Using a semantic EO data cube for analysing snow cover alterations in the Hohe Tauern National Park

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Abstract

The impacts of climate change are manifold and need to be monitored in a frequent manner. In mountainous regions, one of the main climate variables is the snow coverage. Time series analysis are commonly used to detect and quantify earth surface dynamics. This analysis method is supported by earth observation data cubes, since they serve as storages for the required big earth observation data. Semantic enabled earth observation data cubes are an advancement of the state-of-the-art data cubes, because they offer tailored information. They provide one or more categorical interpretation for each observation and deal thus with the issue that big earth observation sensory data lack semantic meaning. The aim of this seminar paper was to demonstrate the potential of the first semantic earth observation data cube operating on a national level by performing a time series analysis based on the Sentinel-2 data stored in the Semantic Data Cube Austria. In particular, a semantic model for snow cover detection is proposed for the Hohe Tauern National Park located in Austria within a period between 2016 and 2021. By applying semantic concepts, cloud-free results were obtained. No clear increasing or decreasing trend of the snow coverage per year was discernible. In contrast, dynamic alterations per month were observed. Although the snow cover time series analysis performed in this seminar paper is related to the Hohe Tauern National Park, the generated semantic model can be applied to any user defined spatio-temporal extent supported by the Semantic Data Cube Austria.

1 Introduction

As a consequence of climate change, the global temperatures are rising successively (Pachauri et al., 2014, Poussin et al., 2019). According to several studies (e.g., Pepin et al., 2015, Poussin et al., 2019), mountainous sites are among the regions most affected by the warming trend. Pepin et al. (2015) provided an overview about the key mechanisms that cause faster temperature fluctuations in higher altitudes than in lower ones (i.e. elevation dependent warming). Warming in mountainous regions induces, for instance, glacier retreat (e.g., Fischer, 2010, Zemp et al., 2006), decreasing snow cover extent, quantity and duration (e.g., Poussin et al., 2019, Notarnicola, 2020) and permafrost degradation (e.g., Mollaret et al., 2019). Snow cover is a particularly important climate variable because melting decreases the albedo (Pachauri et al., 2014). The consequence is a positive feedback between the snow cover retreat and the warming rates (Poussin et al., 2019).

In order to asses and understand the environmental changes caused by climate change in mountainous regions, such as the snow cover retreat, frequently conducted monitoring is necessary (Giuliani et al., 2019, Poussin et al., 2019). The acquired data serve as the foundation for decision-makers from a variety of disciplines (Lehmann et al., 2017, Poussin et al., 2019). When monitoring an equidistant location over a certain period of time, long-term alterations and dynamics on the earths' surface can be detected by performing time series analysis based on the acquired data (Kuenzer et al., 2015). This analysis technique enables a deeper understanding of environmental processes, since alterations of phenomena can be displayed easily through time (Sudmanns et al., 2019). However, in-situ monitoring of the changes in mountainous regions is associated with some challenges (e.g., difficult and dangerous terrain, uneconomical costs, insufficient data). Those can be overcome by acquiring Earth Observation (EO) data with various satellites in a continual way (Poussin et al., 2019). With regard to the analysis of snow cover changes, EO imagery is well suited due to the typically high contrast between snow and other (natural) surfaces in mountainous regions (Poussin et al., 2019). Since the 1970s, remote sensing methods have been used to monitor the extent of snow from space. As a consequence of the technological developments, both the sensors and the processing algorithms have improved considerably over the years (Dietz et al., 2015). However, the differentiation between snow and cloud cover is still a challenge according to Nolin (2010).

Due to the rising number of satellites, a vast amount of EO data is collected every day (Simoes et al., 2021). Big EO data causes various challenges that are well-known at the present, since numerous studies (e.g., Laney, 2001, Nativi et al., 2015) analysed and discussed them within the last decades. Furthermore, a contemporary and secure access to the EO data is crucial (Augustin et al., 2019). Based on open data policies, EO imagery is mostly publicly accessible through various repositories (Giuliani et al., 2019, Simoes et al., 2021). Handling and managing the enormous amount of data caused however a paradigm change. Instead of local data processing that requires time consuming data transfers, the algorithms are moved to the data in recent years. Consequently, the efficiency of EO data handling and visualizing is increased (Giuliani et al., 2019).

As a new paradigm, EO data cubes represent efficient big EO data storages and analysts (Poussin et al., 2019, Sudmanns et al., 2019). By using multi-dimensional arrays, they improve and facilitate data analysis as well as management and information derivation (Sudmanns et al., 2019, Nativi et al., 2017, Baumann, 2017). Because of the multidimensional concept (i.e. the management of n-dimensional datasets), the term cube is a shortening of hyper cube (Nativi et al., 2017). According to Nativi et al. (2017), data cubes are also considered promising in terms of time series analysis of big EO data that can be acquired by different satellites, such as Landsat or Sentinel. One of the main reasons for this is the improved vertical (i.e. temporal) data access (Sudmanns et al., 2019).

However, the development of EO data cubes is heading towards a more analytical environment in which users themselves can derive information from the EO images. Within the so-called semantic EO data cubes, semantic analysis is enabled by explicit and comprehensive queries and rule-sets. EO images can be searched and queried based on semantic content. Those semantic content-based queries can refer to a specific study site and temporal extent. Semantic EO data cubes offer therefore an increasing opportunity to generate customized information and to exploit the potential of big EO data. Thus, they are more suitable for the forthcoming challenges with big EO data than non-semantic state-of-the-art EO data cubes (Augustin et al., 2019).

In the scope of this seminar paper, the potential of semantic EO data cubes is demonstrated by presenting a case study. The main objective of the case study was to investigate the snow cover alterations in an alpine region through time. To accomplish this, a time series analysis was conducted with the Semantic Data Cube Austria for the Hohe Tauern National Park, located in Austria. The aim of the case study was to analyse the snow cover evolution influenced by the climate change, motivated by the fact that no study used the Sentinel-2 Semantic Data Cube Austria for such a time series analysis before. This required the definition of a semantic model, using Sentinel-2 data. By generating time series, the following three research questions are answered:

1) Is the Sen2Cube.at data and information cube suitable for this approach?
2) Is there a detectable increasing or decreasing trend in the snow cover over the last few years within the study site?
3) Is the snow cover subject to seasonal fluctuations?

2 Theoretical framework

Time series analysis are supported by data cubes, since they store the required EO data (Simoes et al., 2021). Recently, semantic EO data cubes establish as an advancement of state-of-the-art EO data cubes, since they offer tailored information derived from the EO data (Augustin et al., 2019). Both, the concept of EO data cubes and the principle of time series analysis are explained further below.

