Vector data cubes for features evolving in space and time

Lorena Abad Martin Sudmanns Daniel Hölbling

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The amount of geospatial data generated, in particular from segmentation techniques applied to Earth observation (EO) data, is rapidly increasing. This, in combination with the rising popularity of EO data cubes for time series analysis, results in a need to adequately structure, represent and further analyse data coming from segmentation approaches. In this study, we explore the use of vector data cubes for the structuring and analysis of features that evolve in space and time with a particular focus on geomorphological features due to their high spatio-temporal variability. Vector data cubes are multi-dimensional data structures that often contain spatio-temporal data with n-dimensions, with a geometry as the minimum spatial dimension and time as the temporal dimension. We consider two vector data cube formats, i.e., array and tabular, and further extend their conceptualisation to contain features that evolve in space and time. We showcase our implementation for two geomorphological features, the Fagradalsfjall lava flow in Iceland and the Butangbunasi landslide and landslide-dammed lake in Taiwan. Finally, we discuss the potential and limitations of vector data cubes, regarding their technical implementation and application to geomorphology, and further outline the future research directions.

Introduction

To represent and analyse geographical features in a geographic information system (GIS), polygon outlines are commonly created based on field measurements (e.g., GPS surveys), aerial photography or Earth observation (EO) satellite imagery. The delineation can be the product of manual interpretation or of (semi-)automated image segmentation and classification techniques. Examples of the latter are object-based image analysis (OBIA) (Blaschke et al. 2014) and deep learning techniques such as convolutional neural networks (CNN) (Hoeser, Bachofer, and Kuenzer 2020) or segment anything models (SAM) (Kirillov et al. 2023). Consequently, a series of objects in vector formats representing geographical features can be created for different points in time. Such geospatial objects intrinsically deal with geometries changing over time and can be seen as regions that grow or shrink, i.e., change their shape over time (Erwig et al. 1999).

The ability to analyse EO data time series with EO data cubes (EODC) can prove promising when combined with segmentation techniques. EODCs facilitate the querying of dynamic information at high temporal intervals, allowing a more comprehensive understanding of landscape dynamics. Although segmentation approaches for satellite image time series analysis have not been fully implemented within EODCs (Lang et al. 2019), advances in deep learning techniques can quickly develop towards this end (Belgiu and Csillik 2018; Abidi et al. 2021; Simoes et al. 2021). Hence, ways to adequately represent and analyse the objects resulting from segmentation approaches, considering their changes in space and time, are needed.

In this study, we explore the use of vector data cubes for the structuring and analysis of features or objects that evolve in space and time, i.e., shape-evolving features. In particular, we focus on polygon features that do not change their location (in contrast to trajectory data) but rather change their extent and shape at different points in time. We have selected geomorphological features as an exemplary case because of their high spatio-temporal variability. Nevertheless, vector data cube approaches can be extended to any other geospatial feature like urban area expansion, vegetation patches, or wetlands, to name a few examples.

Vector data cubes

Geospatial data cubes are defined as multi-dimensional data structures based on regular or irregular grids (represented as arrays), often containing spatio-temporal data with n-dimensions (Strobl et al. 2017; Baumann et al. 2018). The structured manner of representing spatio-temporal data has become an intuitive way to organise big EO data, usually in raster or gridded formats, with minimum two spatial dimensions, i.e., x / y or latitude / longitude. However, vector data can also be organised within data cubes, where the minimum spatial dimension required is a geometry. When talking about spatio-temporal data cubes, be them raster or vector, an additional dimension, i.e., time, is often included.

The typical example of the use of vector data cubes is locations that contain multi-temporal data such as in-situ sensor station datasets, aggregation of raster information over specific areas, or the results of raster data sampling at point locations (Pebesma 2021). In these cases, the geometry of these locations does not change over time, but their associated parameters do. Representing multi-temporal data with unique locations in vector data cubes in comparison to traditional data structures in GIS, such as long or wide table formats, has several advantages. For instance, data replication in the form of duplicated rows or an excessive amount of columns for table formats is avoided. Further, an array-like representation of vector data allows indexing for fast lookup tasks and the use of several operations popular for raster data cubes such as filtering, aggregation, reduction and resampling.

