PINGU
Principles of Interactive Navigation for Geospatial Understanding

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Figure 1: Screenshot from our proposed application, consisting of the following linked views: (a) schematic *Map View* with the spatial layout of measurement spots, (b) *Chart View* consisting of two graphs, displaying the snow level and the evolution of temperature measurements and wind speed, (c) *Wind Rose View* for conveying the wind speed, (d) navigation *Timeline View* incorporating the information about the quality of input data extracted from trail camera images.

Abstract

Monitoring conditions in the periglacial areas of Antarctica helps geographers and geologists to understand physical processes associated with mesoscale land systems. Analyzing these unique temporal datasets poses a significant challenge for domain experts, due to the complex and often incomplete data, for which corresponding exploratory tools are not available. In this paper, we present a novel visual analysis tool for extraction and interactive exploration of temporal measurements captured at the polar station at the James Ross Island in Antarctica. The tool allows domain experts to quickly extract information about the snow level, originating from a series of photos acquired by trail cameras. Using linked views, the domain experts can interactively explore and combine this information with other spatial and non-spatial measures, such as temperature or wind speed, to reveal the interplay of periglacial and aeolian processes. An abstracted interactive map of the area indicates the position of measurement spots to facilitate navigation. The design of the tool was made in tight collaboration with geographers, which resulted in an early prototype, tested in the pilot study. The following version of the tool and its usability has been evaluated in the user study with five domain experts and their feedback was incorporated into the final version, presented in this paper. This version was again discussed with two experts in an informal interview. Within these evaluations, they confirmed the significant benefit of the tool for their research tasks.

Index Terms: Human-centered computing—Visualization—Visualization techniques—Treemaps; Human-centered computing—Visualization—Visualization design and evaluation methods

1 Introduction

Ground monitoring in Antarctica plays a crucial role in understanding the impact of climate changes on the natural environment. Antarctica is considered a significant region for environmental research because of its profound effect on the climate and ocean systems [23, 34, 48]. Although the data from satellite monitoring can be very valuable, they provide limited granularity in terms of detailed measurements about environmental conditions on the surface of the ground. Therefore, many countries have established permanent research stations in Antarctica, where geologists and geographers are operating mostly seasonally. We have established a close collaboration with a group of geographical researchers, operating at the Johann Gregor Mendel Station on the Northern coast of James

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Ross Island of the Antarctic Peninsula. Within their short research stays several weeks per year, they are arranging sensors, cameras, and other equipment to collect measurements throughout the rest of the year without their physical presence at the station.

One of their main research foci is monitoring an area of particular environmental interest and acquiring several measurements throughout a period of time. This area comprises approximately 64 m^2 around a natural formation, i.e., a *hyaloclastite breccia boulder*, located close to the polar station. By measuring the ground and air temperature, wind speed and its direction, and snow cover, the domain experts want to **quantify and understand the interplay of geomorphic processes**, leading to the formation of a specific landsystem around the boulders. Monitoring the snow coverage also helps them to assess snow precipitation. This is a significant problem, as strong winds relocate the snow on the ground and make the measurements unreliable. In essence, the correctness of snow precipitation measurements is significantly lower than in the other places on Earth, due to the large snow relocations in a radius of miles, which is one of the main research foci of geologists and geographers [6]. However, being able to measure the precipitation more reliably is anticipated to have a significant impact on assessing the amount of water leaking into the soil during the melting season and on understanding how it influences the ecosystem of the area.

Until now, there have been few attempts by Antarctic researchers to perform these measurements as accurately as possible [14, 45]. One of the cheapest—yet, time-efficient—methods requires the placement of several bamboo sticks in the area of interest, as well as trail cameras capturing the respective sticks. The cameras are taking images at regular intervals, e.g., every three hours, and the snow height is measured from the images by evaluating the parts of sticks not being covered by snow. At this point, the first problem of the researchers occurs: there is no method available to help them derive the snow levels around the sticks from the photos. They are currently limited to a fully manual approach for the interpretation of the captured images, going through them one-by-one. This is a very tedious process, especially for larger datasets.

