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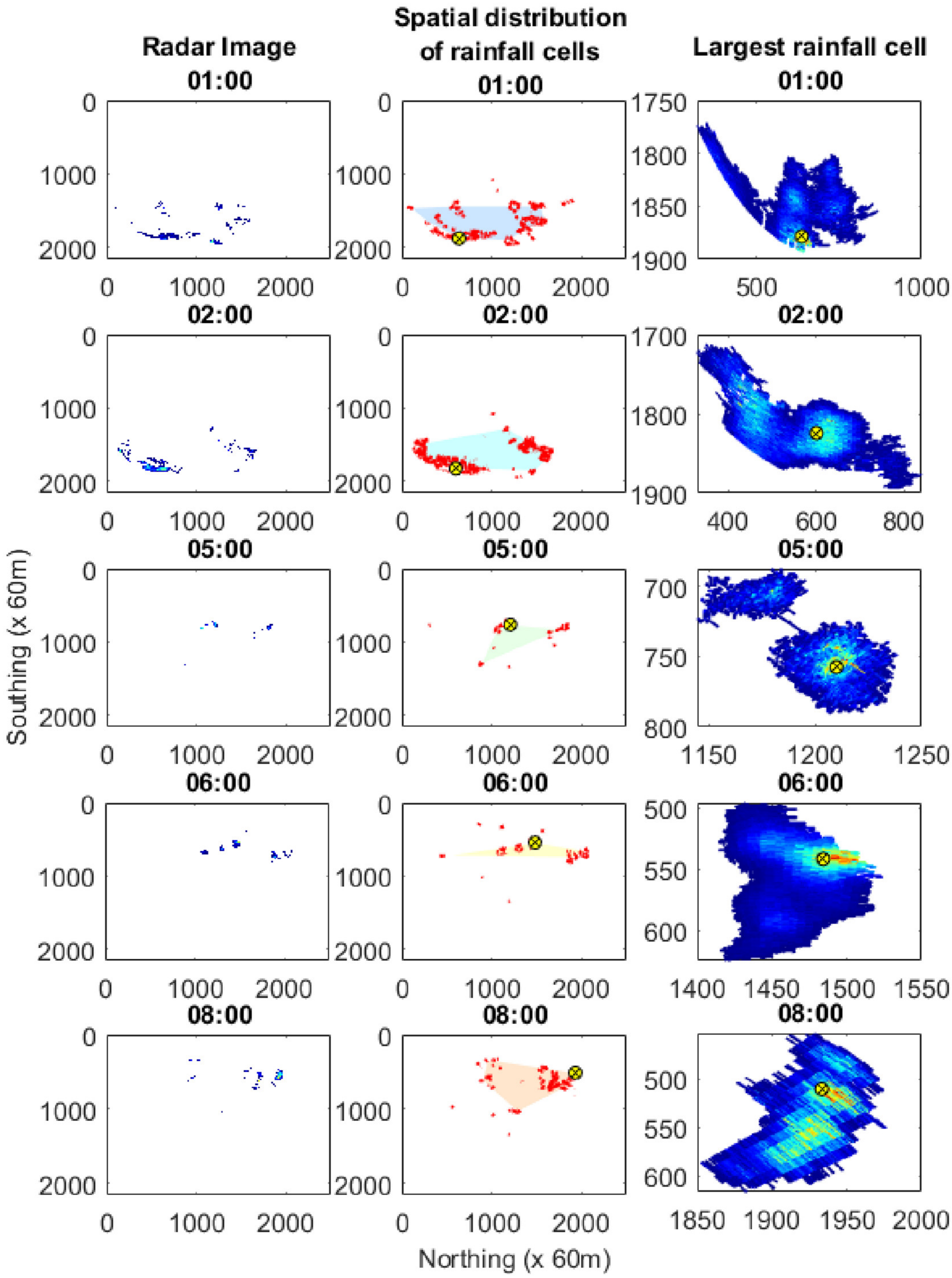
**Text S1. Processing radar rainfall**

