Intelligent IoT Monitoring System Using Rule-Based for Decision Supports in Fired Forest Images

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Abstract. Recently, many investigations focus on studying to detect of forest fires using IoT devices such as remote sensors or conventional fire detector sensors. However, supports in fire forest in real-time are hard for current studies in large forests. This paper has presented a novel approach to forest fire detection implemented using an improved rule-based integrated with k-means algorithm to improve the detection of forest fires. The rules in knowledge based can be considered in a camera as forest fires in real-time detection. The research explores the construction of Time-Lapse Videos from cluttered consecutive image. Mechanisms have been developed to automatically render the images with these elements from the scenes to produce more 'truthful' videos which more accurately describe of forest fires. The experimental results show that our proposed IoT monitoring system achieves significant improvements in 'real-time' fire detection.

Keywords: Video time lapse · Rule-based · Clustering · K-means · IoT fire forest system · Intelligent forest monitoring

1 Introduction

Recently, remote sensing and image processing of IoT devices, including image segmentation [2] and machine learning [1], have been a feature of research over an extended period and there exists a large body of published research on these topics. Clustering is the process of classifying a group of abstract objects into classes of similar objects, the task of image segmentation function is to process the original image into many different clusters [3,4]. The processing of satellite images enables the segmentation [of satellite images] and the classification of entities into specific types such as trees, soil, and water.

In the K-means clustering algorithm [4,5], the simplest idea about a cluster is to gather points which close to each other in a defined space that can be applied to image processing in a domain of monitoring forest under uncertainty.

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Research has identified a number of proposals to improve the performance of the K-means algorithm [5]. The proposed methods have significantly enabled enhancement of the traditional K-means method. For example, Linde et al. [7] have proposed a method for vector quantizer design and C. Huang et al. have introduced an approach to enable direct search using a binary division method based on the principle of structural analysis [8,9].

Muhammad et al. considers the early detection of fires and introduced an approach based on Convolutional Neural Networks (CNN) to enable surveillance for effective disaster management. The proposed method uses fine-tuned CNN for tracking surveillance cameras with an adaptive prioritisation mechanism is used in surveillance systems to ensure the autonomous response [6,19]. Zhang et al. has introduced an approach to address 'wildland' forest fires and smoke detection based on faster R-CNN using Synthetic Smoke Images and video sequences [18]. In [19] the use of an approach based on unsupervised training is applied to the quantification of large historical data sets for use in decision-support for disasters and securities. The limitations of these approaches are high computational cost combined with large image and video large data sets for the monitoring of forests [11–13,15].

Santiago et al. [16] in a paper entitled "A Forest Fire Detection algorithm using a fuzzy system approach based on overlap indices to effectively control the fire detection" presents a study which employs the convex combination of several overlap functions and overlap indices to realise improved results based on the use of fuzzy Logic Systems. Haifeng Lin et al. [17] have introduced a fuzzy inference system combined with a big-data analysis algorithm to enable the prediction of forest fires based on rechargeable wireless sensor networks. The proposed approach applies an advanced quantitative technique to estimate the potential fire risk predicated on the conversion of the data into triangulated numbers. All wireless sensor derived weather data [captured over continuous 24 h periods] is used to illustrate prevailing status of forest environments [20–22].

In this paper has presented a novel approach to enable the effective detection of forest fires based on our proposed method called the BK-fired forest (BKFF) algorithm. It is based on a development of the K-means clustering algorithm using a rule-based approach. Our contribution lies in the development of an approach to the classification of satellite imaging based on a development of the K-means clustering algorithm using a rule-based approach. Rules in the knowledge based can be considered in a camera as forest fires extracted by video time lapse in real-time detection. When applied to the detection of forest fires through a camera.

This paper is organized as follows: Several related works are shown in Sect. 1. In Sect. 1, the theory of the K-means clustering algorithm and several evaluation methods are briefly reviewed. The details of the new method are discussed in Sect. 2. Experiment results which show the advantages of the algorithm are proposed in Sect. 3, as well. Finally, conclusions are drawn in Sect. 4.

2 The Proposed Model

In this section, Figure 1 shows an overview of the proposed model with the image segmentation method.