To support geologists and geographers in their workflow for the analysis of the measurements acquired at the polar station, i.e., ground and air temperature, wind speed and its direction, and snow cover, we designed and implemented `PINGU`. It consists of the following components: a semi-automatic tool for processing photos and extracting the information about the snow levels at the stick positions over time, passed into the second component, a tool for interactive visual analysis of all the acquired measurements.

Within a subsequent pilot study, conducted with one junior and one senior researcher in geography, we tested the application in its early stage. Their initial feedback helped us to improve the tool into a second version, which was evaluated in a qualitative user study. In the second study, five other domain experts, different from those participating in the pilot study, were involved. The drawbacks revealed within this study were subsequently removed and the final version was informally discussed again with two of the participants of the second study (those having the most comments, problems, and suggestions).

In summary, the main *contributions* of this paper are:

• Semi-automatic extraction of the snow level information, taken from a series of photos from trail cameras.

• Design and implementation of `PINGU`, a visual analysis tool for the interactive exploration of multi-variate datasets, supporting the needs of geologists performing their research in Antarctica.

• Evaluation process and results of the pilot study, user study, and informal discussions after the study, revealing the benefits and limitations of our proposed solution.

2 Related Work

The design and implementation of `PINGU` revolves around several topics, tackled in the previous work. In particular, we will review here some applications from the domains of visualization of geospatial and climate data, as well as some related applications from the domain of temporal data visualization. We also discuss work in the domains of monitoring and interaction, tackling similar approaches to ours.

Geospatial Visualization Applications: Purely geospatial visualization applications are only marginally relevant to our work, as we need to incorporate into the visual framework the multivariate temporal data from measurements of several environmental components. Traditional geospatial visualization employs choropleth maps [12] to ensure intuitive, geographical correspondence. Other representations—in particular, parallel coordinate plots [24]—have also been proposed for the exploration of complex spatial and spatiotemporal information [20]. Johansson and Jern [27] propose `GAV`, a GeoAnalytics visualization tool that employs a multiple linked views approach based on parallel coordinate plots. With `GAV`, they target the extraction of complex patterns in large data sets by interaction. Andrienko and Andrienko [2] have elaborated on previous research for the analysis of temporal and spatio-temporal data in geovisualization and propose a number of strategies for the exploration of this kind of data, paying particular attention to scalability and interactivity. Kraak et al. [29] discussed how maps can be used to support better geospatial visualization applications. Scheepens et al. [41, 42] and Tominski et al. [46] are only few of the works that have investigated trajectory movement, while Andrienko and Andrienko have published an overview of visual analytics for movement [5]. More details on (spatio-)temporal data visualization are given below, while a position paper on challenging problems for geospatial visual analytics by Andrienko et al. [3] gives interesting directions for future work. Other more recent approaches relate rather to illustrative visualization for geological modeling. For example, Rocha et al. [40] recently proposed a multivariate visualization to assist geologists and reservoir engineers in visualizing geological attributes in a multi-layer approach without visual inference.