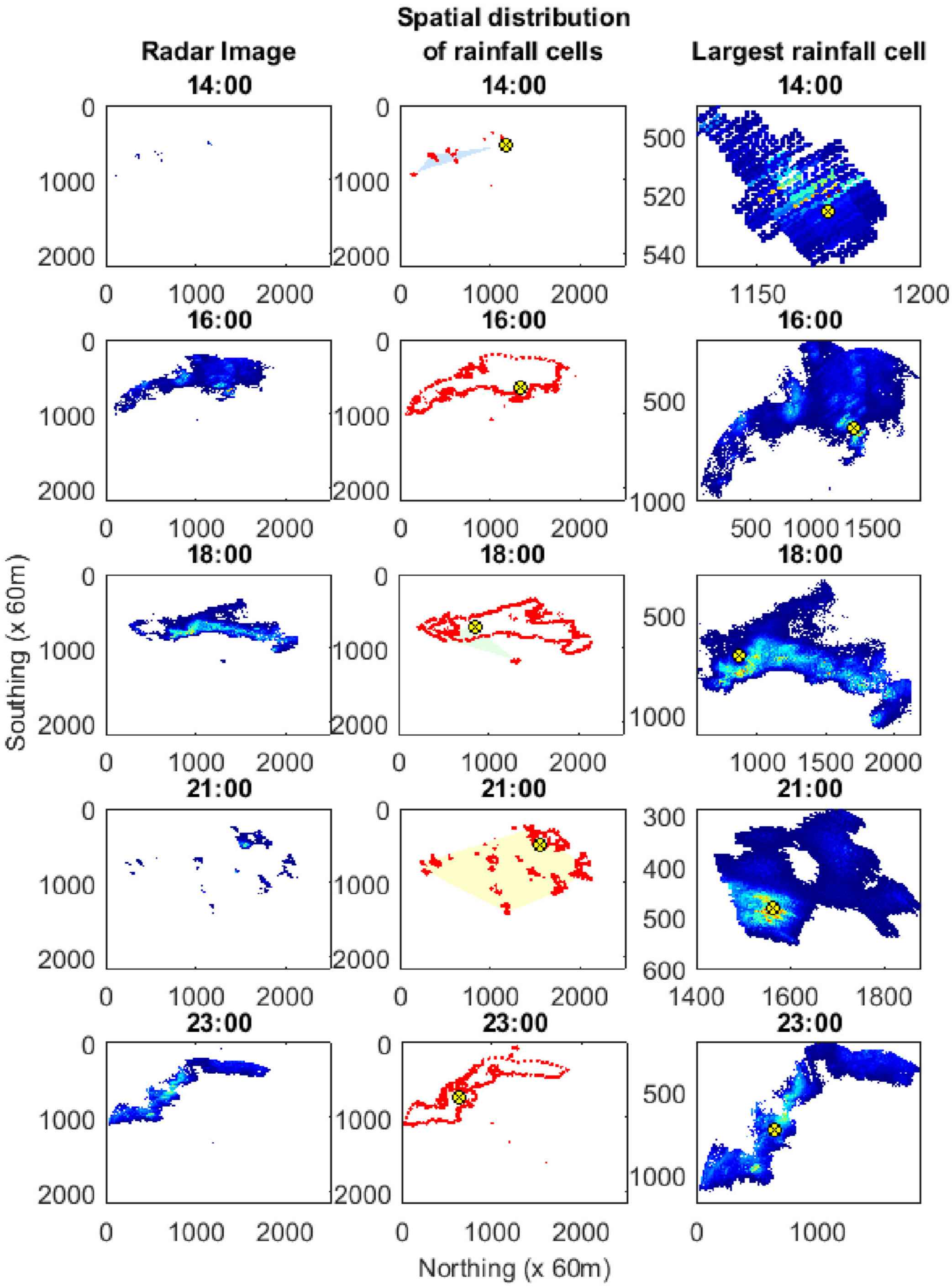
The rainfall reflected by radar images on the tested day in Guangdong, China can be explained as: the scattered area of rainfall in the first three hours shrinks and moves southward, then it decreases in the south.  it started to rain in the north region and the scattered area of rainfall centres increased in the following three hours. From 06:00 to 09:00 the scattered area moves eastward and reduces after an increase around 08:00. There is no rainfall in the next several hours and rainfall starts from 13:30 and the scattered area is northwest-orientated and located in the east region. Then rainfall moves to southwest and scattered area shrinks during 15:00 and 18:00. In the following three hours, the scattered area keeps relative still after the rainfall centres move north. In the same regions, the scattered area of rainfall in the last three hours is finally centralised in the east (i.e., 0~1000 and 500~2000).

Fig. S1 presents the radar image and the way to process/detect the rainfall cells by the SPER toolbox. The left column shows the rainfall reflected by radar and rainfall cell is defined as a rainfall area with a closed boundary. For each rainfall cell, the boundary is automatically detected by the toolbox and showed as red dashed curves in the middle column of Fig. S1. As the rainfall centre (i.e., the core) can also be calculated by the toolbox, the encompassing area of all centres of rainfall cell is used to indicate how scattered the rainfall areas is and showed as the back covering region in middle column of Fig. S1. With the support of SPER toolbox, every rainfall cell its changes over time and space can be detected. However, in this case, we focus on the rainfall cell with the largest size which is presented in the right column of Fig. S1. The rainfall centre of the largest rainfall cell is presented by the yellow circle mark. Besides, to compare the tracking monitored by the toolbox and the movement of rainfall measured by Radar, two animated figures of radar images are provided (Fig. S2 and Fig. S3) where Fig. S2 demonstrates the temporal changes of rainfall cells over the threshold of 5mm and Fig. S3 shows original rainfall in 24 hours in Guangdong, China.



