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A Fast Detection Algorithm for Change Detection in National Forestland "One Map" Based on NLNE Quad-Tree

Fei Gao [1,2], Xiaohui Su [3], Yuling Chen [4], Baoguo Wu [3], Yingze Tian [2], Wenjie Zhang [3] and Tao Li [1,*]

[1] School of Cyber Science and Engineering, Sichuan University, Chengdu 610065, China; gaofei2019@stu.scu.edu.cn
[2] Sichuan Forestry and Grassland Survey and Planning Institute, Chengdu 610084, China; tianyingze@iCloud.com
[3] School of Information Science and Technology, Beijing Forestry University, Beijing 100083, China; suxhui@bjfu.edu.cn (X.S.); wubg@bjfu.edu.cn (B.W.); zwenjie@bjfu.edu.cn (W.Z.)
[4] Institute of Remote Sensing and Geographic Information System, School of Earth and Space Sciences, Peking University, Beijing 100871, China; chenyuling92@pku.edu.cn
* Correspondence: litao@scu.edu.cn

Abstract: The National Forestland "One Map" applies the boundaries and attributes of sub-elements to mountain plots by means of spatial data to achieve digital management of forest resources. The change detection and analysis of forest space and property is the key to determining the change characteristics, evolution trend and management effectiveness of forest land. The existing spatial overlay method, rasterization method, object matching method, etc., cannot meet the requirements of high efficiency and high precision at the same time. In this paper, we investigate a fast algorithm for the detection of changes in "One Map", taking Sichuan Province as an example. The key spatial characteristic extraction method is used to uniquely determine the sub-compartments. We construct an unbalanced quadtree based on the number of maximum leaf node elements (NLNE Quad-Tree) to narrow down the query range of the target sub-compartments and quickly locate the sub-compartments. Based on NLNE Quad-Tree, we establish a change detection model for "One Map" (NQT-FCDM). The results show that the spatial feature combination of barycentric coordinates and area can ensure the spatial uniqueness of 44.45 million sub-compartments in Sichuan Province with 1 m~0.000001 m precision. The NQT-FCDM constructed with 1000–6000 as the maximum number of leaf nodes has the best retrieval efficiency in the range of 100,000–500,000 sub-compartments. The NQT-FCDM shortens the time by about 75% compared with the traditional spatial union analysis method, shortens the time by about 50% compared with the normal quadtree and effectively solves the problem of generating a large amount of intermediate data in the spatial union analysis method. The NQT-FCDM proposed in this paper improves the efficiency of change detection in "One Map" and can be generalized to other industries applying geographic information systems to carry out change detection, providing a basis for the detection of changes in vector spatial data.

Keywords: vector data; change detection; National Forestland "One Map"; NLNE Quad-Tree

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1. Introduction

In 2013, the sub-compartment was used as the smallest unit of forest management for the first time in China, and the national, provincial and district departments worked together to build the National Forestland "One Map" [1,2]. Through a series of dynamic monitoring exercises such as forest inventory and land change surveys, sub-compartment data can be updated annually. The high-frequency updating mechanism can effectively guarantee the timeliness of forest resource data, providing strong support for timely mastery of the current situation and dynamic changes in national forest resources [3]. The National Forestland "One Map" uses vector data to express the boundaries of sub-compartments and attribute data to express the administrative, stand and management

information of sub-compartments so that the master spatial data of forest land have integrated and fused graphic and attribute data. On this basis, superimposed multi-source data such as topographic maps and remote sensing images achieved a breakthrough in the management of China's forest resources [4–7]. They provided a unified national base map for forestry scientific research, daily resource management and forestry development planning for the first time [1,8–10].

In the updating of "One Map", the detection and analysis of changes in the spatial and attribute data is the key to obtaining the characteristics of changes in forest land, trends in its evolution and the effectiveness of its management [4,11]. Through accurate forest vector data, staff can capture changes on a much smaller scale, leading to a more accurate understanding of how forest lands are evolving. In addition, forest land change detection also provides strong support for sustainable forestry development. By obtaining the spatial location and quantity of forest land inflows and outflows, the government and relevant agencies are better able to strengthen regulation, formulate protection policies and provide a basis for rational planning of the use of forest resources [12]. Overall, the spatial-data-based detection of changes in "One Map" not only has the advantage of the frequency of data updating, but also provides more comprehensive information in terms of precision and details; it provides a powerful tool for China to effectively manage its rich forest resources and has far-reaching significance for the global response to climate change [7].

Currently, the "bottleneck" facing the detection of changes in "One Map" is the efficiency problem [2,7,13]. For example, in Sichuan Province, the number of sub-compartments was 14.39 million in 2013, and the number of sub-compartments in 2022 reached 44.45 million. When carrying out forestry-related scientific research or management work, it is necessary to compare the changes in "One Map" at different times. Moreover, the detection of changes in "One Map" includes the detection of changes in graphic boundaries, as well as the detection of changes in forest attribute information such as forest stand factors and management factors. Therefore, there is an urgent need for an efficient detection method that quickly and accurately obtains forest land change results. The detection of changes in vector data refers to verifying whether a shape is exactly the same in two-dimensional space. However, shape is a concept that is difficult to accurately describe in mathematical language, and it is difficult to express the geometric shape of vector data with a model and measure the shape with a simple index [2,14,15]. Typically, sub-compartment vector changes include splitting, merging and reorganizing, as shown in Figure 1.

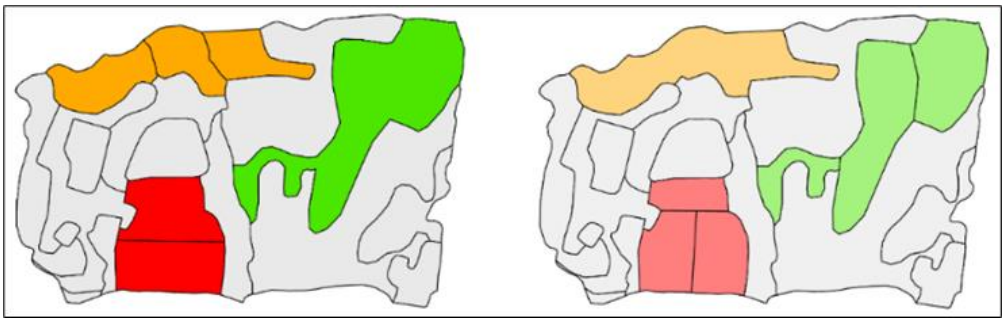


Figure 1. Changes in sub-compartment vectors. Yellow represents sub-compartment mergers, green represents sub-compartment splits and red represents sub-compartment reorganizations.