Climate and Environmental Visualization Applications: A comprehensive survey of visualizations for the physical sciences has been presented by Lipsa et al. [33], including also visualizations for the earth sciences. Based on the proposed taxonomy of this survey, most of the work in the earth sciences has been conducted with regard to 3D time-dependent data and a few with regard to 2D time-dependent data. The most relevant to our application are the previous works of Kehrer et al. [28] and of Drocourt et al. [19]. Kehrer et al. [18] propose a `SimVis`-based framework for climate research—especially for hypothesis generation for climate change. The work is based on interactive visual data exploration of large amounts of multivariate and time-dependent climate data that facilitates the generation of hypotheses to be confirmed or rejected in a user-steerable environment. However, this approach does not support the data derivation from acquired images, which is important in our case for the derivation of the snow precipitation. Drocourt et al. presented a design study for the visualization of a 10-year record of seasonal and inter-annual changes of glaciers in Greenland. Their geospatial focus is on the coastal boundaries, which allows for dimensional reduction of the space into a radial visual encoding scheme that supports both spatial and temporal information. However, in this case, the conveyed information relates to glacier movement and not the encoding of additional environmental information and the analysis thereof. Similar to this approach, Li et al. [31] visualize climate change data of multidimensional, time-series, and geo-related characteristics, also in a radial configuration. For climate change analysis, Poco et al. [38] proposed `SimilarityExplorer`, a visual analysis tool with multiple linked views that targets the visualization of simulation models to facilitate understanding of climate change patterns, which is only marginally relevant to our case. Patel et al. [37] propose a toolbox for fast interpretation and creation of illustrations from 2D slices of seismic volumetric reflection data. The similarity to our work is that it is also based on a series of acquired 2D images that reflect seismic information and subterranean consistencies. However, this approach targets the illustration of seismic information and the annotation thereof—not the exploration and analysis. This approach also relates to visualizations for geological storytelling [32]. A survey of visualization in meteorology has been published by Rautenhaus et al. [39] covering all kind of previous work in simulation visualization, temporal evolution, comparison and fusion of heterogeneous data, uncertainty, and interactivity.

Temporal Visualization Applications: For the visual analysis of time series, the survey of Aigner et al. [1] provides an overview of previously employed techniques. Among the discussed approaches, the most important for our application are those related to geospatial information. These include the work of Shimabukuro et al. [43] for the analysis of multi-scale temporal behavior in climate models using coordinated views, and the work of Tominski et al. [46], where a 3D map configuration has been employed to visualize geo-referenced time dependent data of multiple attributes in large datasets. Space- and time-referenced categorical data have been addressed by von Landesberger et al. [49] for the visualization of categorical changes over time. Of particular interest is the work of Diehl et al. [17] for the visual analysis of spatio-temporal patterns in short-term weather forecasts using an interactive visualization interface that guides users from simple visual overviews to more advanced visualization techniques. This work was extended to `Albero` [16] for the study of probabilistic forecasts.

Monitoring: Hinkel et al. [21] monitored the maximum annual development of the active layer above permafrost at seven sites in northern Alaska for six years between 1995-2000. During this period, air and soil temperature measurements were made at each site, and soil moisture was monitored. Their results concluded that at the landscape scale, end of season thaw depth is strongly correlated with local air temperatures on an inter-annual basis. Crimmins et al. [15] explored the utility of repeated digital photography for monitoring phenologic events in plants. A challenge here was to capture the exact date of key events and require daily observations during the growing season. While these observations could be costly and relatively labor-intensive, repeat photography is one way to solve this issue. By using mathematical algorithms they could extract an estimate of green pixels and count individual flowers from the photo time series. Also, Brown et al. [8] monitored the vegetation status and environmental changes over long periods of time by using automated digital time-lapse cameras called phenocams. Such special cameras can be used for documenting changes in phenology (the seasonal activity of plants and animals), snow cover, fire frequency, etc. A challenge with such collected data is to quantify climate-driven changes over large areas at appropriate timescales. Furthermore, Hrbáček et al. [22] conducted a study for collecting key data, such as active layer thawing depth and active layer thickness, from sites in different Antarctic regions between 2006-2015 for reviewing the state of the active layer in Antarctica and effectiveness of the Circumpolar Active Layer Monitoring-South (CALM-S). The gathered data from their study was used in this study when developing the visual analytics tool.

Interaction: Our application is heavily based on interaction. In particular, multiple coordinated views [7, 9, 50]. Within these views, focus+context [7, 13] and brushing/linking [13] strategies are employed for a facilitated sense making. Brushing/linking is meant to overcome the shortcomings of single techniques and provides more information than the exploration of individual views, while focus+context is required to present items at different levels of detail.