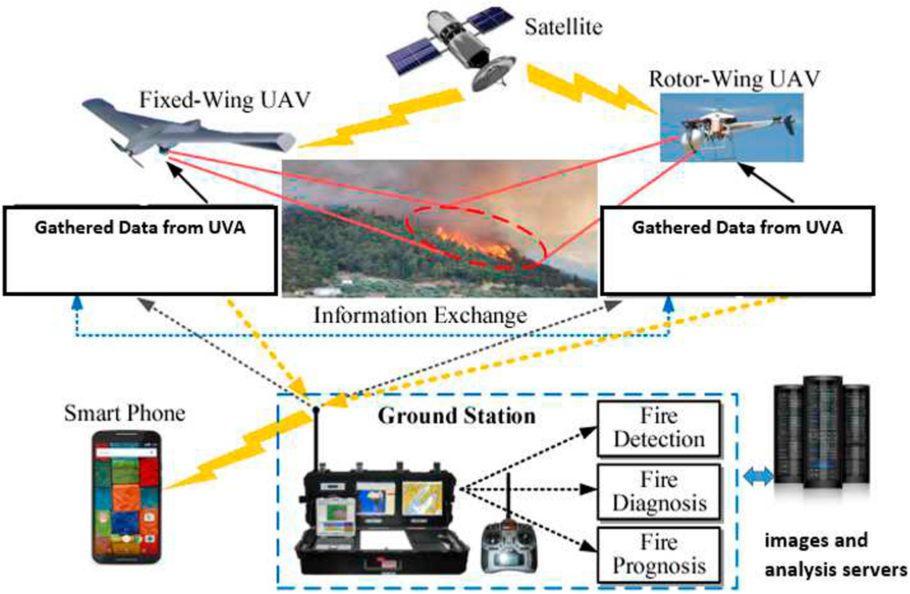

Fig. 1. The proposed model of image segmentation method using IoT devices

All data sets are collected from UAVs, including fired images of forests. All of image files are stored in image and analysis servers. The proposed model has presented fire detection and diagnosis. End users using smart phone can be given in decision making in real time under an uncertain environment.

2.1 The Proposed Algorithm to Color Image Segmentation Problem

In this paper, we have proposed a novel model called BK-means algorithm for color image segmentation problem based on the development of basic K-means clustering algorithm as follows:

Input Picture **X** and the number of clusters **K**.

Output the center **M** and the label vector for each data point **Y**.

Step 1: Read color image **X**

Step 2: Pre-process image **X** is as follows: The processing photo step is to apply techniques for improvement of the image quality. This method uses Successive

Mean Quantization Transform (SMQT). The basic unit of SMQT is Mean Quantization Unit (MQU) that includes the average value of all pixels in the image, then the average value is used to quantify the value of the data either 0 or 1, depending on the value of the pixel [3], depending on the value of the pixel as shown in Eq. 1 and 2:

$$Pixel\,(D) \rightarrow Mean \rightarrow M\,\{0,1\} \tag{1}$$

$$M\,(x) = \begin{cases} 1, \; if D\,(x) > Mean \\ 0, \qquad\quad esle \end{cases} \tag{2}$$

Step 3: Convert image $\mathbf{X}$ from RGB color space into $L*a*b*$ in the details as follows: The basic of segmenting images with the K-means clustering algorithm is to create clusters based on the color value of each pixel. It is possible to consider the color components of pixels see [4,10]. In this section we apply K-means clustering for identified images on color space $L*a*b*$. In the color space $L*a*b*$, it is possible to reduce features of brightness L and keep 2 color components of channels $a*$ and $b*$ [4,10]. Note that the method converts images from the color standard RGB to the color standard $L*a*b*$:

Step 4: Reduce data dimensions including image format and convert $\mathbf{X}$ from 3D space into 2D space [4,10] and then obtain the pixel matrix $\hat{\mathbf{X}}$ as shown in Eq. 3:

$$I\,(h,w,c) \rightarrow A\,(h \times w, c) \tag{3}$$

where h, w is size and c is the number of color channel of image I

Step 5: Select a parameter K from the matrix $\hat{\mathbf{X}}$: using Elbow and Silhouette methods. This is described as shown in Eq. 4:

$$wcss\,(C) = \sum_{i=1}^{K} \sum_{o \in c_i} d\,(o, cen_i)^2 \tag{4}$$

where o_i is the object and cen_i is the center of the i^{th} cluster, d is the Euclidean distance, K is the number of clusters.