There have been many studies on change detection in "One Map", and the methods used in these studies are broadly classified into the vector rasterization method, object matching method, spatial union analysis method and quadtree retrieval method [16,17]. Zhu, X, Azubike, C.S divided the vector layer into regular chunks and then rasterized it for independent data change analysis [3,5]. Although this method can effectively decompose large areas into easy-to-handle units, it is not practical enough to handle large-scale and real-time applications, especially in the conversion of vector data, which may lead to loss

of information. Li, L, Yin, J, et al. detected changes in ground cover by matching geometric objects in the old and new databases, which is simple and direct. However, this method is not applicable to large-scale vector change detection due to the differences in the geographic coordinate system of different databases and the slow limitations of the traverse full table query [18,19]. Chughtai, A.H, Mishra, P.K and other scholars use the spatial union analysis method, in which the spatial information dispersed in different layers according to the same spatial location is superimposed together, resulting in new spatial graphics and a new spatial location of the new attributes and the results of the original two or more layers of the map elements of the attributes of the synthesis [6,20]. However, the spatial union analysis method requires a large number of spatial operations, produces a large number of intermediate layers and has a high time complexity, which makes it impossible for this method to detect changes in a large number of spatial data in real time. Xia Y et al. use the "number of nodes—arc length" in the quadtree area to retrieve whether there is a change or not. The geometric features used in this method are the number of nodes and the number of arcs, which are able to improve the query efficiency to a certain extent in the spatial query. Zhu X, Guo, T et al. proposed an unbalanced quadtree, DQ-Tree, which recursively checks each node by setting the maximum number of elements of the node. Organized by the number of nodes, coordinates and area, it can achieve full-element checking and is more efficient when there are few changes [3,18]. However, this method has three core problems: (1) the determination of the depth of quadtree with different data volumes; (2) the delineation of the quadtree boundary entity objects; (3) the stable and fast detection of leaf node element changes.

In response to these issues, this study used an unbalanced quadtree based on the maximum number of leaf nodes to improve the efficiency of change detection in "One Map". The main objectives of this study are as follows:

(1) Construct the uniqueness expression model of sub-compartments based on spatial features.
(2) Construct the unbalanced quadtree based on the number of leaf node elements (NLNE Quad-Tree), and construct a change detection model for "One Map" (NQT-FCDM).
(3) Test the performance of the above algorithms with varying amounts of data (100,000~500,000) and compare it with the performance of spatial union analysis and the normal quadtree method.

The rest of the article is structured as follows: Section 2 outlines the materials and method. The results are presented in Section 3, and the discussion is given in Section 4. Section 5 provides conclusions based on the results and discussion.

2. Materials and Methods

2.1. Data and Platforms

The test area was Sichuan Province, which ranks first in terms of forest land area in China and is located at 102.54°–104.53° E, 30.05°–31.26° N. Sichuan Province is located in the transition zone from the Qinghai–Tibet Plateau to the plains of the middle and lower reaches of the Yangtze River, with an area of 25,419,600 hectares of forested land. At the same time, Sichuan is also one of the most populous regions in China and the world, where forests and agriculture are intertwined and human activities are frequent, and the number of spots on the "One Map" and the number of spots with annual changes are always among the highest in China. The location map of Sichuan Province is shown in Figure 2.

For this paper, the study was carried out at the county level, and the data were the "One Map" in Sichuan Province in 2021 and 2022. The "One Map" contains full coverage-type vector data of 183 counties. The county boundaries are identical in the same coordinate system, and there is no internal topological error. The various statistical indicators of the study data are shown in Table 1.

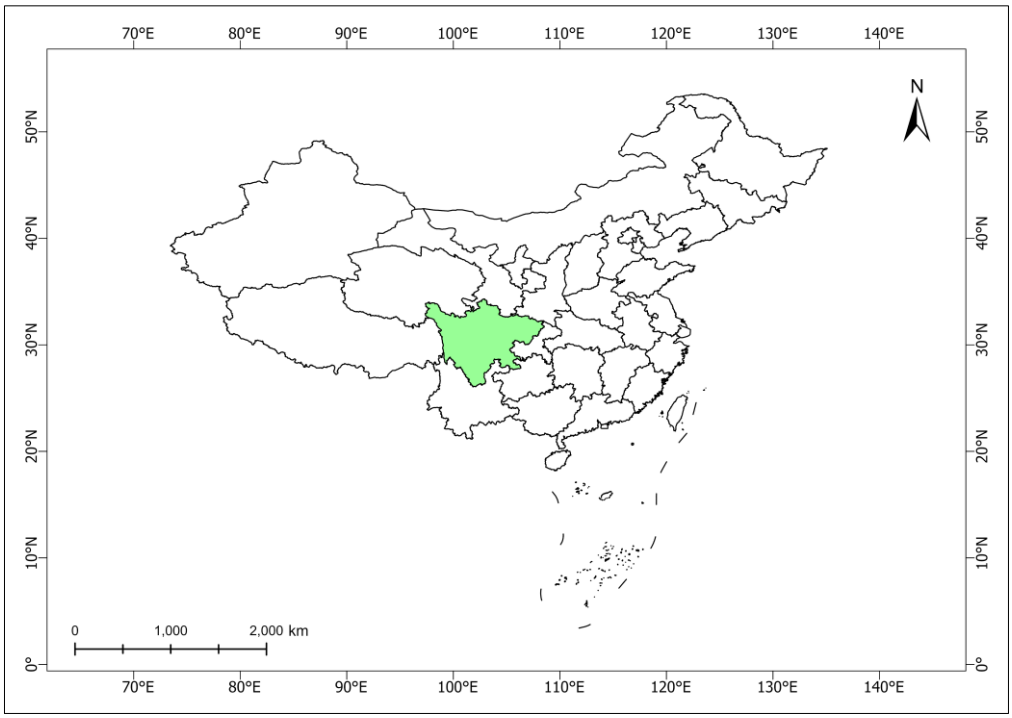


Figure 2. Location map of Sichuan Province in China. The green color is Sichuan Province.

Table 1. Data indicators of "One Map" in Sichuan Province in 2021 and 2022.

Statistical Term [1]	Year 2021	Year 2022
Number of layers (counties)	183	183
Minimum number of sub-compartments	9020	10,825
Maximum number of sub-compartments	677,058	770,911
Average number of sub-compartments	218,300	242,887

[1] The data volume of "One Map" in 2021 is 49.7 GB, with about 40 million elements, and the data volume of "One Map" in 2022 is 53.5 GB, with about 44 million elements.

The table structure of the "One Map", shown in Table 2, was used to detect changes in forest land attributes.

Table 2. Attribute fields for forest land attributes in "One Map".

