August 27-31, 2023
FLORENCE - ITALY
ICWE 16
16th International Conference on Wind Engineering

Rapid Repair Demand Estimation Method for Damaged Residential Roofs Under Wind Disaster Using Remote Sensing Images and Machine Learning

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SUMMARY:
In wind disasters caused by typhoons, restoration of houses delays due to the inability to secure the necessary construction materials and human resources for repairs have become a problem. For the purpose to overcome this challenge, we propose a method for repair demand estimation, which is facilitated to quickly estimate the demand after a wind disaster and to disseminate the information on the situation in the affected areas; thereby, to reduce the mismatch between supply and demand. In the proposed method, deep learning techniques were employed to analyse images taken soon after a disaster with aerial photographs and their processed data to identify the location and extent of roof damage for each type of roofing material. Although the accuracies of the image analyses have rooms to improve and the performance of the method is still to be examined, the paper demonstrates on how to estimate the repair demand for an actual case of Typhoon Faxai in 2019.

Keywords: Typhoon, Aerial photos, Repair demand estimation

1. INTRODUCTION

Delays in restoration due to the inability to secure the necessary building materials and human resources for repair works have often become a problem after wind disaster caused by typhoon. Information collected by municipalities after disasters usually does not include detailed information on damaged building components and their extents as well as types of building materials. Therefore, with such information it is difficult to estimate the amount of building materials and human resources required for repairs works.

A method that facilitates a rapid estimation of repair demand in terms of building materials and human resources is useful to reduce the mismatch between supply and demand by disseminating information on demand outside affected areas; hence, minimize the delays in restoration. Authors have accumulated data on damage to residential houses through surveys after typhoon Jebi in 2018 and typhoon Faxai in 2019, which include data on repair works as well as satellite images, aerial photos taken by airplanes and UAV's before and/or after the typhoons. In this paper, a method on rapid repair demand estimation is developed and their usefulness is investigated using those accumulated data, with focus on repair of damaged roof, which is the dominating damage type in wind disasters in Japan. The developed method is applied to the cases of residential house damages after typhoon Faxai in 2019 in order to investigate the applicability of the developed method.

2. METHOD ON ROOF REPAIR DEMAND ESTIMATION

The flow of roof repair demand estimation is shown in Figure 1. First, a point cloud and an ortho image are generated based on aerial photos taken from UAV's and/or airplanes before disaster. Second, using the generated point cloud and the ortho images, footprints, roof shapes and roof materials of residential houses are specified. Once a disaster occurs, aerial photos are taken or satellite images are collected, which are then utilized to identify the locations/extent of damage to roof of each target house located in areas in concern. Then, by supposing the building information such as footprint, roof shape and roof material with the identified locations/extent of roof damage, the types and the amount of building materials and the amount of human resource required for repair work is estimated. Here, the data on actual repair work obtained for the damage due to typhoon Jebi in 2018 is utilized in order to estimate human resource based on the identified locations/extent of roof damage.

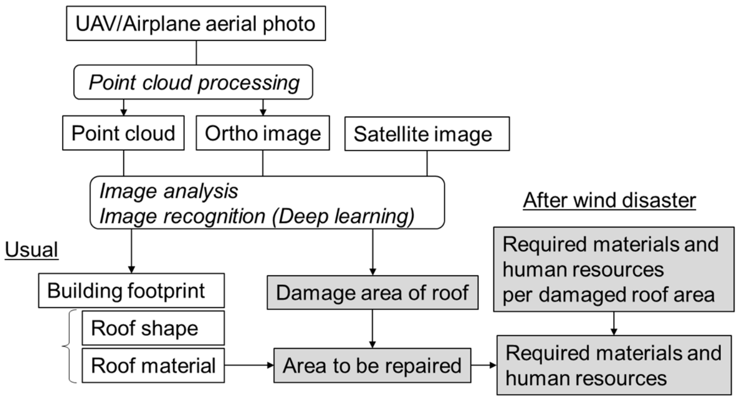


Figure 1. Flowchart for estimating roof repair demand.

3. CASE STUDY OF REPAIR DEMAND ESTIMATION IN AFFFECTED AREA BY TYPHOON FAXAI

3.1. Building information collected before disaster

Two deep learning models are developed; one is for identifying building footprint, and the other is for identifying roof material type. In order to develop these models, ortho images that are generated based on aerial photos are utilized. The deep learning model to identify the footprints of individual buildings utilizes aerial photo taken by airplane and its detail is presented in Xu et al. (2022). The deep learning model to identify the roof material type adopts FasterRCNN. For training, aerial photos taken by an UAV in an area T in Chiba prefecture, Japan are utilized. The training data consists of 526 building roofs, each of which has a label for roof material type; clay tile, slate, metal, concrete and solar panel. The numbers of samples of respective roof material types as well as the precision score are listed in Table 1. Out of the total numbers, 90% of them are utilized for training and 10% of them are utilized for verification. "Clay tile", whose sample number is larger, shows higher precision score, whereas "concrete", whose sample number is smaller, shows lower precision score. However, the latter will be improved by training with a larger number of samples; else, other deep learning model may result in better precisions. This call for further investigation.