Step 6: Create an original $\mathbf{K}$ cluster centers: Arrange the matrix $\hat{\mathbf{X}}$ in non-decreasing order, divide the entire of sorted image data into $\mathbf{K}$ equal parts ($\mathbf{K}$ clusters are predicted in step 4). We calculate the average of each part in step 5 and the average value is assigned to the center for the corresponding cluster and is saved as the original cluster center.

Step 7: Apply K-means clustering algorithm to the image matrix with the number of clusters $\mathbf{K}$ and original cluster centers optimized in steps 5 and 6.

2.2 Applied Rule-Based to the Proposed Model by Detecting Fires in Photos and Videos

Vision-based fire detection has many advantages as follows: a large area can be monitored, determined the exact location of fire and be warned along with surveillance cameras. The image data is extracted from video by surveillance cameras. The video is continuously cut into frames, these frames continuously put into the image processing system in order to detect the fire area. When it recognizes the fire area in the image at any time, the video would immediately be alerted to the fire at the place where the surveillance camera is located. Rule-based methods minimize false alarm rate in comparison with fires/smoke sensors. These rules are described significantly as integrated with the camera, shown in Fig. 2.

Fig. 2. Fire detection model using a camera.

Rule 1: For pixels at coordinates $e(x, y)$, if pixels are fire, the following rule must be satisfied [18] as shown in Eq. 5:

$$R_1(x,y) = \begin{cases} 1, \, if \; R(x,y) > G(x,y) > B(x,y) \\ 0 \quad\quad\quad\quad otherwise \end{cases} \tag{5}$$

Rule 2: Determination of threshold values for fire pixels [19] as shown in Eq. 6:

$$R_2(x,y) = \begin{cases} 1, \, if \; (R(x,y) > 190) \cap (G(x,y) > 100) \cap (B(x,y) < 140) \\ 0, \quad\quad\quad\quad otherwise \end{cases} \tag{6}$$

Rules 3 and 4: These rules are described as shown in Eq. 7 and Eq. 8 [19]. Additionally, these rules embedded in the demonstration with AI camera are shown in Fig. 2:

$$R_3(x,y) = \begin{cases} 1, \, if \, Y(x,y) > Cb(x,y) \\ 0, \quad otherwise \end{cases} \tag{7}$$

$$R_4(x,y) = \begin{cases} 1, \, if \, Cr(x,y) > Cb(x,y) \\ 0, \quad otherwise \end{cases} \tag{8}$$

3 Experiments

3.1 Data Sets in Experiments

The proposed model have been tested with datasets containing 600 Natural Images and 1000 Ground Truth images (manual segment image). All the images are (481 × 321) pixels in size. The data source is available from Berkeley University[1] [23,24]; the test dataset consists of 5331 images, including 2400 images with fire (labelled as *fire*) and 2931 images without fire [(labelled as *notfire*). The satellite image data sets are available from earthengine[2]. The dataset for satellite image segmentation problems is collected from Google Image; the outputs (for the segmentation steps) are labelled in areas of the forest images. In the detection of fires in pictures and videos, the outputs of images have been cut from the video time lapse in real-time detection then labeled as *fire* or *notfire*.

3.2 Evaluation Methods

Appropriate methods such as Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Metric (SSIM), and Evaluation based on clustering results are used to evaluate the proposed model.

– Mean Squared Error (MSE) as shown in Eq. 9 [6]

$$MSE = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(I_{ij} - \hat{I}_{ij} \right)^2 \tag{9}$$

where $\hat{I}$ *- the original image,* I *- the segmented image,* M, N *are the size of the image* I. The smaller the $RMSE = \sqrt{MSE}$ value is, the better the output image will be.