2.1 EO data cubes

2.1.1 State of the art EO data cubes

EO data cubes are used to organize data within a multi-dimensional structure (Baumann, 2017, Simoes et al., 2021). They aim to facilitate the data storage as well as the access, management and analysis (Sudmanns et al., 2019). Data cubes represent thus an improved approach in comparison to file-based data storage and access (Table 1). In general, EO data cubes are based on a three dimensional construct, including the latitude, longitude and time (i.e. spatial and temporal dimensions) (Figure 1) (Augustin et al., 2019). The EO data is thus organized along two spatial axes and one non-spatial axis that typically refers to the time (Sudmanns et al., 2019, Sudmanns et al., 2021). Within the EO cubes, data is organized by indexing or by defining an individual data structure. This so-called logical view describes the access to the EO data. Instead of file names, spatio-temporal coordinates are used in an application programming interface (API) or a query language. This not only optimises data retrieval, but also increases the efficiency in realising certain access patterns (e.g. time series analysis) (Augustin et al., 2019). EO data cubes enable thereby various access types within a single data structure. This results in an access- and not an acquisition-oriented data storage (Sudmanns et al., 2019).

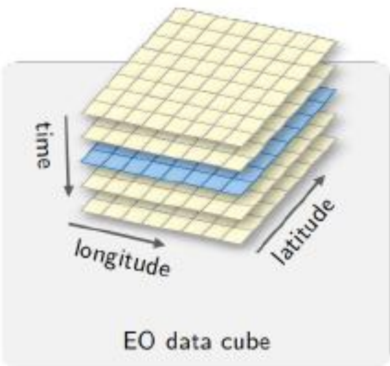

Figure 1: 3D construct (i.e. two spatial and one temporal dimension) of EO data cubes (Simoes et al., 2021).

Within the last decades, various EO data cubes have been established. They differ in scale, data sets and sources, spatial and temporal resolution, and other aspects (Sudmanns et al., 2019). Australia was the first country launching an EO data cube on a national scale (Lewis et al., 2017). The technology behind it is not only the basis for Digital Earth Australia (DEA) (Dhu et al., 2017) but also for the Open Data Cube (ODC) (Killough, 2018), since it is freely available and open source (Giuliani et al., 2017). However, there are other software implementations, such as the Earth System Data Cube from the European Space Agency (ESA) (Gans et al., 2018) or SciDB (Appel et al., 2018, Sudmanns et al., 2019). Besides the software implementation, EO data cubes differ in the infrastructure and user interface (UI) (Sudmanns et al., 2019).

Through state-of-the-art EO data cubes, data delivery is facilitated (Baumann, 2017). They provide access to Analysis Ready Data (ARD), whereby data transfer is supported (Dwyer et al., 2018, Sudmanns et al., 2019, Tiede et al., 2019). Data derived from ARD is pre-processed to surface reflectance based on a minimum set of requirements (Tiede et al., 2019). As a result, only minor user processing is needed afterwards (Dwyer et al., 2018, Augustin et al., 2019). ARD is necessary to process EO data through time in an automatic way (Tiede et al., 2019). It enables time series analyses to be carried out based on high scientific standards directly within the user application (Poussin et al., 2019). Moreover, data access is facilitated via web-based EO data cubes, which implement computational platforms (Augustin et al., 2019, Sudmanns et al., 2019).

Despite the improvements through web-based access and the usage of ARD, there are still serious obstacles for users due to big data and the ill-posed problem (i.e. derivation of a scene from single or multiple images) (Augustin et al., 2019). However, the possibility of adapting the data according to specific user requirements avoid unnecessary data transfer (Sudmanns et al., 2019). In comparison to a simple provision of downloadable images with predefined extent (Table 1), the efficiency of data transmission is thus highly increased through EO data cubes (Augustin et al., 2019).

2.1.1 Semantic EO Data Cubes

According to Augustin et al. (2019), a EO data cube is semantic-enabled if one or more nominal or categorical interpretations are available for each observation. In other words, semantic enrichment is achieved by interpreting the EO imagery, for instance, by associating observations with icons that represent common concepts. Similarly, in the case of gridded EO images, each raster cell must be assigned to at least one nominal interpretation (Sudmanns et al., 2021). A data cube can however not be semantically enabled by only integrating indices (e.g., the normalized difference vegetation index (NDVI)), since they have no semantic meaning by nature. For example, the NDVI does not provide information on whether a pixel belongs to vegetation or to another category. Thus, indices rather enhance prevailing interpretations. Overall, EO data cubes are semantically enabled as a result of the interaction via semantic concepts. EO data is searched and retrieved using semantic content-based information rather than metadata, tags or digital numbers (Figure 2) (Augustin et al., 2019). Nevertheless, the semantic enrichment is supported by reflectance values and supplementary data (e.g., DEM) (Table 1) (Tiede et al., 2019). Semantic EO data cubes provide the possibility to generate customized image derived information. They are thus an advancement of the state-of-the-art EO data cubes in terms of data queries and analysis (Augustin et al., 2019).

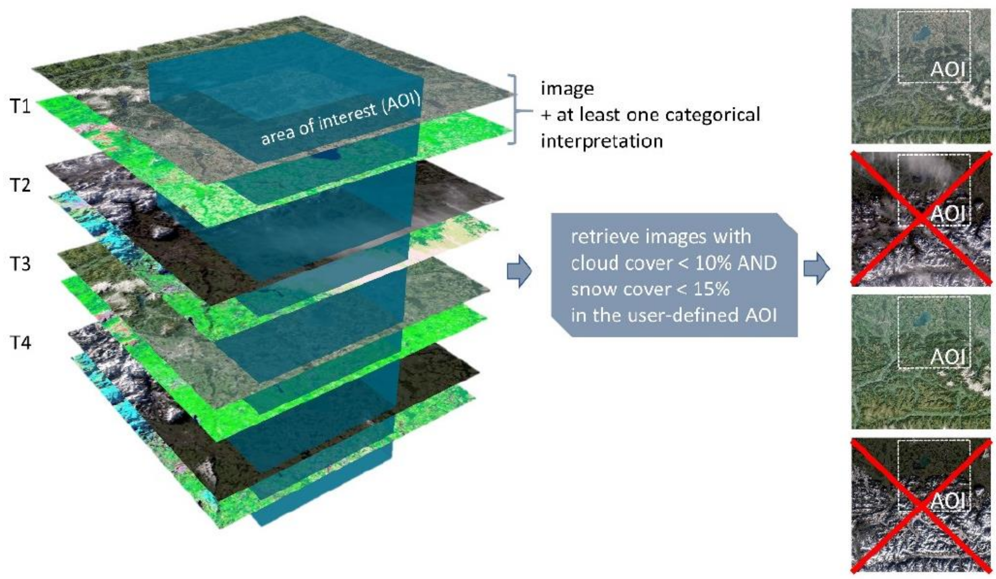

Figure 2: Using a semantic EO data cube (left) for an exemplary semantic content- based image retrieval (SCBIR) query. Based on tailored semantics, the query searches for EO images with minor cloud and snow cover within a user-defined area of interest (AOI). The retrieved images (right) correspond to the specified conditions (Augustin et al., 2019).

