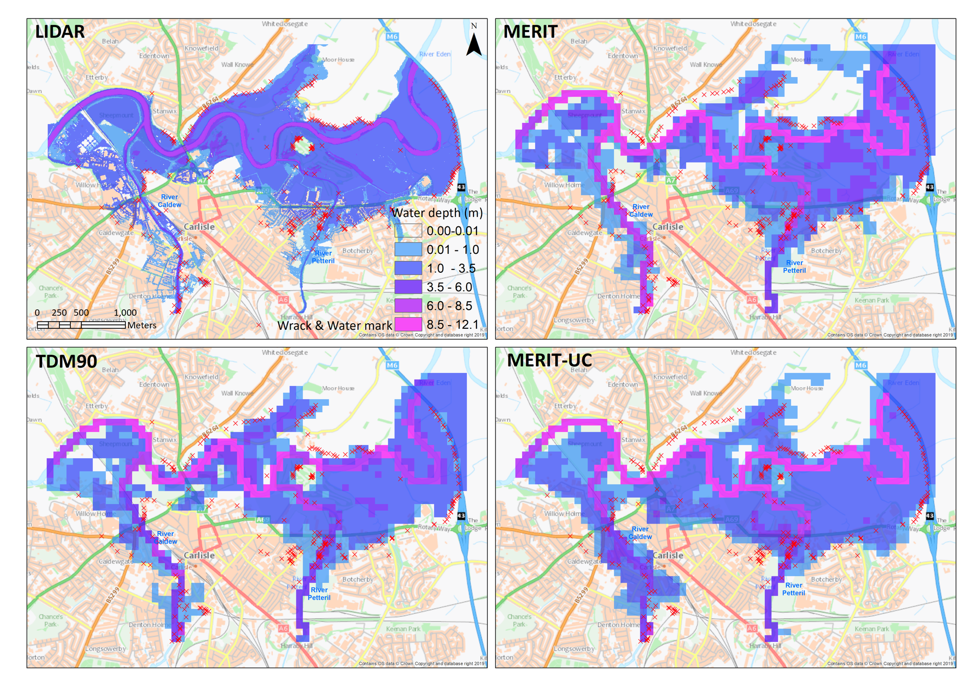


Fig. 11 Maximum water depth for DEMs at calibrated models.

With calibration, all the three GDEMs flood model can simulate a fair inundation extent regarding to that of the LIDAR. At building coverage areas, both MERIT-UC and TDM90 performed better than MERIT (Fig. 11).

6. Conclusions

1. In urban areas, RMSE of GDEMs error is in the range of 2.3 - 6.0 m. And there isn't a sinlge global DEM is better than others at all cities. Generally, TDX90 tends to have lower RMSE than others except cities which experienced significant construction activities over 2000 to 2015, like Beijing. In that case, MERIT can be a better option.
2. The method proposed in this research can be used to remove MERIT error in urban areas effectively.
3. The MERIT-UC DEM performs better than MERIT DEM in terms of inundation depth, but it didn't exceed the flooding performance by TanDEM-X, at least in this case of a small city.

References

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