– Signal-to-noise ratio calculation is shown in Eq. 10 (SNR) [6]:

$$SNR = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} I_{ij}^2}{\sum_{i=1}^{M} \sum_{j=1}^{N} \left(I_{ij} - \hat{I}_{ij} \right)^2} \tag{10}$$

where $\hat{I}$ - the original image, I - the segmented image, M, N are the size of the image I.

[1] https://people.eecs.berkeley.edu/.

[2] Earthengine: https://earthengine.google.com/timelapse/.

– Peak Signal-to-Noise Ratio (PSNR) calculation is shown in Eq. 11 [6]:

$$PSNR = 10 \times \log_{10}\left(\frac{MAX_j^2}{MSE}\right) \tag{11}$$

Note: the higher value of PSNR corresponds to a better quality image.

– Structural Similarity Index Metric (SSIM) calculation is shown in Eq. 12 [6]:

$$SSIM\left(x,y\right) = \frac{\left(2\mu_x + \mu_y\right)\left(2\sigma_{xy}\right)}{\left(\mu_x^2 + \mu_y^2\right)\left(\sigma_x^2 + \sigma_y^2\right)} \tag{12}$$

in which $: \mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i, \mu_y = \frac{1}{N}\sum_{i=1}^{N} y_i$
and $\sigma_x = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \mu_x\right)^2}, \sigma_y = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(y_i - \mu_y\right)^2}, \sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \mu_x\right)\left(y_i - \mu_y\right)$

(N) is the total number of pixels, (x) is the segmented image, and (y) is the original image.

– Mean Absolute Error (MAE) [6]: this method is used to detect the ‘blue effect’ in any ‘real-time’ image, the most common is a satellite image. Normally, satellite images are blurred due to atmospheric disturbance. The computation of the MAE for an image is shown in Eq. 13:

$$MSE = \frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left|I_{ij} - \hat{I}_{ij}\right| \tag{13}$$

where $\hat{I}$ - the original image, I - the segmented image, M, N are the size of the image I.

– Structural Content (SC) [6]: the structure contents provides the similarity between two images. As the similarity between two images increases, the (SC) approaches (1) as shown in Eq. 14:

$$SC = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} I_{ij}^2}{\sum_{i=1}^{M}\sum_{j=1}^{M} \hat{I}_{ij}^2} \tag{14}$$

where $\hat{I}$ - the original image, I - the segmented image, M, N are the size of the image I.

– Evaluation based on clustering results: each $\frac{N(N-1)}{2}$ pair of pixels in the data layer is assigned to the same cluster IFF they are similar. A True Positive (TP) decision is to assign two similar pixels to the same cluster, a True Negative $(()TN)$ decision is to assign two different pixels to different clusters. There are two types of potential errors: (a) one is where a (FP) assigns two different pixels to the same cluster, and (b) the second is where a (FN) decides to assign two similar pixels for different clusters. The index (RI) indicates the percentage of correct decisions as shown in Eq. 15:

$$RI = \frac{TP + TN}{TP + FP + TN + FN} \tag{15}$$

The method to determine a *positive* class, *Precision* [1] is defined as the rate at which (TP) points are correctly classified as *positive* $(TP + FP)$ as shown in Eq. 16:

$$Precision = \frac{TP}{TP + FP} \tag{16}$$

Recall [1] is defined as the rate at which (TP) points among those points that are actually *positive* $(TP + FN)$ as shown in Eq. 17:

$$Recall = \frac{TP}{TP + FN} \tag{17}$$

The value F_1 [6]: lies in the $[0,\ 1]$ range where a higher value of (F_1) represents a better classification. When both *Recall* and *Precision* are equal to 1, $F_1 = 1$. Figure 3 models this evaluation based on clustering results is from as shown in Eq. 18:

$$F_1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{18}$$

3.3 Experimental Result and Evaluation

The proposed BK-means and the basic K-means methods have been tested with the same data sets under the same conditions for image detection as shown in Fig. 3. The proposed method and K-means algorithm are used to automatically identify the lake area, forest area and vegetation area, land area, sandy area along the lake. We can also visually predict a forest image, categorized in five main colors: blue is the lake area, green is the forest and vegetation area, brown is the land area, white is the sand area, and gray is the swamp area.