Field Name	Field Type	Field Length	Field Meaning
di_lei	text	6	Land class
di_mao	text	1	Landforms
hai_ba	float		Altitude
po_xiang	text	1	Slope orientation
po_wei	text	1	Slope position
po_du	float		Slope gradient
tu_rang_lx	text	3	Soil type
tu_ceng_hd	int		Soil thickness
you_shi_sz	text	6	Dominant tree species
ling_zu	int		Age group
yu_bi_du	int		Canopy density
pingjun_xj	float		Average diameter at breast height
pingjun_sg	float		Average tree height
mei_gq_zs	int		Number of trees per hectare

[1] The data volume of "One Map" in 2021 is 49.7 GB, with about 40 million elements, and the data volume of "One Map" in 2022 is 53.5 GB, with about 44 million elements.

The experimental environments are shown in Table 3, and the hardware configuration and system environment of the platform are relatively common, which means that on other computers with similar configurations, users will obtain similar performance to the results of this test.

Table 3. Experimental environment.

Statistical Term	Environment
CPU	Intel i7-13900H
RAM	32 GB
System	Windows 11
Database	Sqlite 3 with support for space expansion
Software	ArcGIS Pro 3, Dbeaver 22.0

2.2. Expression of Spatial Uniqueness in Sub-Compartments

For this paper, we selected the representative point, geometric contour and the combination of the two as the sub-compartment unique identifier (SE-UUIDs) of the vector data and verified their performance under different accuracies. The representative point is a point in the geometry with specific properties representing the whole geometry, and the location of the representative point coordinates can distinguish the geographic elements within the same layer, which is easy to calculate and more intuitive in the vector data of the sub-compartment as the center of mass coordinates. The geometric contour is a conceptual definition that describes the overall shape of a sub-compartment. Since the perimeter and area change once a sub-compartment is deformed, it is necessary to utilize the perimeter and area as quantitative descriptors of the contour [14,21,22]. The center of mass coordinates, area and perimeter can be defined by the Structured Query Language (SQL), which conforms to the standards of the International Organization for Standardization (ISO) and the Open Geospatial Consortium (OGC).

2.3. Construction of Unbalanced Quadtree Based on the Number of Leaf Node Elements

A quadtree is a tree-like data structure in which each node has four children, representing the four quadrants in which space is partitioned [23]. This partitioning of space can continue until a certain stopping condition is reached. At each node, data associated with that node can be stored. The structure of the quadtree makes it efficient to perform data retrieval in the space. By traversing the nodes of the tree, the data can be retrieved by quickly locating the node that contains or is closest to the target location [24]. Spatial division by quadtree indexing not only solves the purpose of uniformly dividing spatial elements, but also ensures the establishment of a spatial grid structure applicable to both old and new spatial data, as the overall spatial distribution of the old and new elements will not be changed too much by giving a grid range that contains all the old and new elements [25].

In a quadtree, each geospatial object is stored on a leaf node according to its minimum outsourcing rectangle. Figure 3 shows the structure of a grid division in a two-dimensional space. Letters A, B, and C are geospatial objects, and 0 to3 and 00–03 are the grid cell codes of depths 1 and 2, respectively.

The index structure of this grid space built according to the normal quadtree approach is shown in Figure 4, where it can be seen that the intermediate nodes and the root node do not store geospatial objects, and a geospatial object can only be on a leaf node.

Since the depth is fixed in the quadtree structure, the phenomenon of uneven distribution of spatial elements in a leaf node will occur. For example, the number of sub-compartments in the hilly area of western Sichuan is much larger than that in the Tibetan Plateau area of northwestern Sichuan under the same area [22,26]. This unbalanced indexing not only causes the depth of the quadtree to be difficult to determine, but also leads to an uncontrollable timeframe for detecting changes in the elements of each leaf node. In view of this, this paper proposes the NLNE Quad-Tree, in which the depth of the tree is

determined by the granularity of the grid division, in order to ensure that the elements stored in each node are as uniform as possible. The NLNE Quad-Tree grid division is conditioned on the fact that the number of elements in each grid should be less than the maximum number of elements to be indexed in the grid division of the grid as the index unit [27,28].

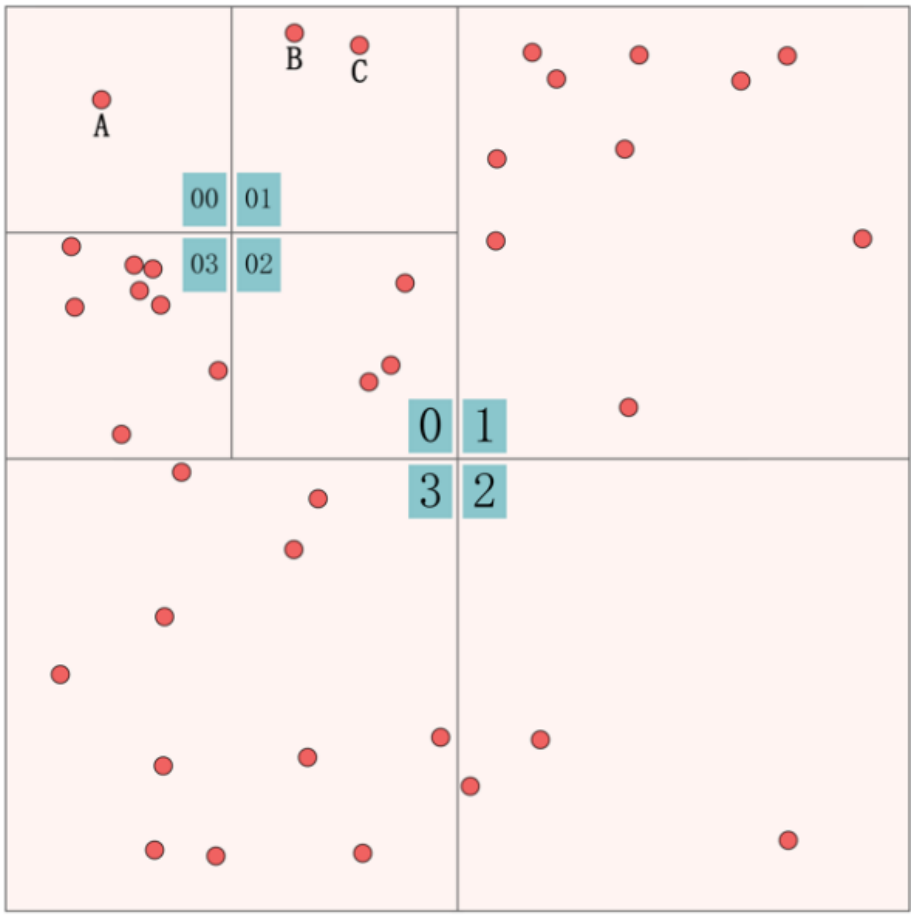


Figure 3. Schematic diagram of quadtree splitting. The red dots represents the geospatial objects. 0–4, 00–03 represents the coding of quadtree in this region.