Table 1 gives an overview of the supported features by semantic EO data cubes in comparison to other approaches. By providing analytical services, semantic EO data cubes support the extraction of new information (Nativi et al., 2017). They offer an increasing opportunity to exploit the potential of big EO data. Because despite the fact that the number of public available EO data is rising significantly, new information is not derived from it with an equal rate, regardless of the great potential. One reason for this is the complexity of deriving information from sensor data that lack semantic meaning. In order to overcome this issue, sensory data requires interpretation and knowledge. Semantic EO data cubes provide nominal or categorical interpretations that are executable as queries directly within the spatio-temporal data cube (Augustin et al., 2019). This concept corresponds to the 'bringing the users to the data and not the data to the users' paradigm (Tiede et al., 2019).

Table 1: The availability (marked with a 'x') of a several features in different approaches (Tiede et al., 2019).

Feature	File-based EO image hubs	State-of-the-art EO data cubes	Semantic EO data cubes
Image download	x	x	x
Metadata-based search	x	x	x
Image-wide processing	x	x	x
AOI based processing		x	x
Time series analysis (statistical)		x	x
Time series analysis (semantic)			x
AOI-based cloud-free image search and mosaicking			x
Semantic content-based image retrieval			x
No expert-knowledge required to produce information on a higher level			x
Generic approach with re-usable and sharable tools			x
Additional data can be used in high-level queries			x

Converting EO data into information is necessary to describe a scene. Information can be understood as a subjective interpretation (i.e. knowledge derived from a process). It is what images reveal about a scene. Thus, a scene is the image content that results from the interpretation or classification of images. In contrast, an image is defined as an area discretized in a vast amount of pixels that represent the reflectance from the earth's surface based on various wavelengths. EO images are thus 2D representation of the 4D world. Consequently, three spatial and one temporal dimensions are included. The reconstruction of scenes or the derivation of information from a single or multiple 2D images over time is thus complex (Augustin et al., 2019). The fact that not a single but multiple solutions exist is challenging (Sudmanns et al., 2019).

The issues with reconstructing scenes from optical EO images are related to the so-called sensory gap (Smeulders et al., 2000, Bahmanyar et al., 2015). It deals with the uncertainties between real objects and their interpretation via the acquired signals (Bahmanyar et al., 2015). The sensory gap thus describes the differences between the 2D imagery (e.g., digital numbers) and the 4D world (e.g., processes or objects) (Augustin et al., 2019, Baraldi and Tiede, 2018). Classifying images require expert knowledge about the physical world (Sudmanns et al., 2019). This causes uncertainties in the interpretation of images (Smeulders et al., 2000). The sensory gap comprises two main characteristics that allow varying interpretations. 1) The sensor transfer function that addresses the issues associated with the ability to resolve phenomena (e.g., spatial, temporal or spectral) when using certain sensors. 2) The reduction of dimensionality during image acquisition (e.g., the transformation of a 4D flood event to a 2D momentary shot). In summary, several interpretations of similar observations arise, resulting in various divergent EO image classifications. For instance, a green pixel in a true-colour image could correspond to a forest as well as to a football field or another phenomenon. The sensory gap is thus also known as an ill-posed problem (Augustin et al., 2019).

Besides the sensory gap, the so-called semantic gap complicates the derivation of information from EO images (Bahmanyar et al., 2015). It deals with the difference between raw sensory data and meaningful categories (Sudmanns et al., 2019, Baraldi and Tiede, 2018). Semantic in EO refers to the fact that images per se have no intrinsic meaning (Giuliani et al., 2019), but instead depend on expert interpretation (Augustin et al., 2019). EO images need to be interpreted or considered in relation to other images in order to gain meaning (Santini et al., 2001). However, the interpretation depends on the user and the aim of the research. As a result, the so-called vocabulary problem arises, whereby users denote the same object differently. In addition, varying interpretation occur between user and computer-based image interpretation. In order to overcome the semantic gap, different image interpretations must be supported. Moreover, users should be able to develop their own interpretations within the semantic EO data cube, tailored to their needs (Bahmanyar et al., 2015).

2.2 Time series analysis

Time series analysis based on EO data is an efficient method to detect and quantify earth surface dynamics (Kuenzer et al., 2015). The term defines the comparison of the same phenomenon at varying times (Simoes et al., 2021). Thus, time series analysis refer to a specific monitoring period (Kuenzer et al., 2015). These are based on data collected by a single or multiple sensors, but the main requirement is a frequent revisit (Simoes et al., 2021). The foundation for time series is consequently a continuous or discrete series of data relating to homologous sites over time (Figure 3). Within the last decades, EO data is increasingly free and open available in high spatial and temporal resolution (Kuenzer et al., 2015). Time series analysis are thus supported by EO data cubes, since they serve as big EO data storages. They are frequently conducted in different applications, for example deforestation monitoring, ecological dynamics or snow cover retreat (Simoes et al., 2021).

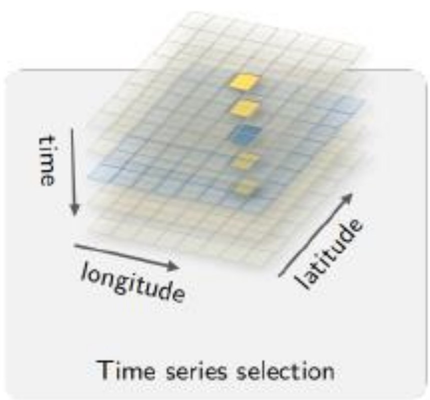

Figure 3: Conceptual illustration of a time series selection within an EO data cube (Simoes et al., 2021).

Time series analysis conducted with EO imagery typically relies on the raw digital numbers (DN), the reflectance values, and on various variables, such as topography (e.g., altitude, slope), dimensionless indices (e.g., NDVI) or binary thematic variables (e.g., ice extent, snow coverage, water area). The alterations of those variables can be analysed and monitored within different time intervals (e.g., daily, weekly, monthly, annual). Subsequent derivation of statistics (e.g., mean, minimum, maximum) is also possible (Kuenzer et al., 2015). Monitoring snow cover change is commonly based on the spectral properties of the reflectance (Kulkarni et al., 2002). These characteristics can be used to distinguish snow-covered areas from others, such as vegetation or ice. Limitations in differentiation usually come from sensor restrictions such as the resolution or the spectral band width (Dietz et al., 2015).