3 Design of `PINGU`

In this section, we start with the description of requirements for the visual analysis system, which were obtained from numerous informal sessions with the geography experts and a pilot study, conducted with one junior and one senior researcher. First, we summarize the input datasets and when required, also the preprocessing steps to make them ready for the analysis by our tool. Then, we discuss the requirements for the visual analysis system and describe the design rationale behind the proposed tool and details of individual views and their linking and interaction options.

3.1 Input Data

The datasets obtained from the domain experts are the following:

• Sequence of photos from trail cameras, each capturing a set of bamboo sticks. For the better reading of snow level values, the sticks are equipped with black labels, uniformly distributed along the stick. The time span between the photos is three hours.

• Position of thermometers buried in the soil in different depths (5 cm and 15 cm) and their temperature measurements over time (capturing the values every 30 minutes).

• Wind speed and direction, measured at one spot for the whole monitored area and captured every 30 minutes.

• Air temperature, also measured as one value for the whole monitored area and captured every 30 minutes.

The photos from the trail cameras serve primarily for deriving the information about the amount of snow accumulated around the bamboo sticks over year. Here we provide the experts with a semi-automatic tool for deriving snow level information from all available images, as described in the following section.

3.1.1 Extraction of Snow Level from Images

In the first phase, we developed a simple semi-automatic tool for reading the snow level values from trail camera images. A fully automatic approach, e.g., by machine learning methods, would not be suitable in our case for now, as the currently available pool of annotated data is too small for it to perform well. However, in the future, with the growing amount of data, this option will be in focus of our research direction. Additionally, the quality of the images is highly variable. The images might have been acquired at night or might have been taken against the sun, and under other non-favorable conditions that do not allow a reading. To account for the bad quality of certain images, we can take advantage of the sequence of images “before” and “after” the bad quality ones. As the images are captured in intervals of 3 hours, if, e.g., the previous image in the sequence is of reasonably good quality and the user can easily read the snow level, we are still able to derive the snow level, driven by the knowledge of the previous image (Figure 2).

Figure 2: Example of input images of good (left) and bad (right) quality where, because of the sunlight, some sticks or their parts are invisible.

As it can be seen in Figure 2, most of the image area is irrelevant for reading the snow level values from the bamboo sticks. Given the fact that the sticks and cameras are stationary, each stick is approximately at the same position in the image-space across all images taken by a particular camera. However, minor differences in positions might be created due to the effect of the wind on the camera and stick placement and we need to address this as well. Therefore, for each stick we first determine a region of interest in one image from the whole dataset (Figure 3). We define the region of interest as a rectangular area, determined by manual annotations at the top and bottom end of the stick. The center of this rectangle is positioned at the center of the line representing the stick and the size of the rectangle was selected to make sure that the stick will be fully inside the rectangle over the whole dataset. After specifying the regions of interest, i.e., the locations of all sticks in one image, we can propagate this information across the entire dataset of images for each camera. This simple approach generated the input dataset for our semi-automatic application for reading the snow level, described further.

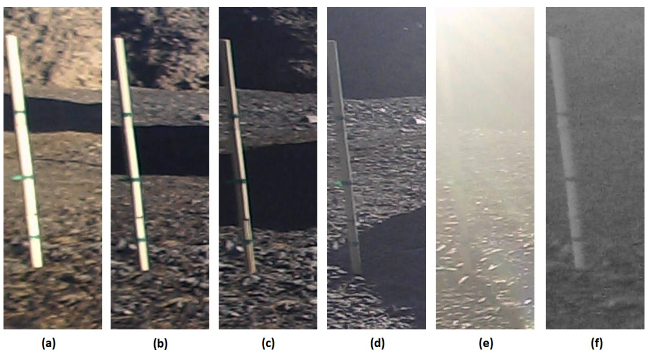

Figure 3: Six closeup views of a stick under different conditions.

A stick location is specified by clicking on top of a stick and dragging the mouse to its bottom and releasing. This creates a line with two ends. A rectangle that contains the entire line is calculated. The center of the rectangle is at the center of the line. The rectangle's width is 400 pixels and its height is set so there are 50 additional pixels over and under the stick. Such rectangle is called region of interest (ROI) and it specifies the location of each stick in the image. The ROI is created for each of the sticks and applied to each image taken by one camera. As the sticks in the image-space can move over the year, the last ROIs in the dataset may not feature the stick at their centres but rather towards their sides. But with ROIs of 400 pixels, we have enough margin to contain the movement of each stick in the given dataset.