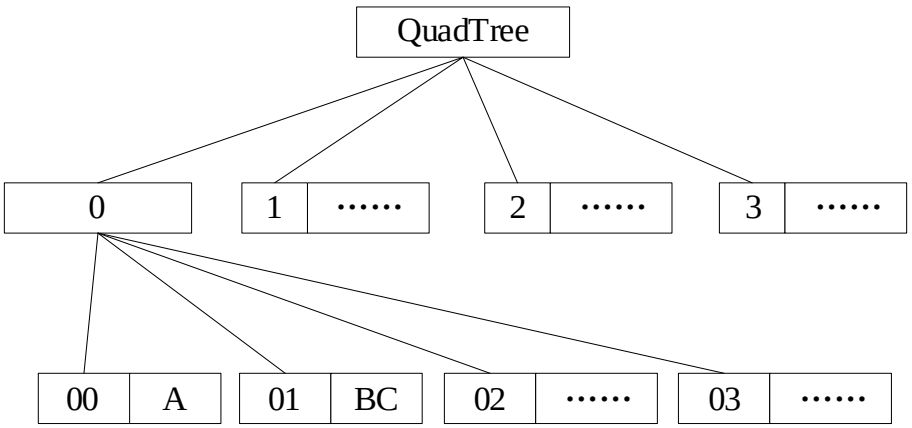


Figure 4. Schematic diagram of the indexing of the quadtree structure.

The NLNE Quad-Tree is constructed as follows:

(1) For the initial two-dimensional space to establish the root node, the two-dimensional space according to the X and Y dimensions of each folded in half divided into four quadrants, the partition encoding rule for the first quadrant is 1, the second quadrant is 0, the third quadrant is 3, the fourth quadrant is 2, continue to divide the grid cell encoding on the basis of its parent node encoding in this way to superposition.
(2) All the elements after the division is completed are sequentially judged to belong to the partition based on the feature points, and the element is moved to the index unit of the corresponding node of the partition.
(3) After the traversal is completed, the four partitions are judged on whether the number of internal elements meets the maximum number of elements; otherwise, the recursive division is carried out in accordance with the above manner until all the grid cells meet the conditions, and in a hierarchical relationship, each level of the division is linked to the others according to the parent node and the child node, thus constituting the NLNE Quad-Tree index structure.
(4) According to the above method, the NLNE Quad-Tree index structure is built with 5 as the maximum for the grid space shown in Figure 3, as shown in Figure 5.

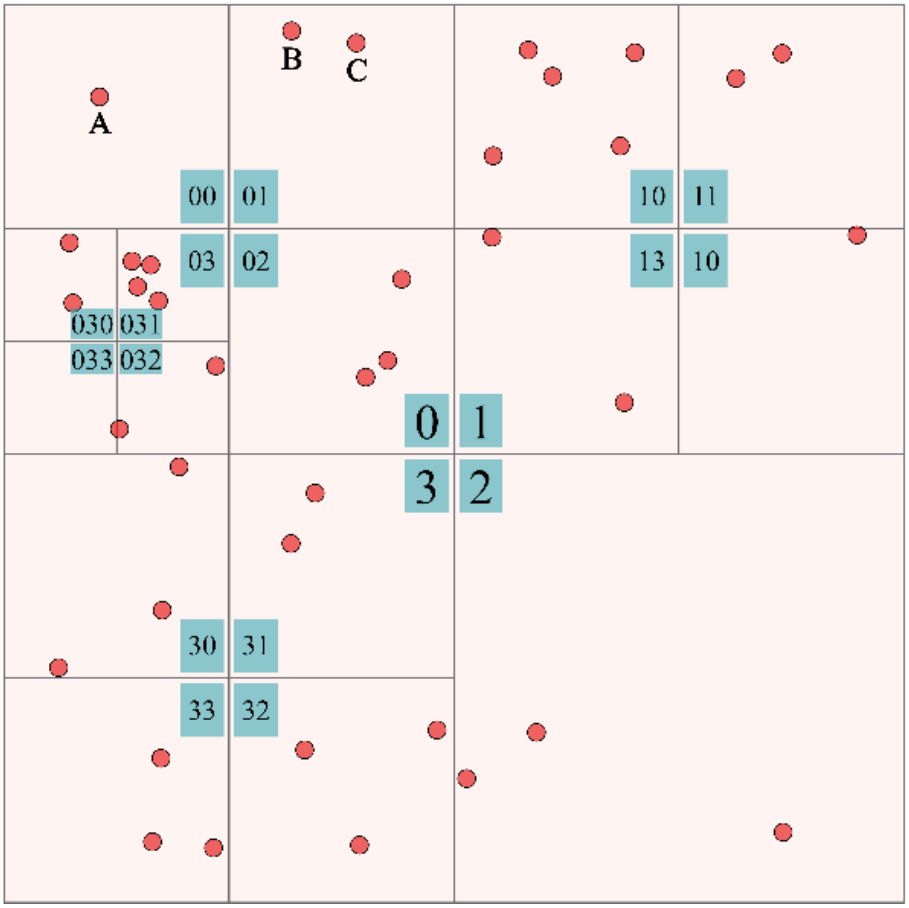


Figure 5. Schematic diagram of NLNE Quad-Tree segmentation. The red dots represents the geospatial objects. 0–4, 00–03, 030–033 represents the coding of quadtree in this region.

2.4. NLNE Quad-Tree Based Change Detection Model for "One Map" (NQT-FCDM)

The process of constructing a change detection model based on NLNE Quad-Tree for "One Map" (NQT-FCDM) is as follows:

Step 1: Establish NLNE Quad-Tree for the old and new "One Map".

In the change detection process of this paper, it is necessary to establish the O-NLNE Quad-Tree and N-NLNE Quad-Tree corresponding to the old and new data, respectively. At the same time, it is required that both of them must have the same lattice structure, so

the establishment processes are slightly different, and the algorithm flowchart is shown in Figure 6.