Another way of representing spatio-temporal data in tabular formats has been implemented by Zhang et al. (2022) in their R package {cubble}. The concept behind {cubble} relies on the tidy data framework (Wickham 2014) by structuring the relational temporal and spatial data in two different, yet interlinked tables or data frames. These are referred as spatial and temporal tables or faces of a spatio-temporal cube. {cubble} combines the power of the {sf} package for spatial vector data analysis (Pebesma 2018) and the {tsibble} package for time series analysis (Wang, Cook, and Hyndman 2020). In this manner, data replication is minimised and a flexibility between analysing the spatial or temporal component of the data is introduced.

In this study, we have explored array and tabular formats for spatio-temporal data, considering that both represent ways of structuring data as vector data cubes. This is because even if the approach by Zhang et al. (2022) is mostly tabular, it can be directly coerced (i.e., translated) into and from array formats, namely the ones supported by the R package {stars} (Pebesma and Bivand 2023). Therefore, for the purpose of this paper, we refer to vector data cubes in 1) array and 2) tabular formats.

Extending the cube design

The organisation of geospatial data in the domains of space, time, and theme is a known concept (Sinton 1978; Yuan 1999), as these domains are inherent to geospatial phenomena. Subsequently, different approaches with varying focus have been implemented (e.g., online analytical processing (OLAP) data cubes, temporal GIS, raster data cubes, and array databases). What is common is that access of the values (often called measures) is facilitated through coordinate values or indices along dimensions that represent the domains (e.g., latitude / longitude for space). For instance, organising weather station data into a data cube would at least involve the *geometry* dimension with the unchanging locations of the stations, and the *time* dimension with the data timestamps.

In the case of shape-evolving features such as geomorphological landforms, one of the parameters that changes, or in other words, the measure, is the geometry itself. Therefore, we have assigned the changing geometries to the cell values. This approach leaves only the *time* as a dimension of the data cube. A unique group identifier for each feature set could become a second dimension, which is used to index the feature set. However, a spatial dimension is required to perform any spatial analysis. To handle this, we have come up with the concept of *summary geometry*, which, as its name implies, is a geometry that represents all the changing geometries for a feature. The *summary geometry* (symbolised as `geom_sum`) can be defined depending on the use case and the way we want to analyse the data. We have identified the following cases, where `geom_sum` could be:

a) the union and dissolve operation of all polygons over time corresponding to the same feature,

b) the centroid of a),
c) the bounding box of a), or
d) a representative point of the temporal feature set

Representative points in d) for geomorphological features could be, for example, the location of the crater from which lava erupts, or the location of the landslide dam that blocked a river and generated a landslide-dammed lake.

For data cubes in tabular format, Wang, Cook, and Hyndman (2020) define two contextual semantics: *index*, which is a variable ordered from past to present, and *key*, a set of variables that define observational units over time. Each observation is identified by an index and key. Hence, for the tabular format, the `geom_sum` dimension becomes the key for the spatial table. The `time` dimension becomes the index column for the temporal table.

The resulting spatial table contains one row per feature set, with the `geom_sum` and a list-column `ts`, which stands for time series. The `ts` list-column stores the time series data in a nested format. For shape-evolving features, the `ts` list-column contains the `time` as the index, along with the changing geometries and other attributes that change over time. This information is then stored in the temporal table.

In practice, the tabular format requires an identifier other than a geometry column, and hence an `id` column or another type of identifier is recommended for a seamless interaction between the spatial and temporal tables.

Figure 1 demonstrates how the shape-evolving features are represented in both an array and tabular vector data cube.

Geomorphology applications

Geomorphological features are often highly dynamic in space and time. Assessing the evolution of landforms such as glaciers, proglacial lakes, lava flows, landslides or gully erosion allow the understanding of landscape patterns and interrelations. Moreover, some of these features are related to natural hazards, where monitoring their evolution becomes relevant for disaster risk reduction (DRR) and mitigation. Depending on the activity level of the landform, changes in their shape or surface area over time are expected. Extracting the outlines of these dynamic landforms allows spatio-temporal analysis, for example, to compute changes in area or volume, or to aggregate information from gridded datasets to represent zonal statistics for the landform. Therefore, we have considered geomorphological landforms as exemplary features to test vector data cubes.