Radar Image
Spatial distribution of rainfall cells
Largest rainfall cell
01:00
02:00
05:00
06:00
08:00
Southing (x 60m)
Northing (x 60m)

(a)




(b)

**Figure S1.** Demonstration of the step processing radar images of 24-hour rainfall in Guangdong in the morning (a) and afternoon (b).

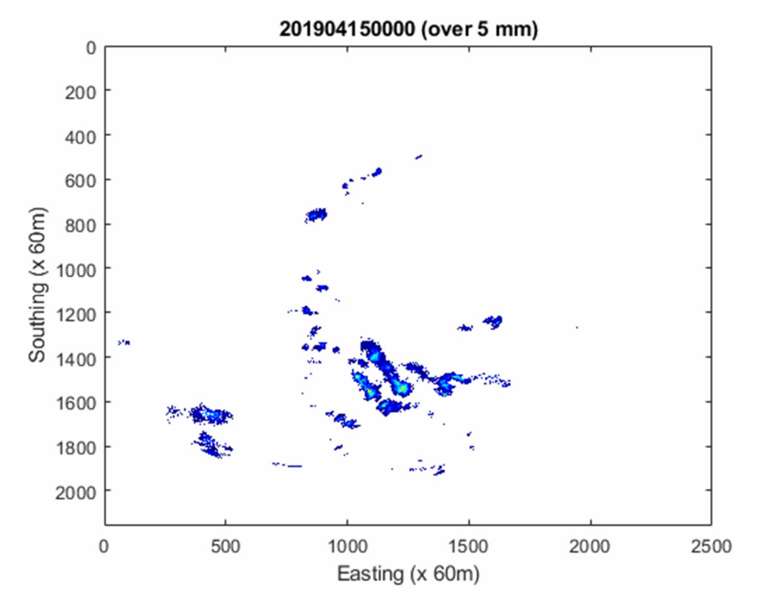



**Figure S2.** Animated radar images (threshold 5mm).

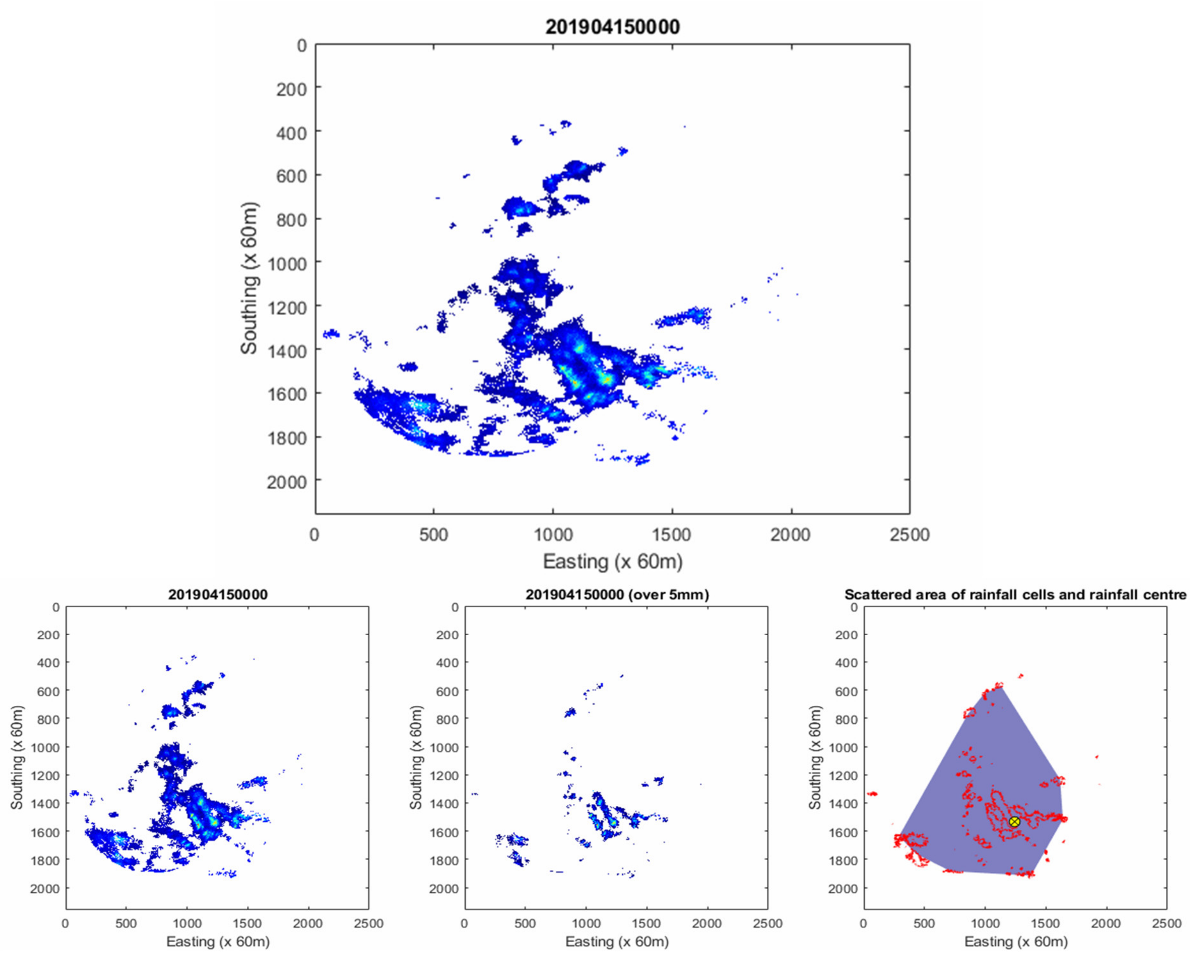



**Figure S3.** Animated raw radar images (without setting threshold).

**Text S2. Generating the training sets and testing the deep learning study**

The new integrated classification capacity of the SPER toolbox makes it possible to automatically produce labelled training sets from tens of thousands of large-scale environmental images for deep-learning applications in feature recognition and forecasting. In this process, the attributes such as those spatial features (location, size and orientation) can be quickly identified to pre-catalogue the data or images into different labels/classes. To present this, an Alexnet model of convolution neural network (CNN) is built to demonstrate the process of auto-identifying the daily rainfall patterns in GB, using the training sets auto-labelled by the SPER toolbox. There are four labels used in this test, i.e., no rainfall (L0), concentric pattern (L1), elongated pattern (L2) and compound pattern (L3).

To address the issue of the overhead demand for computation (e.g., more than 40 thousand of daily rainfall images), Alexnet which is a type of CNNs was constructed for training because it reduces the over-fitting and allows for multi-GPU training which reduces the training time (Krizhevsky et al., 2012). There are eight layers in the Alexnet model (Alom et al., 2018), with the first five being convolutional layers with the kernel size of 11×11, 5×5 and 3×3 and the last three fully connected layers. The structure is designed as: the first convolutional layer (11×11) following by an overlapping max pooling layer is connected to the second convolutional layer (5×5) which is also followed by one overlapping max pooling layer; then the rest three convolutional layers (3×3) are connected directly and the end links to one overlapping max pooling layer; and the final link is to the last