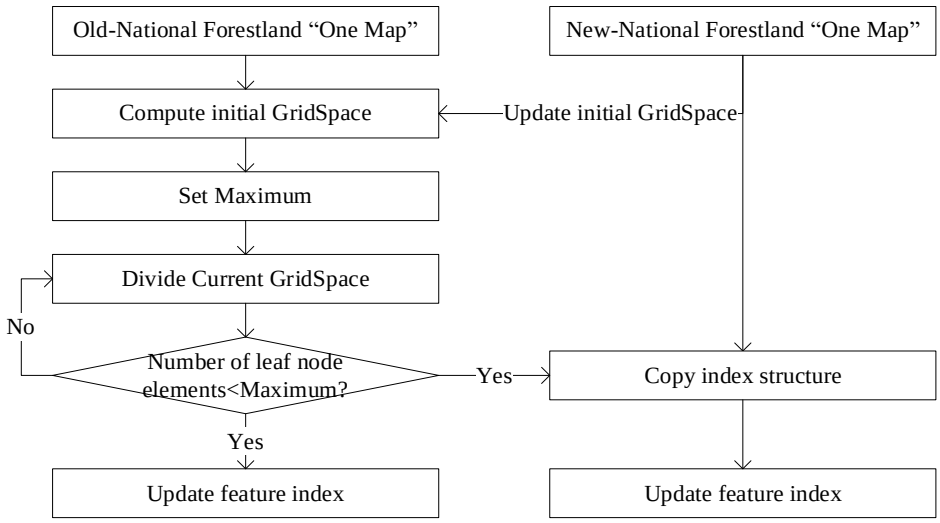


Figure 6. Construction of NLNE Quad-Tree for "One Map" in old and new tenses.

The detailed algorithm steps are as follows:

a Obtain the maximum spatial range xmin, xmax, ymin, ymax of the "One Map" in the first and second periods, respectively.

b Based on the maximum spatial extent of the two-phase "One Map", determine the grid division space (GridSpace) that completely covers the old and new temporal data. In order to exclude the case that the elements just fall on the boundary, the GridSpace is expanded outward by a certain distance Span.

c Determine the maximum number of leaf node elements Maximum.

d Based on the previous data, traverse the division of "One Map" from the root node in accordance with the NLNE Quad-Tree construction method.

e Determine whether the number of elements of the divided child nodes is greater than the set Maximum.

f If yes, update the index of the current leaf node element and copy the current index to the later forest land data and update the index of the later forest land data.

g If no, repeat the above process.

Step 2: Extract changes from "One Map".
The detailed algorithm steps are as follows:

a Calculate the SE-UUID.

b Iterate through the leaf nodes of NLNE Quad-Tree to match the elements with the same index of the two-phase "One Map".

c Perform a full outer join query by SE-UUID on the same leaf node for the before and after two-phase "One Map".

d Extract sub-compartments whose SE-UUIDs of the two-phase "One Map" cannot match each other and mark them as spatially variable.

e Extract sub-compartments with consistent SE-UUIDs but inconsistent attributes, and mark the pre-period data and post-period data as attribute changes.

f Cycle the above steps until all leaf node traversal is completed.

Step 3: Count the changes in "One Map".
The detailed algorithm steps are as follows.

a Perform spatial union of sub-compartments marked as spatial changes and calculate the changes (splitting, merging, reorganizing) of each sub-compartment.

b Mark the sub-compartments with inconsistent attributes in the above spatial union results as changes in attributes.
c Count the sub-compartments marked as changes in forest land attributes in steps 2.e and 3.b to derive the changes in "One Map" in the two periods before and after.

2.5. Evaluation of Test Results

The assessment of detection results takes time as the evaluation index. Here, 100 thousand, 200 thousand, 300 thousand, 400 thousand and 500 thousand vector elements were used as the evaluation data to count the detection time of different detection methods. The selection of this data amount was based on the upper and lower limits of the number of records of "One Map" in county forests. Since the detection precision of the rasterization method and geometric object matching method cannot reach 100% due to the influence of database type and coordinate system, the comparison was not carried out for this paper.

3. Results

3.1. Sub-Compartment Spatial Uniqueness

Through the detection of more than 50 million sub-compartment data in Sichuan Province in 2022, as shown in Table 4, when the precision is 1~0.00001 m, area and perimeter alone as the eigenvalue cannot achieve the unique identification of sub-compartment space. When the precision is greater than or equal to 0.1 m, the center of mass coordinates as the eigenvalue can achieve the unique identification of sub-compartment space. With the combination of center of mass coordinates–area or center of mass coordinates–perimeter as the eigenvalue, the unique identification of sub-compartment space at the precision of 1~0.00001 m can be achieved.

Table 4. Expression of the inability to uniquely express sub-compartments at different accuracies (per 100,000).

Precision (m)	Area	Perimeter	Center of Mass Coordinates	Center of Mass Coordinates–Area	Center of Mass Coordinates–Perimeter
1	96,657	99,670	18	0	0
0.1	86,886	98,077	0	0	0
0.01	51,613	90,036	0	0	0
0.001	9153	49,051	0	0	0
0.0001	1027	7574	0	0	0
0.00001	118	801	0	0	0

Considering that the area can better reflect the attributes of a sub-compartment than the perimeter, this paper uses the combination of the center of mass coordinates–area with a precision of 0.01 m as the SE-UUID, and the structure of the SE-UUID is (X-Y-AREA), with X, Y and AREA representing the horizontal coordinate of the center of mass, the vertical coordinate of the center of mass and the area, respectively.

3.2. Time Consumed Building NLNE Quad-Tree

Taking Maximum as a variable, the NLNE Quad-Tree is built from 0 to 20,000 in steps of 500 for the test data, and the time consumed in building the NLNE Quad-Tree under different numbers of sub-compartments is shown in Figure 7. It can be seen that when the number of sub-compartments is 100,000–500,000, the time consumed to build the Quad-Tree index is basically inversely proportional to the square of Maximum. When Maximum < 1000, the quadtree index building time decreases rapidly with the increase in Maximum, and when Maximum > 5000, the quadtree index building time stabilizes.

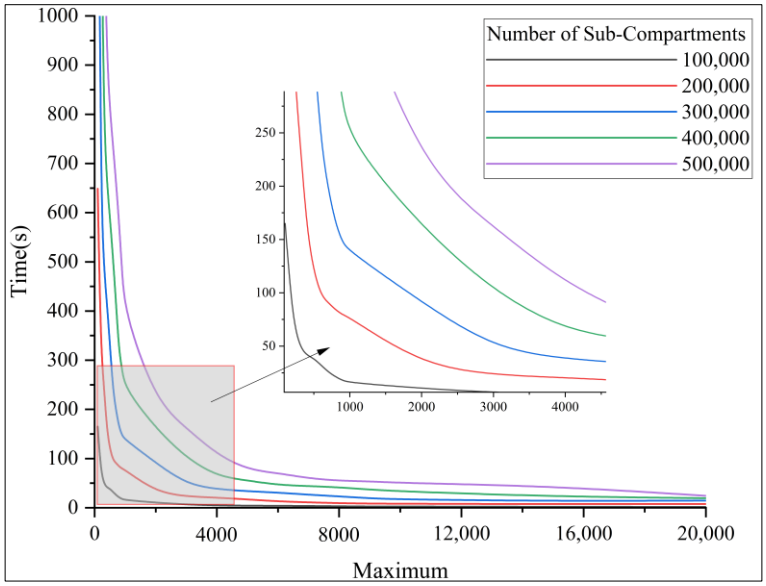


Figure 7. NLNE Quad-Tree construction time consumption under different Maximum values.