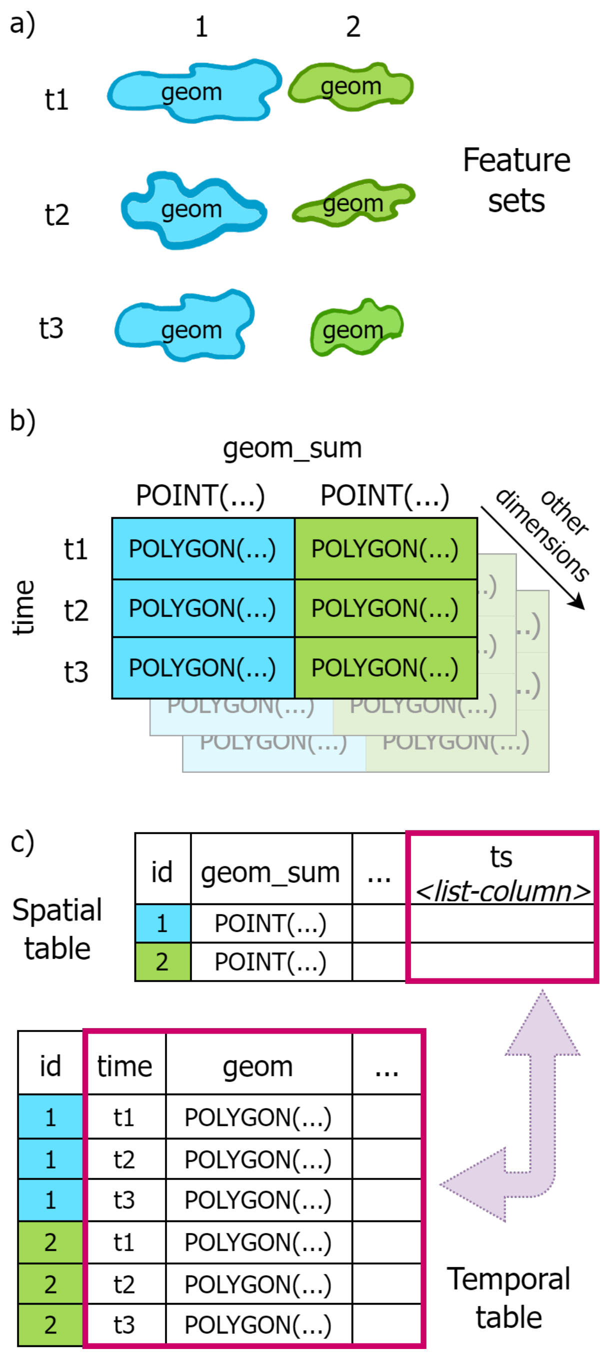

Figure 1: Structuring shape-evolving features in vector data cubes in array and tabular formats. a) Schema of shape-evolving features over time. b) Vector data cube in array format, with the summary geometry `geom_sum` represented by a `POINT` geometry. Adapted from OpenEO developers (2024). c) Vector data cube in tabular format showing the spatial and temporal tables. Adapted from Zhang et al. (2022).

Vector data cube implementation

Geomorphological analyses often focus on the evolution of a limited number of landforms over time. Therefore, to showcase the use of vector data cubes for shape-evolving features we have selected two examples of such studies. The first study by Hölbling et al. (2020) analysed the evolution of the Butangbunasi landslide in Taiwan from 1984 to 2018 and related the changes in area to typhoon events, correlating heavy rainfall with the landslide size expansion, but also quantifying the natural re-vegetation effect. The authors used an OBIA approach to segment and classify the landslide area along with landslide-dammed lakes occurring for a couple of time steps. For the second study, Pedersen et al. (2022) performed a near real-time photogrammetric surveying of the 2021 Fagradalsfjall eruption on the Reykjanes Peninsula, Iceland. The main focus was the lava flow monitoring, where area, volume and thickness change maps were computed. The lava outlines were digitised manually from orthomosaic imagery collected during the surveys.

We performed the experiments in R software v. 4.3.2 (R Core Team 2023). With the delineations from both studies, we proceeded to organise and wrangle the data to combine the different files into a single {sf} data frame. It was important to guarantee that each observation belonged to the same geomorphological landform, that the timestamps were consistent and clearly identified, and that the geometries were valid. Moreover, we worked with a single geometry per time step, meaning that we combined individual polygons into multi-polygons when mapped for the same time step, and ordered them chronologically. Then, we computed `geom_sum`, in this case, the centroid of the union and dissolve of all geometries corresponding to the feature set. The `geom_sum` was repeated for every row corresponding to the same feature set. Once the data were pre-processed, we could coerce the spatial data frames into the vector data cube formats.