Then for each stick, the user traverses through the input dataset and our algorithm suggests the approximation of the snow height at the given stick. In the first image of the dataset, for each stick the application requires the user input in the form of two clicks: one at the top end of the stick and one at the bottom. This gives us the reference points for the subsequent measurement of the stick length and reading the snow height level. Then we define three horizontally aligned rectangular windows which are used for exploring the vicinity of the stick (Figure 4 left). The size of window is set as the width of the stick in the image (i.e., the number of pixels). We are then sliding these windows along the stick axis and checking their content (Figure 4 middle). If the value of the measured properties (average color in that area and standard deviation) in the central window significantly differs from the values in the side windows, we evaluate this area that there is no snow. Otherwise, the stick in that area is surrounded by snow. Here we are using the fact that the stick is almost white, as well as the snow. When the value changes,

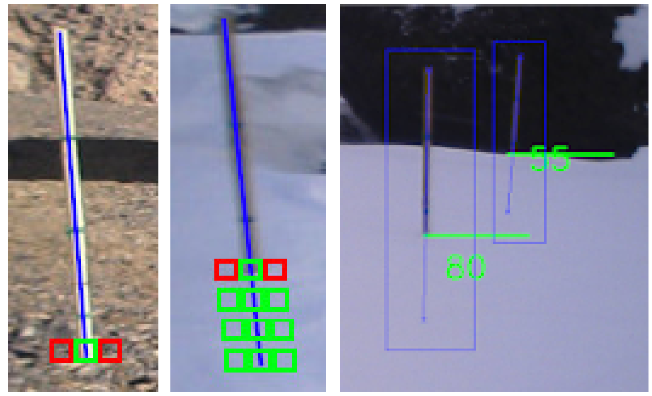

Figure 4: Left: three sliding windows around the stick, enabling to check the stick surroundings. Middle: the windows are moved along the stick axis and the values are compared. Right: in this way, we can calculate the snow height along each stick (here the resulting measures for two sticks).

it signifies the change in the environment, thus in that position, we can detect the snow level (Figure 4 right), measured in centimeters.

This result is then presented to the user (Figure 4 right) who can still manually adjust the values by direct interaction with the endpoints of the blue added line, corresponding to the snow level at the given stick. To minimize, where possible, the number of clicks, we import the position of the clicks from the each image to the next. When the position of the stick has not changed significantly within the neighboring images, e.g., due to strong winds, then the user does not have to click the top end of the stick. This significantly reduces the number of clicks the user has to perform.

When the user is satisfied with the adjustment, he or she then ranks the certainty of the snow level measurement by assigning a value from 1 (low certainty) to 4 (high certainty). This value corresponds to the user's assurance that the snow level is clearly readable, based on the image quality. It serves us to later convey the information about the quality of the displayed information in the PINGU tool. All images of the input dataset are processed in this way and the resulting annotated data serves as one of the inputs for the PINGU application.

Using this approach, the users were able to process a stick figure dataset of approximately 3,500 images in less than one hour. Figure 3 also shows the comparison between six subsequent images captured by a trail camera. With our approach, the users were able to read snow levels even in bad quality images, thanks to inferences from the previous better-quality images.

3.2 Initial Requirements

The domain expert requirements were derived from the interviews and discussions on their research problems. We aimed to understand their current workflow and its main bottlenecks. One of them, reading the snow level from images, has already been described above. Another problem is that currently there is no option to analyze all types of gathered data at once and to observe correlations between them in a comprehensible and intuitive way. Based on this, we together derived the following list of requirements on the application:

R1 All input datasets have to be *comprehensibly visualized* and the selected visualization methods have to be *intuitive* and in-line with the *conventions* of the research field.