3.3. NQT-FCDM Time Consumption

After the NLNE Quad-Tree was constructed, the subsequent "One Map" change query time consumption was calculated, as shown in Figure 8. It can be seen that when the number of sub-compartments is 100,000–500,000, the query time consumed for the change in "One Map" is basically positively proportional to Maximum.

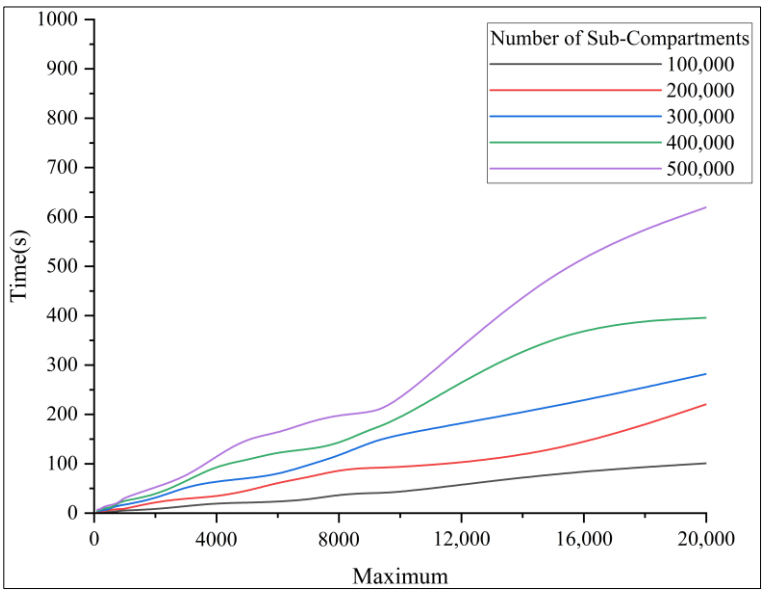


Figure 8. "One Map" change query time consumed under different Maximum values.

The NLNE Quad-Tree construction time combined with the subsequent query time for "One Map" change is the NQT-FCDM total time consumption, as shown in Figure 9.

It can be seen that the efficiency of NLNE Quad-Tree increases rapidly when the Maximum is less than 1000, and then the efficiency gradually stabilizes. Then, the efficiency decreases when the Maximum is more than 8000. The total time consumption of NQT-FCDM is maintained at a low level under the data volume of 100,000–500,000, when the maximum number of leaf node elements is 1000–2000, 2000–3000, 3000–4000, 4000–5000, or 5000–6000.

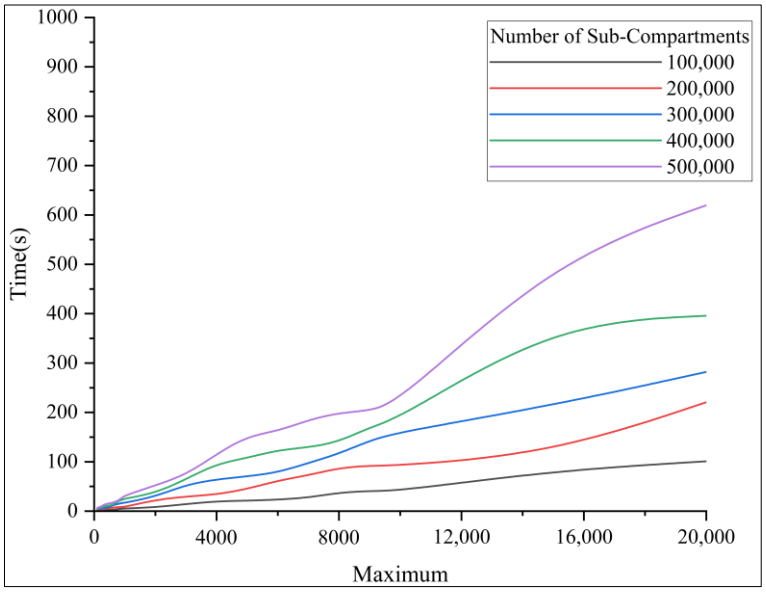


Figure 9. "One Map" change detection time-consuming under different Maximum values.

3.4. Comparison of the Efficiency of Different Methods for "One Map"

By setting the data of two periods of sub-compartment before and after with different numbers of elements (such as 100 thousand, 200 thousand, 300 thousand, 400 thousand and 500 thousand), the spatial union analysis method, normal quadtree method and NQT-FCDM were used to compare their efficiency in sub-compartment vector change detection. As shown in Figure 10, it can be seen that the spatial union analysis method takes the longest time, normal quadtree takes the second longest and NQT-FCDM has the highest detection efficiency. NQT-FCDM shortens the average time by more than 75% compared with the spatial union analysis method and shortens the average time by 50% compared with the normal quadtree method, which is a significant increase in efficiency in the detection of changes in "One Map" [3,13,21].

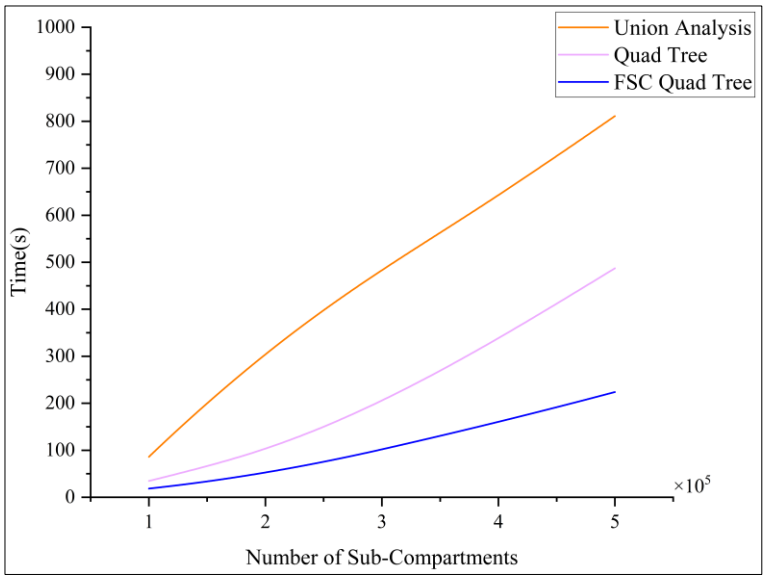


Figure 10. Comparison of time consumed in the detection of changes in "One Map" by each method under different numbers of sub-compartments.