The experimental results are shown in Fig. 4. The proposed model performance is better than traditional K-means's method according to Table 1. For further tests in the experiments, the proposed model has been performed with data sets consisting of 2 subsets, dealing with fire data sets contains 2400 images with fire labelled 1 and the not-fire test set contains 2931 images without fire labelled 0. The results of fire detection in photos are illustrated in Fig. 5

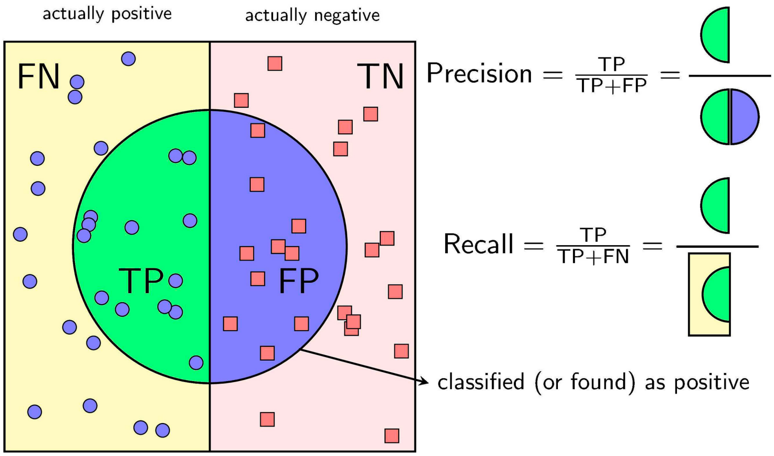

Fig. 3. Recall and precision calculation method for binary classification problem [1]

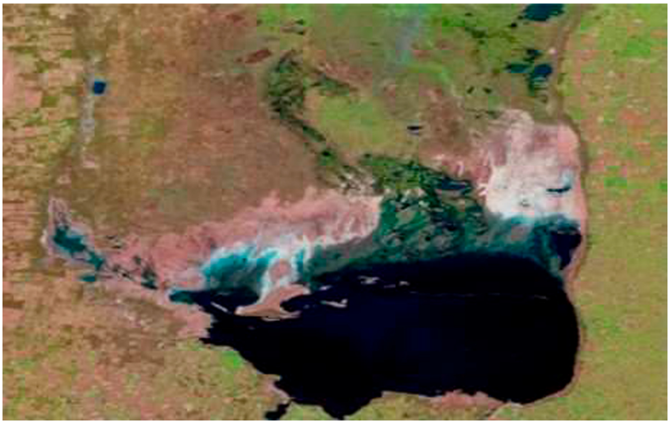

Fig. 4. Satellite image of Lake Chiquita Mar area

Table 1. Comparisons of the proposed BK-means and the K-means algorithm performance

	Time (s)	Iterations	RMSE	MAE	SNR	PSNR	SC	SSIM
K-means	30.8658	28	0.0486	0.0362	18.5860	26.2638	0.9863	0.8550
BK-means	29.2071	26	0.0944	0.0735	15.8679	20.5045	0.9768	0.8369

Fig. 5. Results of fire detection in photos

4 Conclusion

A novel approach has proposed to make real-time decisions caused by forest fire. K-means method does not work well for noisy or low qualitative images. While implementing image clustering with K-means, we have investigated in the quality of the input image, enhancing the features of pixels [14]. In order to distinguish smoke and images like fog, cloudy sky, and color-like images of such as image features and large intensity light, etc. the proposed model detects the movement of smoke in video explores the construction of Time-Lapse Videos from cluttered consecutive image. The novel approach enhance the performance of K-mean algorithm for forest detection problem. It is indicated that the proposed model achieves significant improvements in real-time detection.