R2 All supported views have to be *interactively linked* [7, 9, 50] in order to be able to observe correlations between data.

R3 It has to support intuitive *selection of a time span* of interest and adjusting [13] all views to this span.
R4 It has to support standard *interaction functionalities* of the individual visual representations to enhance the exploration options.
R5 It has to be possible to see the *overview*, i.e., trends, patterns, outliers, as well as *details on demand*, following Shneiderman's mantra [44].
R6 It has to convey the information about the *quality of data* obtained from the trail camera images, i.e., for each stick, in how many time steps we were able to read the snow level value—based on data provenance [10].
R7 *Comparison* of snow level values measured from multiple sticks over time has to be supported as well.

All these requirements are addressed in the design of the tool, discussed in detail in the following sections.

3.3 Design Rationale

Based on the requirements, we proposed a set of mutually linked visualizations [7, 9, 50] (**R2**). The overview of their layout within the application can be seen in Figure 1. The application consists of four basic views. In the following, we will describe these views along with the interaction functionalities available.

3.3.1 Map View

In this abstracted geographical view, we inform the user about the current layout of the scrutinized area by showing its schematic map (Figure 5), containing the bamboo sticks (vertical dashed rectangles), soil temperature sensors (circular glyphs), trail cameras (camera glyphs), and boulder shape and position (grey polygonal object). Although the view does not possess the properties of a classical geographical map, it gives the users the valuable information about the spatial arrangement of the explored area. The user can directly interact with the icons representing these objects and the data corresponding to the selected objects are shown in the other views (**R2**). When an object is selected, it is highlighted in the view, as shown in Figure 5 with the yellow color for camera 2 and for sticks 1,3 and 7. When the user selects the camera object, it automatically selects all the sticks belonging to its camera, i.e., sticks for which we read the information about the snow level from this camera.

As the snow height at the individual sticks within the selected time period is one of the most crucial parameters, we decided to encode this information already into this overall view. Each stick is equipped with a small overview bar chart, showing the evolution of the snow level in the selected time interval. This gives the users also the valuable information about the spatial accumulation of the snow over time with respect to the position of the sticks (**R7**).

3.3.2 Timeline View

This abstracted time-dependent view shows the information read from the images acquired from a specific camera. Each camera is capturing several sticks (Figure 2). Therefore, the Timeline View consists of several rows, and each row corresponds to one stick visible from the selected camera. The user can switch between cameras and this view is adjusted accordingly. Figure 6 shows an example of measurements acquired by Camera 1 that captures four sticks.

Each row, corresponding to one stick, consists of a set of color-coded linear segments. The color of each segment corresponds to the certainty (**R6**) of the user regarding the correct assessment of the snow level, marked by values between 1 and 4 in the initial processing of the input images. Dark grey segments correspond to the absent information, due to poor quality of images (e.g., most of the images captured at night). Light grey stand for low quality results with significant uncertainty level (e.g., Figure 3 (e)). Light green segments represent images with moderate quality where the