4. Discussion

In China, forest land covers about one-quarter of the country's area. Therefore, counting the successive yearly changes of forest land over such a vast surface needs to be supported by effective algorithms. Currently, spatial union analysis is still used in practice for data comparison between the previous and later periods, which is time-consuming and laborious and has difficulty supporting the current huge forest land vector data. In this paper, we construct SE-UUIDs through the spatial characteristics of sub-compartments so that the change detection in "One Map" can be changed from a complex spatial data calculation to an attribute data query. At the same time, we avoid the problem of node duplication of sub-compartments in the process of quadtree splitting. We construct the NLNE Quad-Tree, which solves the problem of unstable spatial computation efficiency caused by unbalanced leaf nodes in the normal quadtree. We put forward the NQT-FCDM and derived the maximum number of leaf nodes at the highest efficiency of change detection in "One Map" under different numbers of sub-compartments, which balances the establishment of NLNE Quad-Tree and the timeliness of the subsequent change query.

In this paper, the combination of the center of mass coordinates and area is used as the SE-UUID, which takes into account both the spatial location and the geometric attributes of sub-compartments. There are two important prerequisites for this SE-UUID; one is that there is no topological error in "One Map" to be detected, and the other is that the graphical representation of the sub-compartments is not that irregular. As shown in Figure 11, for two layers with the same boundary and no topological errors, the common boundary of element A and element B has changed, resulting in a change in the center of mass coordinates of both element A and element B. It is not difficult to understand that if a line segment changes in a face composed of line segments topologically, then the shapes of the elements of the face composed of this line will all change. Since the center of mass coordinates are very sensitive to the shapes and positions of the elements, they are able to capture even subtle boundary changes, so they can be used as important symbols for an SE-UUID.

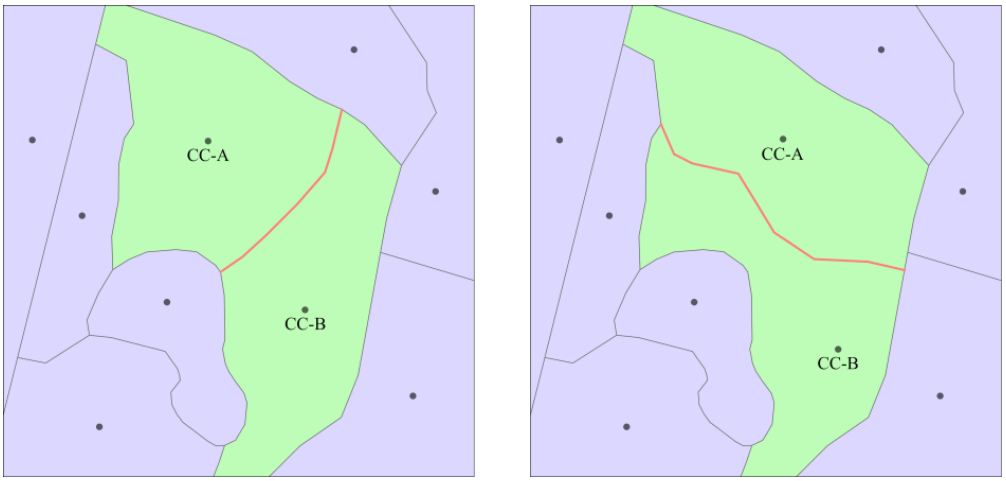


Figure 11. Schematic diagram of the variation in the coordinates of the center of mass of the sub-compartments. The point represents the centroid of each spatial feature, and the red line represents the boundary of spatial features A and B.

It should be noted that in some special cases, even if the boundary of the element changes, its unique identifier remains the same as before. For example, as shown in Figure 12, consider the symmetric position of the four square elements A, B, C and D in the total structure; if they become four up–down–left–right axisymmetric figures with the same area, then the area and center of mass coordinates of the element O with which they share a common boundary are also unchanged, and the before and after SE-UUID of this topology are perfectly consistent. Of course, this kind of perfect topology is basically impossible to

appear in the actual situation, so for the spatial unique identifier constructed in this paper, this kind of situation can be ignored.

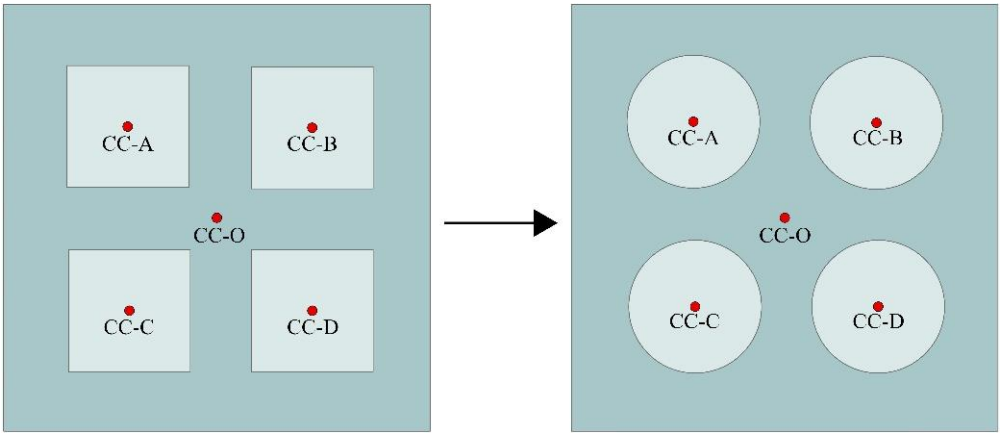


Figure 12. Schematic diagram of special cases of SE-UUID.

Another advantage of using the center of mass coordinates and area as the SE-UUID is that the duplication of leaf nodes can be effectively avoided during quadtree retrieval. As shown in Figure 13, this results in their duplicate storage in leaf nodes when the opposite element is directly partitioned. If the attribution of area occupancy or center of mass coordinates is used to calculate the attributed node, a lot of time will be consumed again. It would be much more efficient to convert face elements to point elements with the unique identifier construction method proposed in this paper and, if the element happens to be situated on a dividing line, categorize the element as north or east.