three fully connected layers. ReLU (Pedamonti, 2018), a non-linear activation function, is applied after all the convolution and fully connected layers to get activation values corresponding to neurons. To apply Alexnet model, we firstly converted all images to the acceptable size which is 227-by-227-by-3 where the last dimension size 3 indicates the three colour channels (e.g., R, G, B). Then we modified the last three layers to specify 4 classes for classification and set a faster learning rate for these newly modified layers and a slower learning rate for the transferred layers in order to obtain an effective and better transfer learning. Finally, 1166 daily rainfall images are randomly selected from all images while the rest are used for training the Alexnet model.

During the training phase, the Alexnet of CNN model learns the training sets and selects 30% for self-validation randomly and the model validates the network every 3 iterations. The testing sets, i.e., 1166 images, are applied for predicting their classifications. The self-validation accuracy is 91.3% when reaching the final iteration and the accuracy of prediction of the testing sets has been evaluated as 93.4% (1089 out of 1166 new figures have been classified correctly). However, the inherent complexities of the environmental data cause complicated patterns as well. Further work is recommended to make the toolbox more robust to process climate projection data at various, often low resolutions. A downscaling or down-sampling method may need to be integrated. Certainly, optimising the CNN algorithm should be carried out for recognising more complex patterns other than the simple example shown in the paper.

## References


1. Alom, M.Z.; Taha, T.M.; Yakopcic, C.; Westberg, S; Sidike, P.; Nasrin, M.S.; Van Esesn, B.C.; Awwal, A.A.S.; Asari, V.K. The history began from alexnet: A comprehensive survey on deep learning approaches. *arXiv* **2018**, arXiv:180301164.
2. Krizhevsky, A.; Sutskever, I.; Hinton, G.E. Imagenet classification with deep convolutional neural networks. *Adv. Neural Inf. Process Syst.* **2012**, *25*, 1097-1105.
3. Pedamonti, D. Comparison of non-linear activation functions for deep neural networks on MNIST classification task. *arXiv* **2018**. arXiv:180402763.