Array format

For the array format, we used the {stars} package. We created an `array` object including the data that would populate the array cells (the changing geometries of the feature set), the dimensions and their names (`geom_sum` and `time`). Next, we created a `dimensions` object with the function `stars::st_dimensions()`, containing the values for the dimensions of the cube. Finally, we combined these objects in a `stars` object. The way the vector data cube is structured is illustrated with the example of the lava flow outlines.

```
stars object with 2 dimensions and 1 attribute
attribute(s):
         geometry
 MULTIPOLYGON : 2
 POLYGON      :28
 epsg:3057    : 0
```

```
 +proj=lcc ...: 0
dimension(s):
         from to                refsys point
geom_sum    1  1 ISN93 / Lambert 1993  TRUE
datetime    1 30               POSIXct FALSE
                                                 values
geom_sum                          POINT (339860 380008)
datetime 2021-03-20 08:45:00,...,2021-09-30 16:20:00
```

Once the data cube is created, we can perform different spatial analyses, for example, computing the area of the changing geometries or filtering the data in the cube within specific dates (Figure 2). Examples of these computations are presented in the computational notebook in the GitHub repository (see Section).

Tabular format

For the tabular format we used {cubble}. Here we exemplify the approach with the Butangbunasi landslide and lake outlines in Taiwan. For this vector data cube format we defined the key as the feature type (i.e., `class`) and the index as the time dimension, in this case called `date`. {cubble} presents the spatial and temporal tables separately. To get each of them one would call `cubble::face_spatial()` or `cubble::face_temporal()`, respectively. When creating the cube, the default table face is spatial, i.e., a nested form. The nested list-column corresponds to the time series, which is stored row-wise per feature set. The temporal face is structured as a long format table.

```r
cube_tab |>
  face_spatial()
```

```
# cubble:   key: class [2], index: date, nested form, [sf]
# spatial:  [271664.917737363, 2567227.57526178, 274148.347513089,
#   2568861.92906261], WGS 84 / UTM zone 51N
# temporal: date [date], sensor [chr], area [[ha]], geom [GEOMETRY [m]]
  class           x        y           geom_sum ts
* <chr>       <dbl>    <dbl>        <POINT [m]> <list>
1 lake      274148. 2567228. (274148.3 2567228) <tibble [20 x 4]>
2 landslide 271665. 2568862. (271664.9 2568862) <tibble [20 x 4]>
```

```r
cube_tab |>
  face_temporal() |>
  arrange(date)
```