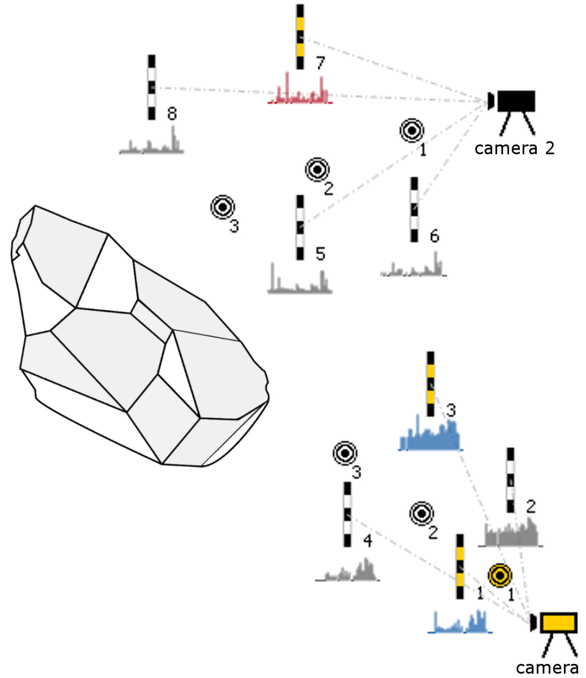

Figure 5: Map View showing the overview of the scrutinized area and the layout of sticks, sensors, and cameras. Icons of these objects with changed color to yellow denote their selection. Each stick is connected with one camera using a dotted line. From this camera, the snow level information for the stick is extracted. For the selected sticks, the bar chart showing the overview of the show evolution in the given time period is highlighted by red and blue colors, corresponding to the coloring scheme in the Chart View (Section 3.3.3 and Figure 1(b)).

snow level was already readable (e.g., Figure 3 (d),(f)). Finally, dark green segments correspond to the high-quality images where the snow level was easily readable (e.g., Figure 3 (a),(b),(c)).

This view also serves for interactive adjustment of the time period which the user wants to scrutinize in detail (**R3**). This can be done in two ways: either with the two red vertical lines in the timeline, which specify the observed time interval, or with the slider. For the former, a brushed selection will trigger an update in the Chart View and Wind Rose View, discussed in the upcoming sections. With the latter, the user can specify the range of the timeline, i.e., a zoom-in functionality that proves useful whenever the user requires a very precise manipulation with the time interval, or when a larger dataset is available.

3.3.3 Chart View

This view consists of two chart representations—the snow level bar chart (in the the top part) and the air and ground temperature and wind speed line chart, positioned below the bar chart (Figure 1(b)). The top bar chart works in two modes, based on the number of selected sticks. When the user selects only one stick in the Map View, the chart shows a simplified boxplot, i.e., with only three values—minimal, average, and maximal. The displayed values are aggregated over months or individual days, depending on the granularity of the time period selected in the Timeline View. If the period is under 90 days, the data is aggregated day-by-day, if it is over 90 days, they are aggregated by in a month-by-month manner (**R1**). The y-axis can be zoomed using the vertical slider on the left side of the chart (**R4**). When the user selects two or more sticks (**R7**), the chart is switched to the multi-series bar chart (Figure 1, top part of (b)), showing on-demand (**R5**) the minimal,

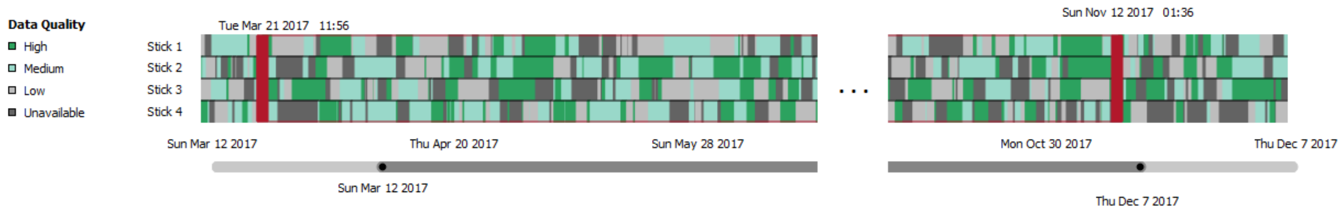

Figure 6: Part of the Timeline View, showing measurements acquired from a selected camera, which faces four sticks. For each stick visible from the selected camera, information about the quality of data is derived from the input images and then color coded (grey = unavailable data or low certainty, green = medium or high certainty).

average, or maximal values of snow level for these sticks, in the selected time period.

The line chart enables to display the temperature values read from the sensors, which are buried in the ground in the depth of 5 and 15 centimeters. Additionally, we can add information about the air temperature and the wind speed. The wind speed property was added to the chart after the study performed with the experts, as they stated that the wind speed is hard to interpret from the Wind Rose View (described below) (**R1**).