3 Study site, data and software

The case study proposed in this seminar paper investigate the snow cover evolution in the Hohe Tauern National Park. To accomplish this, the Semantic Data Cube Austria was used, which stores Sentinel-2 imagery (Tiede et al., 2019). In the following sub-sections, the study site is presented and an overview about Sentinel-2 data and the used software is provided.

3.1 Study site

The study site refers to the Hohe Tauern National Park (HTNP), which is located in western Austria between the federal states of Salzburg, Tyrol and Carinthia (Robson et al., 2016). The HTNP was founded in 1986 and is the largest alpine national park. It covers an area of approximately 1800 km² of the mountainous regions within the Austrian Central Alps (Mose, 2007). The altitudes are ranging between about 980 m a.s.l. and 3785 m a.s.l., but approx. 75 % of the surfaces within HTNP are positioned above 2000 m a.s.l (Figure 4). Since the late 19th century, the temperatures in the alpine regions have risen about twice the average in the northern hemisphere (Auer et al., 2007, Gobiet et al., 2014). Within the HTNP, the Sonnblick Observatory (3106 m a.s.l.) observed a temperature increase of almost 2 °C since 1890 (Behm et al., 2005, Robson et al., 2016). Because the retreat of snow cover is one of the most important indicators of climate change in mountain regions (Poussin et al., 2019), the analysis of its evolution in the HTNP is important.

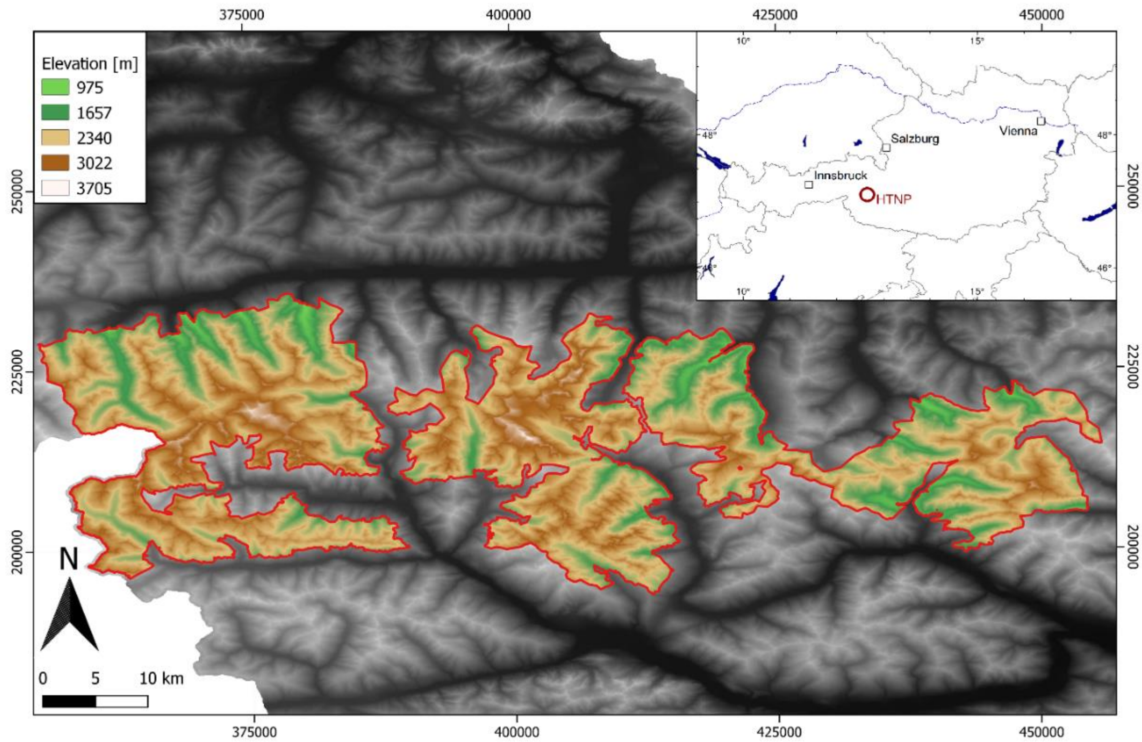

Figure 4: Location (red outline) and topography of the study site. The inset shows the position of the Hohe Tauern National Park (HTNP) (red circle) in western Austria. The cities Salzburg, Innsbruck and Vienna (white squares) are shown for a better orientation (DEM 10 m Austria provided by data.gv.at).

3.2 Sentinel-2

As part of the European Copernicus programme, Sentinel-2 satellites are used to acquire high-resolution (HR) data (Tiede et al., 2019). The Sentinel-2 mission includes the satellites Sentinel-2A and Sentinel-2B that were launched in 2015 and 2017, respectively (Main-Knorn et al., 2017). Multi-Spectral Instruments (MSI) are mounted on the Sentinel-2 satellites. Those are suitable to record 13 wide-swaths bands (Phiri et al., 2020). The spectral bands are ranging between Visible and Near Infrared (VNIR) and Short Wave Infra-Red (SWIR) (Main-Knorn et al., 2017). Since the start of the operational phase, effective monitoring of the earth's surface via the MSI has been achieved (Phiri et al., 2020). Due to the constellation of two polar-orbiting satellites, a revisit time of 5 days at the equator and even less at the mid-altitudes is achieved (Main-Knorn et al., 2017). Because of the high temporal resolution, the satellite monitoring is not far away from real-time information acquisition (Poussin et al., 2019). The aim of the mission is to monitor the land cover and use, disasters and climate change in HR (Phiri et al., 2020). The acquired EO imagery is available in a spatial resolution up to 10 m (Poussin et al., 2019). However, the frequent monitoring results in a vast amount of data. Over 1.7 terabytes are recorded per Sentinel-2 satellite every day, causing several challenges (Tiede et al., 2019).

