



# Tackling Land Surface Temperature Gaps Using Graph-Based Propagation

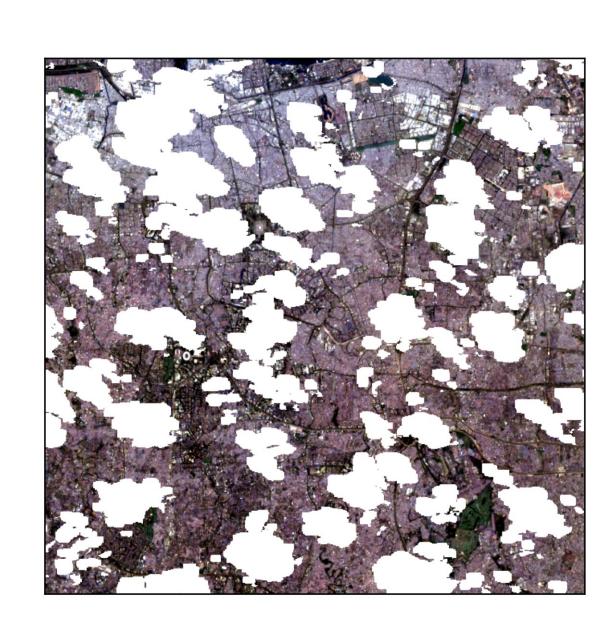
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(IN31F-0721)

## The Problem:

When the inputs used to compute Land Surface Temperature (LST) are obscured, the LST product suffers from gaps. This affects our ability to analyse and understand the dynamics of LST variations.



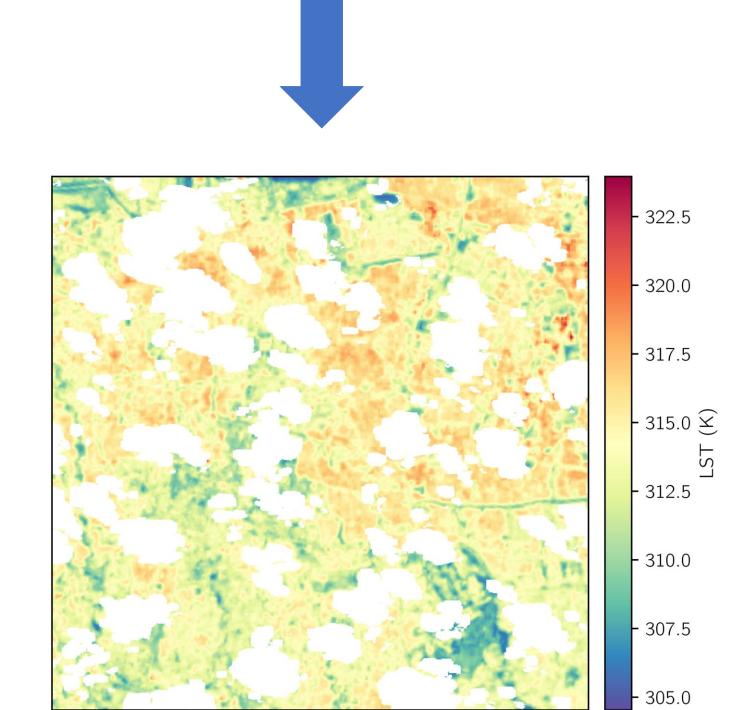


Figure 1: Example Landsat 8 acquisition obscured by cloud cover which causes produces partially-observed LST outputs with gaps corresponding to regions covered by cloud.

# Proposed solution:

By exploiting the spectral similarities observed in previously-acquired measurements of the same region, we construct a graph-based representation of the region. This representation provides the structure upon which propagation of observed values can take place, thus providing a solution for missing entries in the inputs and subsequently allowing for LST to be computed without gaps.