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References

1. Tiep, V.H.: The base of machine learning (2018)
2. Wang, Z., Jensen, J.R., Im, J.: An automatic region-based image segmentation algorithm for remote sensing applications. Environ. Modell. Softw. **25**(10), 1149–1165 (2010)

3. González, J.C., Salazar, Ò.D.C.: Image enhancement with Matlab algorithms. Blekinge Institute of Technology Department of Applied Signal Processing SE-371 79, Karlskrona Sweden (2016)
4. Kajla, S., Bansal, R.: Efficient improved K means clustering for image segmentation. Int. J. Innov. Res. Comput. Commun. Eng. **4**(6) (2016)
5. Bisla, A., Yadav, P.: Image segmentation using K-means clustering algorithm. Machine Learning Project (2019)
6. Rajkumar, S., Malathi, G.: A comparative analysis on image quality assessment for real time satellite images. Indian J. Sci. Technol. **9**(34) (2016). School of Computing Science and Engineering, VIT University, Chennai, 600127, Tamil Nadu, India
7. Linde, Y., Buzo, A., Gray, R.M.: An algorithm for vector quantizer design. IEEE Trans. Commun. **COM–28**, 84–95 (1980)
8. Huang, C., Harris, R.: A comparison of several vector quantization codebook generation approaches. IEEE Trans. Image Process. **2**(1), 108–112 (1993)
9. John, N., Viswanath, A., Sowmya, V., Soman, K.P.: Analysis of various color space models on effective single image super resolution, August 2016
10. Mathur, G., Purohit, H.: Performance analysis of color image segmentation using K- means clustering algorithm in different color spaces. IOSR J. VLSI Signal Process. (IOSR-JVSP) **4**(6), 1–4 (2014). Ver. III
11. Aqil Burney, S.M., Tariq, H.: K-means cluster analysis for image segmentation. Int. J. Comput. Appl. (0975–8887) **96**(4) (2014)
12. Vipin, V.: Image processing based forest fire detection. Int. J. Emerg. Technol. Adv. Eng. **2**(2), 87–95 (2012)
13. Tuba, V., Capor-Hrosik, R., Tuba, E.: Forest fires detection in digital images based on color features. Int. J. Environ. Sci. **2** (2017)
14. Mehaboobsab, S.N., Alamgeer, A.K., Ahmed, M.M.N., Badruddin, A.M.S.: Fire detection system using image processing. Department of Electronics and Telecommunication Engineering Anjuman-I-Islam's Kalsekar Technical Campus, 2015–2016
15. Binti Zaidi, N.I., binti Lokman, N.A.A., bin Daud, M.R., Achmad, H., Chia, K.A.: Fire recognition using RGB and YCbCr color space. ARPN J. Eng. Appl. Sci. **10**(21), 9786–9790 (2015)
16. Garcia-Jimenez, S., Jurio, A., Pagola, M., De Miguel, L., Barrenechea, E., Bustince, H.: Forest fire detection: a fuzzy system approach based on overlap indices. Appl. Soft Comput. **52**, 834–842 (2017)
17. Lin, H., Liu, X., Wang, X., Liu, Y.: A fuzzy inference and big data analysis algorithm for the prediction of forest fire based on rechargeable wireless sensor networks. Sustain. Comput.: Inf. Syst. **18**, 101–111 (2018)
18. Zhang, Q., Lin, G., Zhang, Y., Gao, X., Wang, J.: Wildland forest fire smoke detection based on faster R-CNN using synthetic smoke images. Proc. Eng. **211**, 441–446 (2018)
19. Muhammad, K., Ahmad, J., Baik, S.W.: Early fire detection using convolutional neural networks during surveillance for effective disaster management. Neurocomputing **288**(2), 30–42 (2018)
20. Pham, H.V., Moore, P., Tran, K.D.: Context matching with reasoning and decision support using hedge algebra with Kansei evaluation. In: Proceedings of the fifth symposium on Information and Communication Technology (SoICT 2014), Hanoi, Vietnam, 4–5 December 2014, pp. 202–210 (2014)
21. Moore, P., Pham, H.V.: Intelligent context with decision support under uncertainty. In: Second International Workshop on Intelligent Context-Aware Systems (ICAS 2012), pp. 977–982 (2012)

22. Van Pham, H., Moore, P.: Emergency service provision using a novel hybrid SOM-spiral STC model for group decision support under dynamic uncertainty. Appl. Sci. **9**, 3910 (2019)
23. Image data sets in Berkely Univ. Libaray. https://people.eecs.berkeley.edu/yang/software/lossy_segmentation
24. Image forest data sets. https://earthengine.google.com/timelapse