3.3 Sen2Cube.at

The Sentinel-2 Semantic Data Cube Austria (Sen2Cube.at) is a data and information cube covering Austria (Tiede et al., 2019). Worldwide, it is the first operating semantic EO data cube on a national level. The semantic enabled EO data cube is implemented in a state-of-the-art cloud environment (Sudmanns et al., 2021). Sen2Cube.at assesses and scales the semantic enrichment of publicly available Sentinel-2 imagery (Tiede et al., 2019). Since it is a web-application, the data and information cube is accessible via browser (demo.sen2cube.at, accessed on 06 June 2022). Thus, no software installation is required (Sudmanns et al., 2021). Due to the web interface for generating semantic models of 4D real-world phenomena the usability is enhanced (Tiede et al., 2019). Since it is a graphical interface, programming is not required to perform tailored analysis (Sudmanns et al., 2021). The Sen2Cube.at data and information cube enables the retrieval of semantic content-based image and information from a big EO database based on semantic queries. For detailed semantic analysis of the EO data (i.e. Sentinel-2 images), the semantic EO data cube offers a fully automated semantic enrichment. By providing encoded ontologies, queries and spatio-temporal modelling are facilitated (Tiede et al., 2019). Real-world models are bridging between semantic descriptions of phenomena and its relationships based on expert knowledge and machine-readable codes (Sudmanns et al., 2018). As a result, the Sen2Cube.at data cube comprises semantic enrichments that are appropriate for several applications (Tiede et al., 2019).

Based on the graphical user interface (GUI), users (i.e. experts as well as non-experts) can develop semantic and domain-specific models and thereby build a knowledgebase. The resulting model is thus highly dependent on the user knowledge (Tiede et al., 2019). The knowledgebase (i.e. the real-world model based on ontologies) is linked to a factbase (Sudmanns et al., 2018) (i.e. data and additional information) and both are connected to the web-based inference engine by the GUI. This enables the analysis of the EO data via Semantic Content-Based Image Retrieval (SCBIR), which represents an advancement of text-based queries that are dependent on metadata (Table 1). By providing SCBIR, the data derivation from Sen2Cube.at is simplified (Tiede et al., 2019). The requirement for valid results is the precise and uncompromising definition of the model established in the knowledgebase. Interoperability is therefore necessary for understanding the model correctly and for reusing it (Sudmanns et al., 2018). Another use-case of Sen2Cube.at data and information cube are time series analysis (Table 1) (Sudmanns et al., 2021). With regard to this approach, spatio-temporal queries within configurable sites allow the specific analysis of dynamic processes (e.g. alterations of various land cover types) (Tiede et al., 2019).

The Sen2Cube.at data and information cube aims in the automatic classification of Sentinel-2 imagery. This is achieved through SIAM (Satellite Image Automatic Mapper) based pre-classification, object definition and texture information (Tiede et al., 2019). The SIAM software corresponds to an user independent expert system that generates semantic enrichment without requiring training data (Augustin et al., 2019, Baraldi et al., 2018). It is automated pixel- and spectral rule-based decision-tree classifier. SIAM generates discrete semi-symbolic spectral categories, whereby information can be derived from the EO data (Sudmanns et al., 2018). The decision-tree assigns multi-spectral color names to every single observation within the multi-spectral reflectance cube (Augustin et al., 2019, Baraldi et al., 2018, Sudmanns et al., 2021). Thereby, a discrete vocabulary of mutually exclusive color names for observations results. Recently, the Sen2Cube.at provides 33 SIAM color names for sematic queries. Since the SIAM decision-tree is independent of the senor, the generated semantic enrichment is comparable (Augustin et al., 2019). This is enabled by the leastwise calibration to the top-of-atmosphere (TOA) reflectance (Sudmanns et al., 2021).

4 Methods

Snow cover alterations in the HTNP should be revealed by time series generated with the Sen2Cube.at data and information cube. This required the definition of a semantic model. Before presenting the computational conditions, a general overview about generating semantic models with the Sen2Cube.at is given in the subsequent chapter.

5.1 Overview and workflow

Sen2Cube.at is an expert system that extracts information from data by combining the knowledgebase and the factbase (Sudmanns et al., 2021). The inference engine can thereby process large amounts of data automatically and efficiently. Three components are required in order to successfully apply semantic queries, which are stored either in the knowledge- or in the factbase. Within the knowledgebase, knowledge about a specific entity as a real-world phenomenon is defined in a ruleset and encoded in a model. The model consists of semantic concepts as well as of result requests (Z_GIS, 2022). They are re-usable as well as applicable for different study sites and periods. By providing the possibility to share the semantic models, the usability of Sen2Cube.at is enhanced. In contrast, the factbase stores the satellite imagery and the semantically enriched data (Sudmanns et al., 2021). Moreover, the spatial and temporal extent can be determined here. The spatial extent refers to a selectable area of interest (i.e. by manually defining one or multiple points, lines or polygons or by importing existing data in GeoJSON format) (Z_GIS, 2022). The temporal extent is set by the definition of a specific time interval (i.e. defining the start and end date). Data is available since mid-2015 (i.e. since Sentinel-2A has been in space) and is updated regularly. Finally, the inference engine translates the model defined in the knowledgebase into queries against the factbase. Inferring means thus retrieving information through semantic queries. The inference engine is based on a python library. Due to a driver, the indexed data in the data cube is accessible (Sudmanns et al., 2021).

Figure 5: General workflow for using the Sen2Cube.at data and information cube.

In Sen2Cube.at, semantic models are based on two components, the semantic concepts and the application. Within the first component, semantic concepts are defined. In the application part of the model, the analysis results are specified that are based on the previous defined semantic concepts. Models are generated with building blocks, following a visual drag-and-drop approach (Sudmanns et al., 2021). Each building block contains a specific task by which the building block can be categorised.

Definition blocks contain several other blocks. Thereby, entities can be re-used in both components. Entities define real-world phenomena, like water, vegetation or snow. During a spatio-temporal semantic query, each observation is evaluated to determine whether it belongs to an entity. Entities are populated by one or many properties, which are not allowed to contradict each other. Data and information building blocks are used to populate the entities and can be subdivided into appearance, atmosphere, reflectance and additional data sources (i.e. topography or artefacts). Result definition blocks are used to finally specify the model results and are populated within the application component (Z_GIS, 2022).

With building blocks called verbs, it is possible to specify the action of a process. By applying the ‘with do’ building block, an action can be assigned for example to an entity. Furthermore, the ‘mask’ verb, assigns a boolean value mask (i.e. true or false) to the data cube. Only if an observation within the cube is categorized as true, it is saved. Otherwise the observation will be deleted (i.e. the observation is counted as false). The boolean value mask can be applied to a specific dimension. If the verb should only operate on the spatial dimension, the values are duplicated for each time step. In contrast, values are duplicated for the spatial location when operating in the temporal dimension (Figure 6) (Z_GIS, 2022).