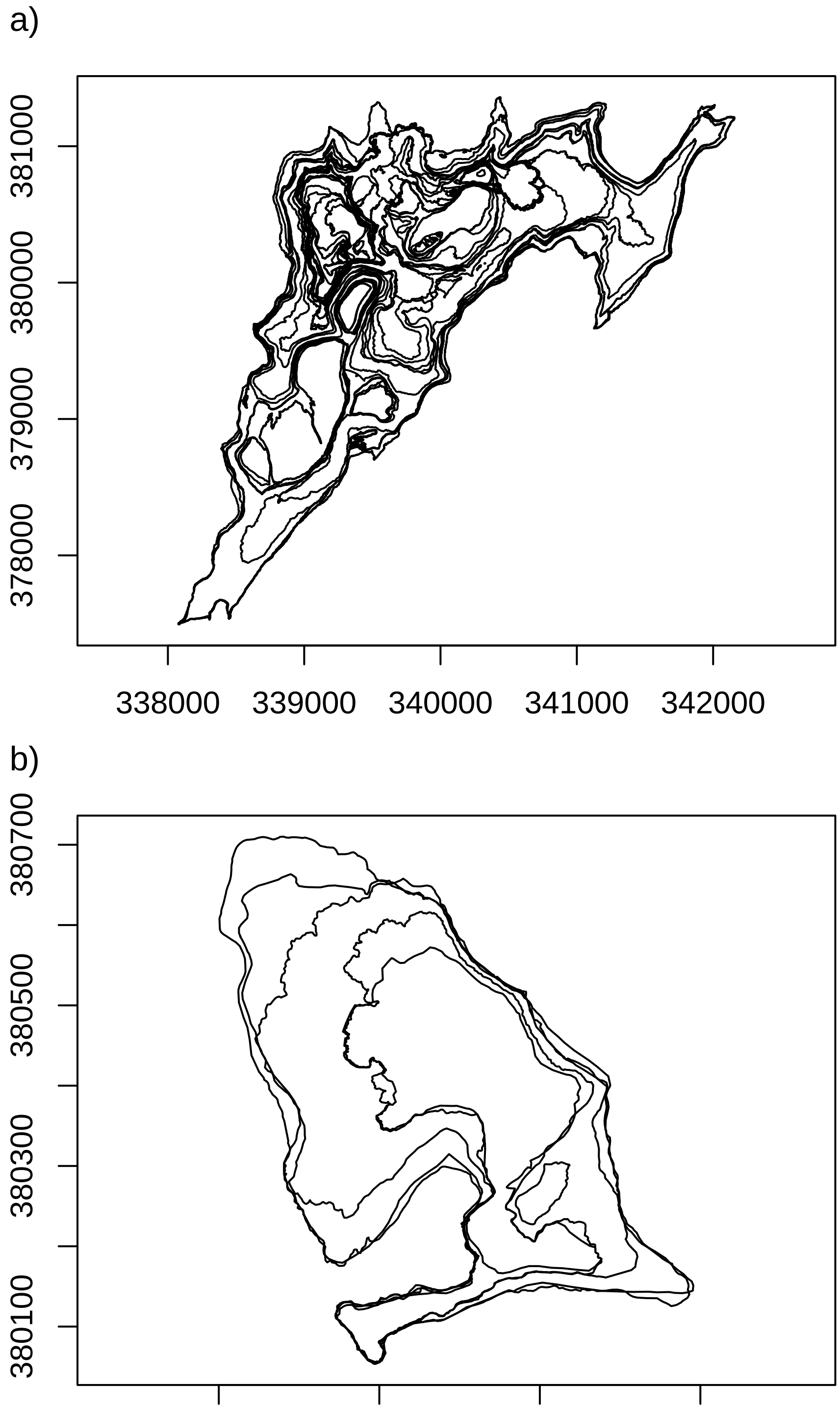

Figure 2: Lava flow outlines in Fagradalsfjall, Iceland a) Lava flow outlines of the complete lava flow time series. b) Filtered lava flow time series between 18.03. and 25.03.2021.

```
# cubble:   key: class [2], index: date, long form
# temporal: 1984-12-12 -- 2021-08-28 [8D], has gaps!
# spatial:  x [dbl], y [dbl], geom_sum [POINT [m]]
   class     date       sensor      area                                      geom
   <chr>     <date>     <chr>        [ha]                             <GEOMETRY [m]>
 1 lake      1984-12-12 <NA>       NA                         GEOMETRYCOLLECTION EMPTY
 2 landslide 1984-12-12 Landsat 5  66.2  MULTIPOLYGON (((271637.5 2568620, 2716~
 3 lake      1989-10-23 <NA>       NA                         GEOMETRYCOLLECTION EMPTY
 4 landslide 1989-10-23 Landsat 5  62.4  MULTIPOLYGON (((273712.5 2566845, 2735~
 5 lake      1990-10-10 Landsat 5   5.31 MULTIPOLYGON (((273887.5 2566870, 2738~
 6 landslide 1990-10-10 Landsat 5  78.2  MULTIPOLYGON (((273737.5 2566845, 2737~
 7 lake      1992-10-31 Landsat 5   3.33 POLYGON ((273950 2566870, 273925 25668~
 8 landslide 1992-10-31 Landsat 5 121.   MULTIPOLYGON (((273462.5 2566820, 2734~
 9 lake      1994-09-03 <NA>       NA                         GEOMETRYCOLLECTION EMPTY
10 landslide 1994-09-03 Landsat 5  94.1  MULTIPOLYGON (((273500 2566820, 273462~
# i 30 more rows
```

This dataset contains further information on the individual geometries, such as the satellite sensor used to map the data and the area of the objects. With these attributes we can do time series plots to visualise the variations in time, as shown in Figure 3.

Data and Software Availability

The Butangbunasi landslide outlines can be obtained from Hölbling et al. (2024). The lava flow outlines for the Fagradalsfjall eruption can be obtained from Pedersen et al. (2023), along with derived digital elevation models (DEMs) and orthomosaics.

A GitHub repository with an example notebook containing the code to download and wrangle the data, create vector data cubes, perform spatial analysis and generate the figures in Section can be accessed here: https://github.com/loreabad6/vdc-space-time-feats. The repository also contains the system set-up and software versions used.