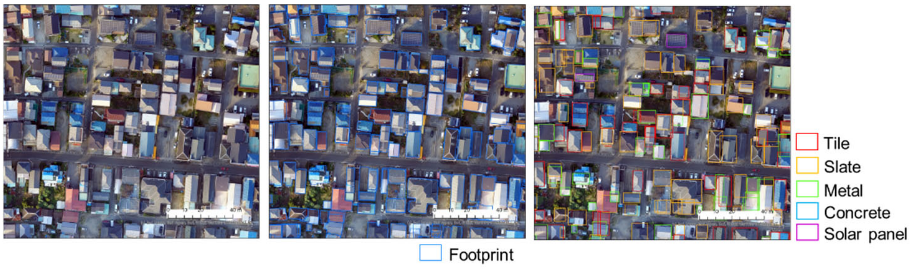
These deep learning models are applied to ortho images in order to identify building footprint and roof material type. The example is shown in Figure 2. Figure 2a is an ortho image generated with aerial photos taken by an UAV in area K. Figure 2b is the identified building footprint. Figure 2c is the identified roof material type. The precision scores generally decrease relative to those scores for area T; however, the scores are still acceptable levels in practical applications.

Table 1. Number of roofing material and the precision score of deep learning.

Roof material	Number of samples	Precision Score
Tile	199	0.84
Slate	132	0.75
Metal	156	0.61
Concrete	16	0.55
Solar panel	23	0.25

3.2. Identified damage locations and extent

The damaged roof location and extent were identified by the abovementioned trained deep learning model. Figure 3 shows the results of the identification of the damage locations and extent, where the blue tarps, which cover the roof after the disaster as first aid, are utilized as roof damage proxy. According to Xu et al. (2022). the accuracy of blue tarps detection is about 90%; however, the blue roof tiles were sometimes incorrectly detected. The model is required to improve in this regard.



a. ortho image **b.** building footprints **c.** roof material

Figure 2. Ortho image, building footprint, and roofing material detected of Area K.

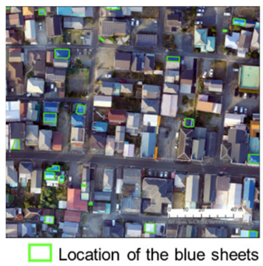


Figure 3. Example of damaged roof detection in area K.

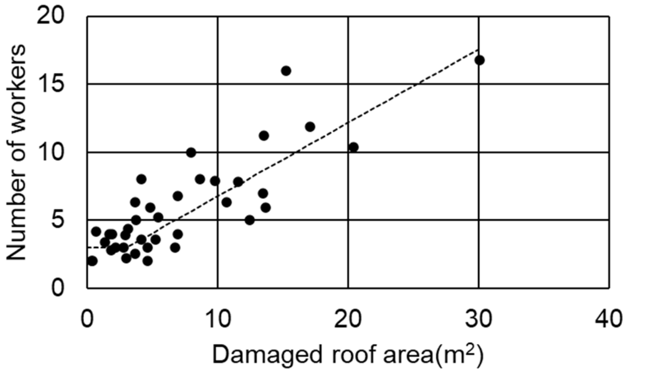


Figure 4. The relationship between the area of roof and the human resources required for repair.

3.3. Human resources required for repair works

The relationship between the area of roof and the human resources required for repair is estimated from the data collected by a local government, which was affected by typhoon Jebi in 2018. Figure 4 shows the estimated relationship. Around 3.0 man-day is required for repair with areas of less than 3 m^2; however, for extended roof damages, the man-day increases in proportion to the area.

3.4. Example of estimation of roofing materials and human resources required for repairs

An example is shown in order to demonstrate how the developed method can be applied in practice. For this purpose, a subarea in area K, which was affected by typhoon Faxai in 2019, is considered. Using the ortho images in the corresponding subarea, 894 buildings are extracted. Among them, the roof material types of 790 buildings are estimated. Out of 790 buildings, 128 buildings received damages to roofs. The damage ratio in this subarea is then 16% (=128/790). The frequency distributions of damage area for respective types of roof material are summarized in Table 2. The total area of damaged roof for each roof material type and estimated human resource for repair work are estimated and summarized also in Table 2.

Table 2. Estimates of affected area per roofing material and worker required for repair.

Roof material / Damage area	Tile	Slate	Metal
3m^2 or less	5	7	3
3-10 m^2	14	7	4
10-30 m^2	9	23	7
30-50 m^2	13	10	3
50-80 m^2	12	2	1
80-100 m^2	0	2	1
More than 100 m^2	2	0	2
Total damaged area	1,695m^2	1,227 m^2	791 m^2
Needed workers for repair	994.6	742.4	459.2

4. CONCLUSIONS

We proposed a method for rapid estimation of repair demand for residential roofs damaged by strong winds using remote sensing images and machine learning techniques. The proposed method is applied to an actual case and is successfully illustrated on how it works. The performance of the deep learning model to identify roofing material type and damage locations and extent have rooms to improve. The evaluation of the performance of the proposed method in terms of precision of the demand estimation is addressed as a future task.

ACKNOWLEDGEMENTS

This work was supported by the collaborative research program (2021G-07) of the Disaster Prevention Research Institute of Kyoto University and JSPS KAKENHI (20H02415).

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