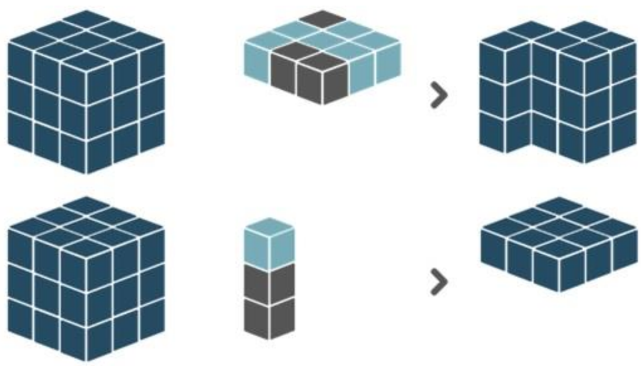

Figure 6: Schematic illustration of the application of a boolean value mask to the input data cube (left), operating on the spatial (above) and temporal dimension (below). Observations are thereby assigned to true (light blue) or false (gray). Only the true observations are saved in the resulting cube (right) (Z_GIS, 2022).

One of the most important actions is the ‘reduce’ verb. It initiates a reduction over the spatial or temporal dimension based on a selectable operator (e.g., count, percentage, mean) (Figure 7). Reducing a cube over time means that the multiple observations are reduced to a single value with respect to the applied operator. Thereby, the temporal dimension is removed. The resulting data cube contains thus only the spatial dimensions. However, space can be eliminated in the same way (Z_GIS, 2022).

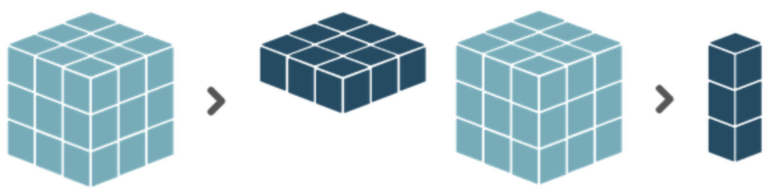

Figure 7: The dark blue data cube shows the reduction over time (left) and space (right) from the original cube (light blue) (Z_GIS, 2022).

Another powerful verb is 'group by'. It splits the data cube into discrete groups depending on a spatial or temporal variable. By applying one of the available temporal grouping variables, the groups only contain observations within a defined period (e.g., week, month, year). In contrast, the spatial grouping variable ‘spatial feature’ establish groups that exclusively inherit observations within specific areas. The prerequisite is that the study site consists of several, separated and non-overlapping spatial features (e.g. polygons). The resulting subgroups thus correspond to those features. Various actions can be applied to all subgroups before using the ‘ungroup’ verb. This verb recombines all subgroups into a single data cube. Overall, the grouping process follows a split-apply-combine workflow (Figure 8) (Z_GIS, 2022).

Figure 8: Workflow when applying the group and ungroup verbs. The data cube is split into two subgroups (displayed as dark and light blue blocks), afterwards actions are applied on both and finally the manipulated subgroups are re-combined to a single data cube (Z_GIS, 2022).

5.2 Computational condition

The proposed semantic model called snow cover was defined with the Sen2Cube.at data and information cube. As shown in Figure 9, the model is based on two entities that are defined within the semantic concepts part of the model. Within the application part, four results are requested. The semantic concepts as well as the application are described in more detail below. In order to populate the factbase, a shapefile covering the HTNP was imported in a GeoJSON format in order to define the spatial subset. The dataset was provided by the state government of Tirol (- data.tirol.gv.at) and consists of three non-overlapping polygons covering the whole national park (Figure 4). The temporal subset was specified as a period from 01. January 2016 to 31. December 2021. However, the whole period of six years was split up to single years or months if needed.

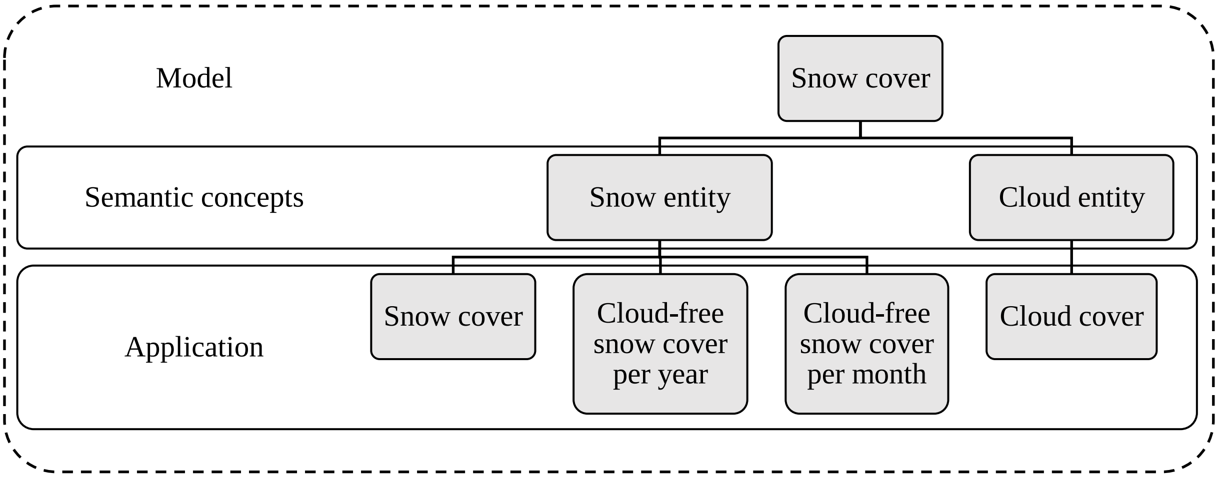

Figure 9: Schematic overview of the snow cover model defined in the knowledgebase. The model includes the semantic concepts required for the definition of the snow and cloud entities and the application for specifying the analysis results based on the entities.

In the proposed snow cover model, two entities were defined based on semantic concepts. The first entity concerns the snow covered areas, the second one the clouds. The snow entity was delimited from other phenomena using the data and information block ‘appearance’. This block is related to the pure appearance of real-world observations, which is based on the different color types generated by SIAM. All observations were evaluated according to the category ‘snow or water ice’. Those who match the category are counted as true and are assigned to the entity. If an observation does not correspond to the category it is assigned to false. In contrast, the cloud entity is based on the data and information block ‘atmosphere’. It inherits information on phenomena appearing in the atmosphere (Z_GIS, 2022). In this case, each observation is evaluated with respect to the category ‘cloud’. Only the observations that match this category are assigned to the cloud entity.