Discussion

Implementation design

We have exemplified the use of vector data cubes for a single geomorphological feature evolving over time, that is the lava flow in Fagradalsfjall; and also with two feature sets that evolve over time, i.e., the Butangbunasi landslide and the associated landslide-dammed lake. However, feature extraction workflows can result in several shape-evolving features, be them of the same

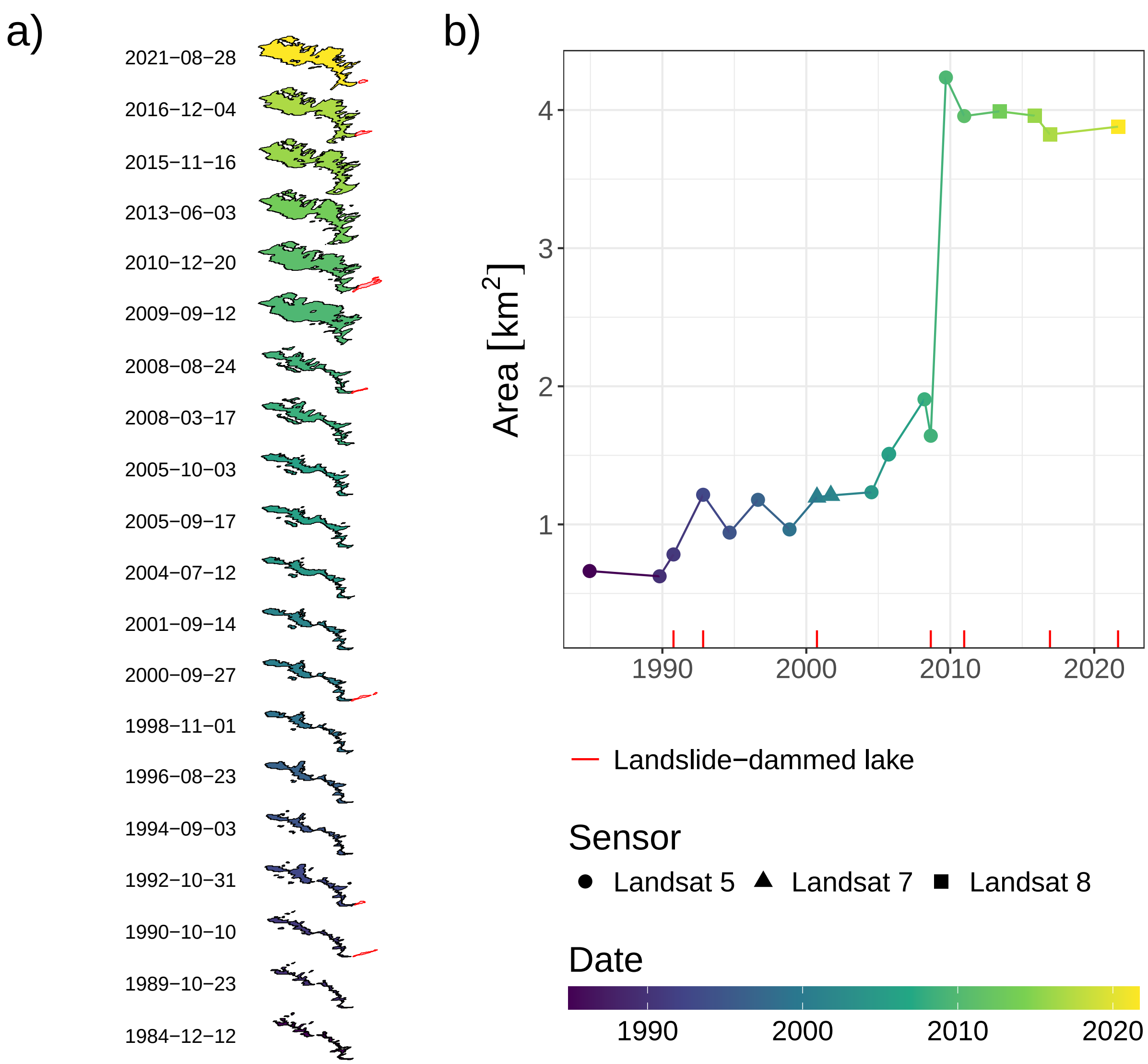

Figure 3: Time series plot of attributes of the Butangbunasi landslide and landslide-dammed lake dataset. a) Butangbunasi landslide and lake delineations at different points in time represented in a multi-dimensional form. b) Time series graph of landslide area with a marker at the bottom of the panel for every lake occurrence.

type (e.g., a landslide spatio-temporal databases) or different (e.g., a spatio-temporal database with several landslides and lakes).