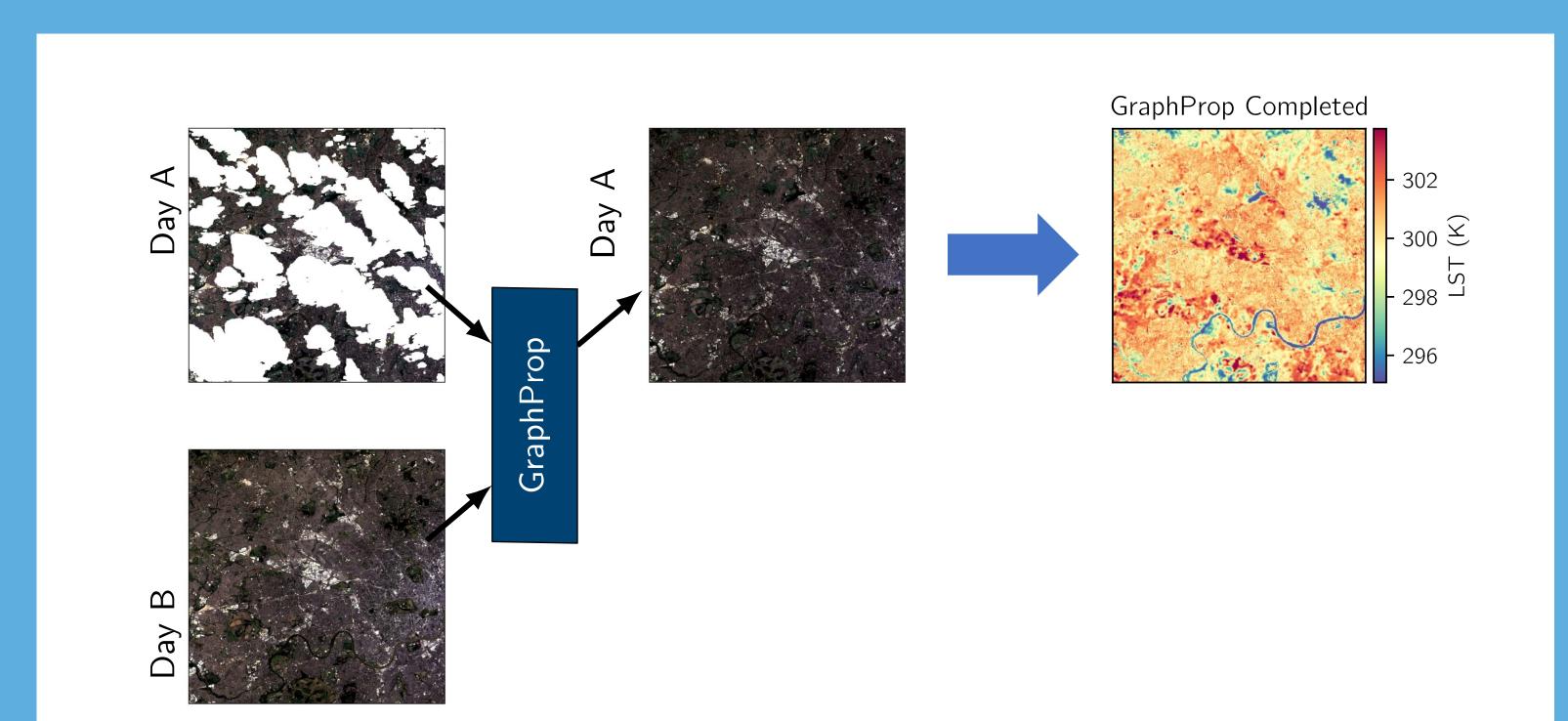


Figure 2: The proposed graph-based propagation approach is applied to tackle the gaps in the Landsat inputs directly. Following the application of our method (named GraphProp) a complete set of Landsat 8 bands are obtained. Importantly, this provides the thermal infrared (TIR) information that is necessary to compute LST.

#### Method:

If an acquisition has gaps (e.g. due to cloud cover/sensor malfunctions), any LST output derived from it will also have gaps. The proposed approach tackles the origin of the LST gaps at the source, by resolving the gaps in the images used as inputs to the LST calculation. The method represents the region using a graph, with each pixel represented by a graph node and graph edges obtained using a reference image of the same region, acquired on a different day, such that the k-nearest neighbour pixels are connected by an edge. To complete the partially-observed acquisition, the observed regions are held constant and diffused on the graph until steady state is reached. The steady state provides the missing entries, allowing the LST to be computed without gaps.