After defining the semantic concepts of the entities snow and clouds, these can be addressed again in the application part of the model. A total of four different outputs based on the defined entities were requested. At first, time series regarding the percentage of snow and cloud coverage were created. To achieve this, a reduction over space was performed using the operator ‘percentage’ for each entity. Subsequently, cloud-free outcomes are requested. Information on the cloudless snow coverage should refer to the average percentage per month and per year. This required the declaration of two groups. Since the area of interest consists of three individual, non-overlapping polygons, the data cube was split into three subgroups by using the spatial feature variable. Subsequently, a boolean value mask was applied. Several actions were performed on all observations within the three groups that constitute the study site. By applying the verb ‘invert’ to the cloud entity, all matching observations were eliminated from the subgroups (Z_GIS, 2022). Afterwards, a reduction over space was performed in order to obtain only the percentage of the cloud-free snow observations over time. In correspondence to the split-apply-combine workflow, the manipulated subgroups were then re-combined to a single data cube by applying the ungroup verb. However, in order to obtain information about the annual and monthly cloud-free snow cover a further grouping workflow was required. In this case, the temporal grouping variables ‘year’ and ‘month’ were used. Sub-groups that only contain observations within the respective defined periods were thereby generated. A reduction over time was finally applied by using the operator ‘mean’. In order to complete the grouping workflow, the ungroup verb was applied as a last step for re-combining all sub-groups. Overall, information on the mean percentage cloud-free snow coverage per year as well as per month was thus obtained.

6 Results

Both the percentage snow and cloud cover were derived in a period from 01.01.2016 to 31.12.2021 and plotted as a time series diagram (Figure 10). Seasonal differences are recognisable for both categories. The percentage snow cover is comparatively lowest in the summer months (i.e. June to September). The maximum values are measured in the winter months (i.e. December to March). The seasonal fluctuations in cloud cover are not as pronounced as in cloud cover. Nevertheless, the maxima tend to occur in late spring to summer (i.e. May to August) and the minima in late autumn and winter (i.e. November to February).

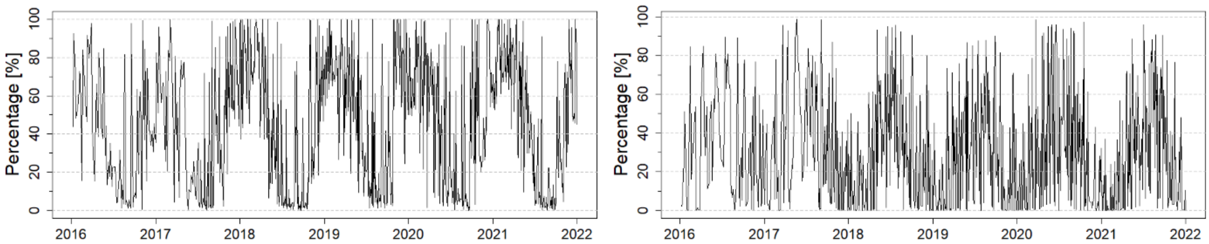

Figure 10: Time series showing the percentage snow (left) and cloud (right) cover occurring between 01.01.2016 and 31.12.2021.

A reduction over space was used to eliminate the cloud coverage. The remaining observations thus solely refer to the snow coverage. Figure 11 displays the mean percentage cloud-free snow cover per year from 2016 to 2021. Due to the short period, no clear increasing or decreasing trend can be identified. From 2016 to 2018 and from 2019 to 2021, the mean percentage snow cover has decreased. However, an increase from 2018 to 2019 is evident. In 2019, the highest mean percentage snow cover value was recorded with about 69%. The lowest value was measured in the previous year 2018 with approx. 60%. These two extreme values show that the mean percentage snow cover does not fluctuate significantly during the measurement period, since the difference between maximum and minimum is only 9%.

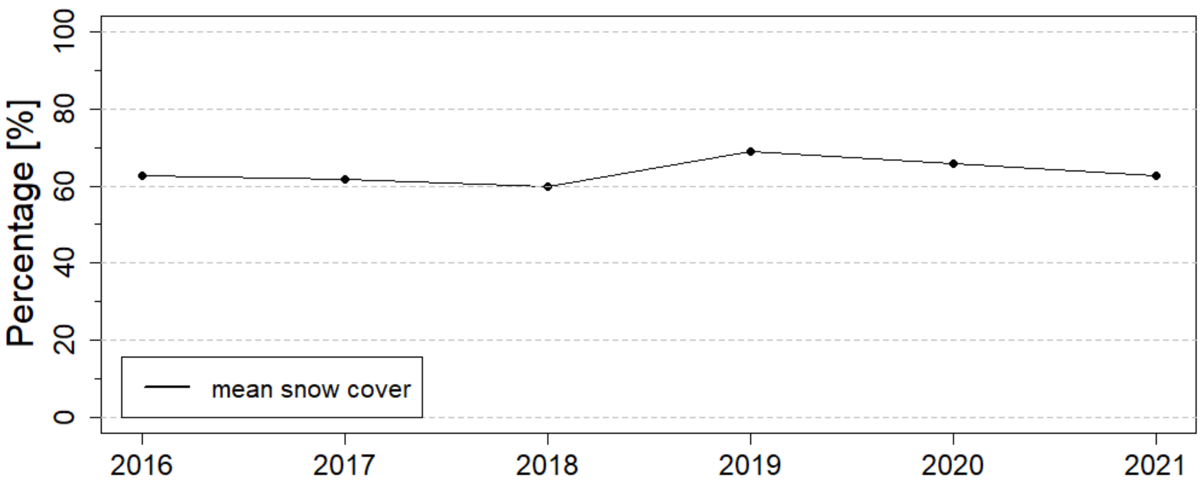

Figure 11: Time series concerning the cloud-free mean percentage snow cover per year (black line) from 2016 to 2021.

Figure 12 shows the mean percentage of the cloud-free snow cover per month during the years between 2016 and 2021. Most mean percentage snow cover observations were made in March with about 90 to 95 %. The only exception is the year 2021, when April had the most observations with about 93 %. A general decrease in the mean percentage snow cover can be seen from March to July. This is mostly continuous, with only a slight increase in 2016 from June (51 %) to July (54 %). From July to September, the mean percentage values are usually low. The minimum snow cover is reached in August, whereby the mean percentage per year is very variable and ranges from 17 % (2016) to 36 % (2019). The exception is the year 2021, which shows a mean snow cover percentage of 9 % in September. After the minimum, there is initially a tendency for a steep increase until November, which subsequently flattens out until March. Except for the years 2017 and 2020, the increase is mostly continuous. In 2017, a locally strong increase in mean percentage snow cover observations is evident from August (17 %) to September (71 %), and in 2020 from September (34 %) to October (78 %). Both local maxima decrease significantly again by the next month.