In these situations, we might face different issues, mainly with the amount of geometries to be handled and the scalability of the approach. As we have seen with the Butangbunasi case, we encounter situations where a geometry is present at a specific point in time for the landslide class, while at the same time the geometry for the lake is absent since there was no lake occurrence for that timestamp. For the array implementation, this means the inclusion of empty geometries within the array cells. Even if we can include such lack of data, the advantages of using the array approach in terms of performance and scalability might become limited. In these cases, working with tabular formats could result in a more efficient approach. However, the array format allows the addition of further dimensions, which is not the case for the tabular format as it is tailored for handling space-time data specifically. The addition of a dimension referring to the geomorphological feature type (c.f., Fig. **code output as figure 4**, the dimension `class`) could become useful when the analysis focuses on different geomorphological feature types in an area. Further exploration towards scaling these approaches will be tested in future work.

Similarly to what is presented by Hamdani, Thibaud, and Claramunt (2020) and Hamdani et al. (2023), we expect that structuring the data in vector data cubes will allow a seamless integration with gridded data structured in raster data cubes. Issues regarding computational performance for such integration still need to be tested in future work.

Even though we have introduced the vector data cube format using the R ecosystem, Python packages could also support similar data structures, for example with the package {xvec}, currently under development (Fleischmann and Bovy 2022). {xvec} follows the concepts and implementation of {stars} and supports the handling of data with {xarray} (Hoyer and Hamman 2017), a package often used for raster data cube analysis. For the tabular format, possible implementations, including approaches that involve {geopandas} (Jordahl et al. 2020) could be further explored.

Finally, the concept of *summary geometry* could be extended to line and point geometries, although the assumptions to conceptualise how to represent the summarising geometry would need to be revised.

Potential for geomorphology

Focusing on a small number of geomorphological feature brings the advantage of guaranteeing that the analyst can match the delineations to the same feature, making it possible to assign a unique identifier to the feature set.

However, geomorphological analyses could require the combination of data from distinct sources that have performed mapping of a feature over time, or could focus on multiple features mapped in an area that evolve over time, e.g., landslide-dammed lakes originating from the Kaikoura earthquake in 2016 in New Zealand (Abad et al. 2022). Here, assigning a unique identifier to individual features could prove useful to track the evolution of single objects over time. Techniques on how to perform such spatio-temporal grouping of feature sets still have to be further investigated.

Moreover, transitioning from a pixel-based analysis of geomorphological features to an object-based representation can enhance the spatio-temporal analysis of regional landscape changes. For instance, instead of reporting overall statistics of water pixels detected for the Kaikoura region, one could calculate statistics on the number of landslide-dammed lake features detected in the area, as well as being able to analyse the evolution of the lakes at the object level. We believe that this study is an initial point towards such analyses, where vector data cube representations could be a way to structure data coming from EODC analyses.

With the rapidly increasing amount of geospatial data, it is essential to develop ways to store, manage, and analyse them efficiently. Enhancing the analysis and representation capabilities of shape-evolving features, particularly geomorphological features, is important in several respects. Vector data cubes can facilitate the generation of pertinent information on the spatio-temporal dynamics of features such as landslides or lava flows, which can contribute to better understanding landscape evolution, be used as input for natural hazard modelling, and support hazard mitigation and DRR efforts.

Conclusion

Several ways to structure and analyse spatio-temporal vector data have been proposed within GIScience. Vector data cubes as outlined in this paper build on top of these concepts. In this study, we presented a proof-of-concept of the use of vector data cubes for features that evolve in space and time. We showcased this with examples of geomorphological features, where established methods for analysing time series at the object level are currently lacking. We expect that the extended use of vector data cubes outlined in this paper can improve the insights derived from EO data.

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Author contribution

LA: Conceptualisation, Methodology, Formal Analysis, Data curation, Software, Validation, Visualisation, Writing - original draft, Writing - review and editing. MS: Conceptualisation, Writing - review and editing. DH: Data curation, Writing - review and editing.

Competing interests

The authors declare that they have no conflict of interest.

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