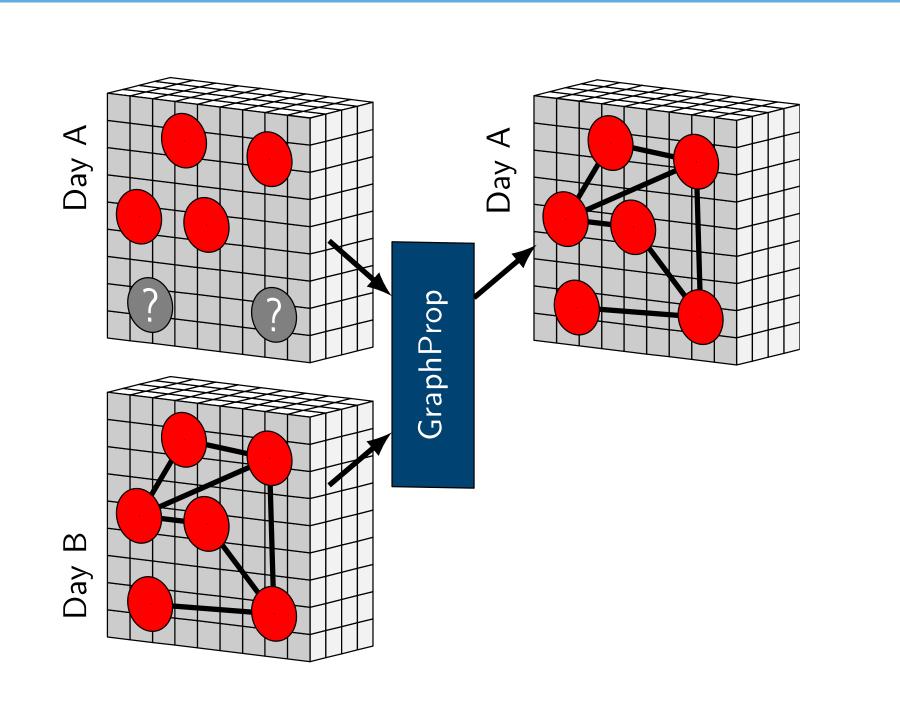


Figure 3: Schematic showing how the proposed graph-based propagation method takes as input reference acquisition(s) captured on different dates in order to construct a graph-based representation of the region. The propagation of observed values takes place on this graph to obtain values in the missing regions.

## **Experiments:**

To test how accurately the proposed method recovers LST values, three urban regions have been tested. For each city (Jakarta, London and Paris) a pair of cloudfree acquisitions was obtained. Experiments synthetically obscure one of the acquisitions to represent a cloud cover scenario. Using the proposed method to complete the missing information, LST values are obtained and compared against values obtained from the unobscured original to assess accuracy. This process is repeated for 10 different cloud masks at 10% intervals in cloud cover ranging from 10% of data removed through to 90%. To compare the accuracy of the proposed method we use a benchmark from the family of low-rank tensor completion methods. The High Accuracy Low Rank Tensor Completion (HaLRTC) algorithm [1] is also applied to the cloud-obscured inputs directly for fair comparison.

# Key Results:

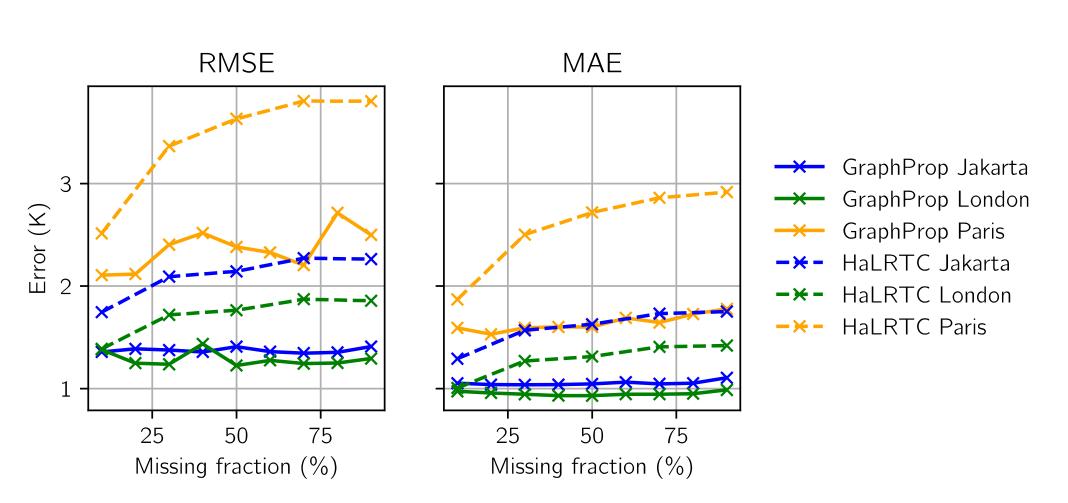


Figure 4: LST root mean square error (RMSE) and mean absolute error (MAE) as a function of the fraction of data obscured by the cloud mask. Values represent mean values computed across 10 mask experiments.

#### Conclusions:

The proposed method, GraphProp, provides LST estimates more accurately than existing methods from low-rank tensor completion literature, most evidently for high missing fraction scenarios.

### References:

[1] J. Liu, P. Musialski, P. Wonka and J. Ye, "Tensor Completion for Estimating Missing Values in Visual Data," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 35, no. 1, pp. 208-220, Jan. 2013, doi: 10.1109/TPAMI.2012.39.

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