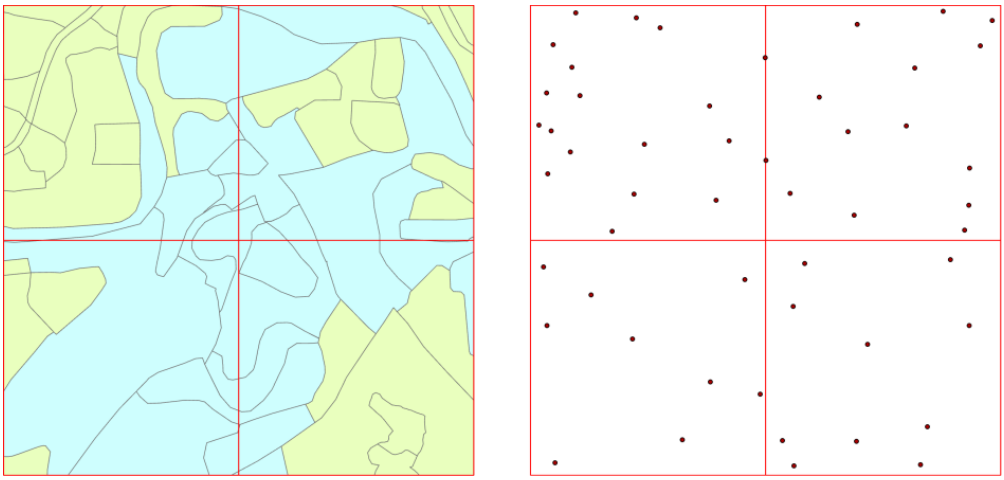


Figure 13. Schematic diagram of leaf node attribution for quadtree splitting elements. The green mark is outside the dividing line, and the blue mark is on the dividing line.

The quadtree constructed with the maximum number of elements of leaf nodes as a condition is different from the normal quadtree balancing the structure of the quadtree itself; it focuses on balancing the number of elements of leaf nodes. When the distribution of spatial elements is more balanced, the normal quadtree is constructed faster because it does not need to judge the number of elements in the current leaf node. However, for data subject to uneven spatial zoning distribution such as "One Map", in the process of change detection, the balanced quadtree will result in a very high query efficiency at leaf nodes with a very small number of elements, but at leaf nodes with a concentrated distribution of

the number of elements, after a traversal of time complexity $O(n^2)$, it will result in a rapid drop in spatial computation and change query efficiency.

Most of the previous vector graph change detection focuses on the construction time of the quadtree index or the query efficiency after construction alone, but in the actual application process, these two are actually inseparable. In this study, we take 500 as the step size and 20,000 as the maximum number of leaf node elements to find the shortest time for NQT-FCDM-based change detection of "One Map" under different data volumes. According to the results in Section 3.3, for different data volumes, the efficiency of NQT-FCDM is within the acceptable range when the Maximum corresponding to the optimal interval is arbitrarily selected. In further observation, it is not difficult to find that the shortest total time consumption of NQT-FCDM exhibits a certain positive correlation with the maximum number of leaf node elements, as shown in Figure 14.

$$y = kx + b \ (0.01 < k < 0.02,\ 0 < b < 1000)$$

where x is the number of sub-compartments in "One Map" and y is the number of maximum leaf node elements. Limited by the differences between data and the instability of computer performance, we cannot accurately simulate the parameters of the above equations, but as long as they are within the above intervals, the NQT-FCDM is still able to operate stably.

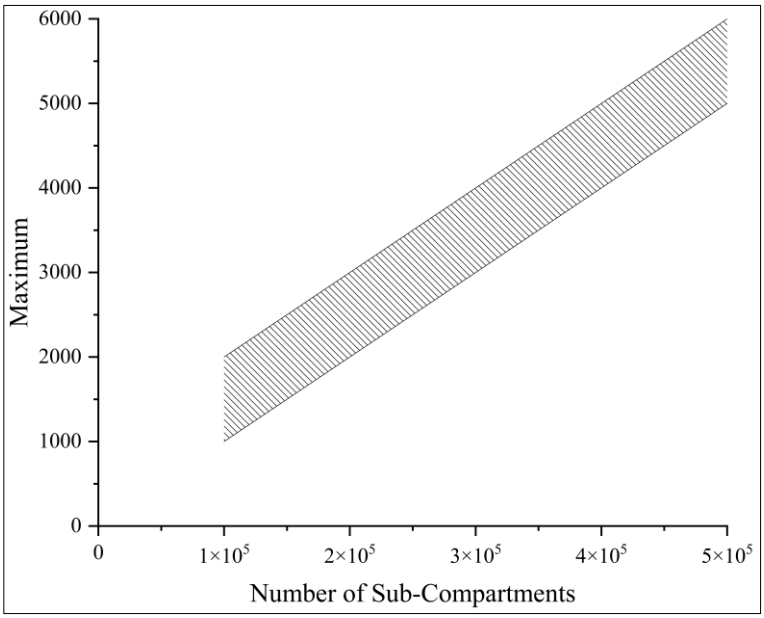


Figure 14. NQT-FCDM shortest total time consumption versus the number of maximum leaf node elements.

The NLNE Quad-Tree plays a very crucial role in the change detection model for "One Map"; it not only provides a spatial index for the change detection process and improves the query efficiency of change detection, but also filters the non-change elements for the subsequent spatial superposition analysis based on the NLNE Quad-Tree structure.

In a comparison with other change detection methods, as shown in Figure 10, the total time consumed by either the spatial union analysis method, normal quadtree method or NQT-FCDM is positively proportional to the number of elements. The time consumed by NQT-FCDM is one-fourth of that of the spatial union analysis method and one-half of that of the normal quadtree. More importantly, NQT-FCDM does not need to do any processing for the changed elements and only needs to superimpose the statistics on the changed sub-compartments, without generating the intermediate layers with a huge amount of data, which greatly saves storage space.

5. Conclusions

Based on the current problem of the low efficiency of change detection in "One Map" under massive data, this study utilizes NLNE Quad-Tree to construct NQT-FCDM and quantitatively analyzes the efficiency of change detection in "One Map" for Sichuan Province in 2021 and 2022. The results of the study show the following: (1) the sub-compartment identifier constructed with the center of mass coordinates–area with a precision of 0.01 m has uniqueness among more than 50 million sub-compartments in the province; (2) the quadtree constructed with a point with a surface is able to solve well the problem of the low efficiency of the boundary elements in the allocation of the leaf nodes; (3) at the county scale, according to the number of different sub-compartments, the NLNE Quad-Tree, constructed with 1000–6000 as the maximum number of leaf node elements, is the most efficient in change detection in "One Map". The NLNE Quad-Tree saves about 75% of time compared with the spatial union analysis and avoids the generation of a large number of intermediate layers. Through this study, the process and efficiency of the detection of changes in "One Map" at the county scale are effectively improved. In the next step, the research scale will be extended to the national level to verify whether the NQT-FCDM proposed in this paper is feasible in the detection of changes in "One Map" at the municipal or provincial level.

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Data Availability Statement: We do not provide the original data used in this paper, but researchers can easily obtain data in a similar format and amount.

Conflicts of Interest: The authors declare no conflicts of interest.

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