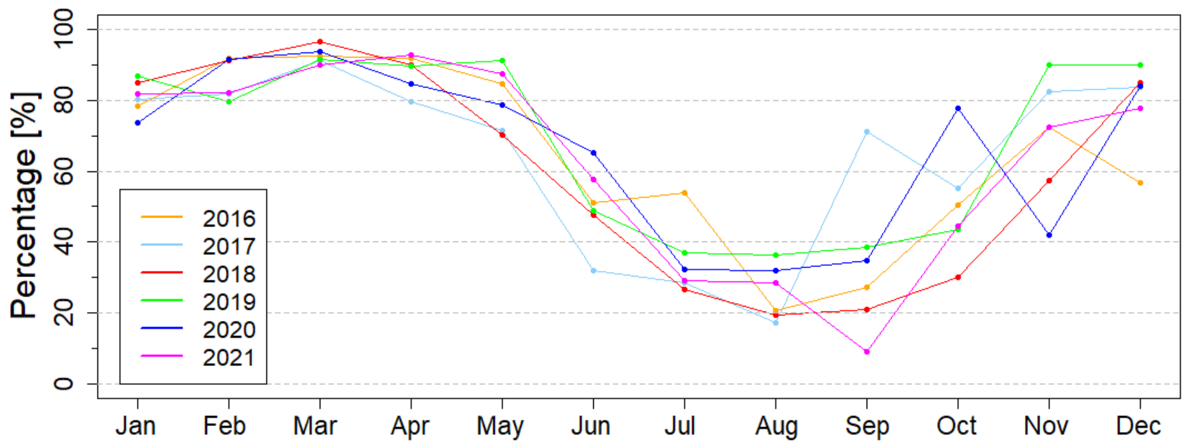

Figure 12: Mean percentage of the cloud-frees snow cover per month. Time series starting from 01.01.2016 to 31.12.2021.

7 Discussion and outlook

In line with the statements made by Augustin et al. (2019) the results of this study demonstrated the capability of obtaining cloud-free results within a user defined spatio-temporal extent by applying semantic concepts. The impact of cloud cover is still considered as a limiting factor when using EO data obtained with optical sensors, as stated by previous several studies (Nolin, 2010, Poussin et al., 2019).

However, by using the Sen2Cube.at semantic data cube, the elimination of the cloud coverage is straightforward and users are not obliged to apply complex algorithms (Augustin et al., 2019). The presented time series concerning the cloud-free mean percentage snow cover per year (Figure 11) does not show dynamic alterations. This result was unexpected since a temperature increase was recorded within the last years according to Behm et al. (2005) whereby a quantifiable decrease in the snow cover was assumed. The fact that no clearly increasing or decreasing trend is discernible can be explained by the short study analysis period compared to other snow cover evolution studies (e.g., Telesca et al., 2014, Bormann et al., 2018). In line with several studies (e.g., Telesca et al., 2014, Hüsler et al., 2014), the results have shown that snow cover is generally lowest in the summer months and highest in the winter months (Figure 12). The snow coverage in the HTNP varies thus considerably over time. An additional seasonal trend analysis would be interesting for a detailed investigation on a further temporal scale, as it was carried out, for instance, by Poussin et al. (2019). Using the verb 'group by' and the temporal grouping variable 'season' that are provided by Sen2Cube.at data and information cube, such an analysis would be straightforward in future studies (Z_GIS, 2022).

In order to investigate whether the snow cover also varies in space, prospective studies should also analyse different altitude levels, as conducted for example by Hüsler et al. (2014). With regard to the Sen2Cube.at data and information cube, semantic altitude-related queries are possible by using the topography data and information building block (Z_GIS, 2022). By defining threshold ranges directly within the EO data cube, semantic queries could refer to certain height levels. This would allow the analysis of different elevation levels without requiring the user to split the study site into different polygons depending on the heights in a pre-processing step.

According to Hüsler et al. (2014), inaccuracies in monitoring snow cover alterations using data acquired by optical sensors, such as Sentinel-2, arise from the lack of information regarding observations below the cloud coverage. This is also reflected in the results of the proposed case study (Figure 10). Comparing the snow and cloud percentage time series from 2016 to 2021 indicates that more snow cover observations are observed when the cloud cover percentage is relatively low. It is unclear how this phenomenon exactly affects the results of the time series in terms of the mean percentage snow cover per month and per year. As stated by Poussin et al. (2019), the cloud coverage strongly influences the snow cover observations, especially on a monthly scale, which may have a negative impact on the analysis of long-term change trends and even on the concordance of snow cover and climatic data. In upcoming studies on the alterations of snow cover in the HTNP, it is therefore recommendable to perform an accuracy assessment as applied by Gao et al. (2010), for instance.

According to Poussin et al. (2019), the accuracy of snow cover observations however increases if the used data has a high temporal resolution. In other words, the snow cover analysis within a certain period is rather inaccurate if it is based on only a few EO images. However, the Sen2Cube.at stores the Sentinel-2 EO images with a recurrence interval of less than 5 days since Sentinel-2B was launched in 2017. But even when only Sentinel-2A was in operation, the spatial resolution was still around 10 days (Main-Knorn et al., 2017). In contrast to the results presented by Poussin et al. (2019), who used Landsat data stored in the Swiss data cube (SDC) in their study, the results of this paper do not show any striking variations since the temporal resolution has been increased after launching Sentinel-2B. It can thus be concluded that the Sen2Cube.at information and data cube is very well suited for time series analysis from a temporal point of view.

8 Conclusion

The aim of this seminar paper was to analyse the snow cover evolution within the HTNP in the scope of a case study and to demonstrate thereby the potential of semantic EO data cubes. To accomplish this, the cloud-free snow coverage per year and per month between 2016 and 2021 were calculated as time series. This required the generation of a semantic model that contains semantic concepts in order to differentiate snow and cloud coverage from other land cover types. In contrast to state-of-the-art EO data cubes, the elimination of cloud observations was straightforward by using Sen2Cube.at. The resulting cloud-free snow coverage per year does not indicate dynamic alterations due to the short analysis period between 2016 and 2021. In contrast the obtained monthly cloud-free snow cover time series show typical fluctuations during the seasons. Overall, the Sen2Cube.at data and information cube proved to be a suitable approach for projects regarding time series analysis. In the proposed case study, only a fraction of the possibilities provided by the semantic EO data cube are used, which gives future studies the opportunity to perform more detailed analyses of the snow cover evolution. Although the cloud-free snow cover time series analyses proposed in this seminar paper are related to the HTNP, the generated semantic model can be applied to other study sites located within the factbase of the Sen2Cube.at data and information cube.

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