As the chart shows two different types of information, we had to pay special attention that the experts can understand the graph and interact with it (**R4**). The experts agreed that it is meaningful to add two vertical sliders, one to the left side of the chart, influencing the zoom in the temperature range, and another to the right side, zooming into the wind speed. The initial range is set according to the maximal and minimal values displayed. Another requirement, which arose within the pilot study, is to visually highlight the 0 °C, so the users can clearly see when the temperature is fluctuating around this value, i.e., denoting changes between freezing and thawing days. Based on the requirements from the experts, the line chart enables to display values only from one sensor at once. This decision was made in order to keep the solution simple and intuitive.

Another requirement was to be able to display detailed information about the measurements when hovering over the charts. This is supported by adding tool tips to both charts. The tool tip displays all known values at a given position, such as the timestamp, minimal, maximal, and average value of the aggregated data.

3.3.4 Wind Rose View

This view serves for conveying the information about the wind direction in the time period selected in the Timeline View. The design is derived from the traditionally used view (**R1**) for this purpose, showing the direction in the angle values where 0 corresponds to the north, 180 to the south, etc. (Figure 7). Distribution of wind speed is depicted by color, aggregated into four intervals defined by the domain experts. The orientation is the same as in the Map View so the user can directly see the correspondence between these two views. By further combining this information with the charts in the Chart View, the experts can understand the influence of the snow level by the boulder position and wind speed and direction. Although this view is commonly used in our target domain and clearly conveys the information about wind direction, the experts admitted that using just the wind rose, it is hard to get a comprehensive overview of the wind speed over a certain period of time. Therefore, upon their additional requirement, we added the line chart representation of the wind speed into the Chart View, as described above.

4 Early Stage Pilot Study

Early in the development process, we faced challenges of understanding domain experts' interests and how an ideal application would look like to address the experts' needs to investigate their data. To examine this, we undertook an initial pilot study with two domain experts. As the pilot study was exploratory in nature, no

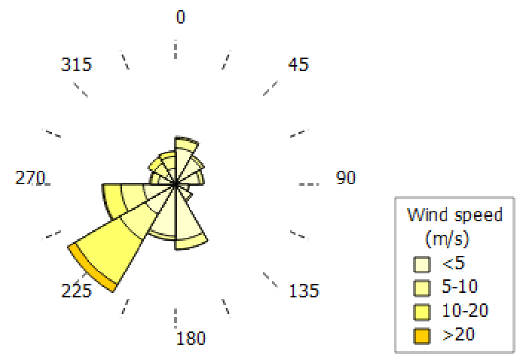

Figure 7: Wind Rose View conveying the information about the distribution of wind direction and speed in a selected time interval (in this case one month, May 2017).

strict protocol on how the study should proceed was set. It was split into two sessions: one semi-structured interview with each expert, respectively, to assess their requirements, and one exploratory experimental setup to find out the desired application design. As the experts recruited had no prior visualization knowledge nor how the application should be designed, we provided them with a highly simplified prototype of the application consisting of two line charts, a static drawing of the boulder, and one timeline. While exploring the data, the participants were encouraged to think aloud [30] so we could collect their feedback. Follow-up questions were asked to collect additional feedback. This helped us understand and derive requirements (**R1**-**R7**) and refine the study design even further.

The feedback collected from the pilot study was transcribed and analyzed to finalize the study design. The overview of the local environment around the boulder was desired, therefore, the interactive local map was implemented, acting as a guide map for selecting sticks, sensors, and cameras. Also, the experts wished for a bar chart to present the snow level for easier comparisons between months/days/hours. Finally, smaller requests, such as the numbering of the sticks, sensors, cameras, more detailed labelling, adding a thawing line around zero in the line chart, filtering the Y-axes for more detailed comparisons, and a color scheme already known by the expert, were desired to be in the application. Based on the results of the pilot study, appropriate changes were made in the application to prepare it for the final study.

5 Evaluation

To evaluate the usability of our proposed tool, we conducted a qualitative user study. Since measuring usability can be a challenging task, we followed Nielsen's definition of *Usefulness*, *"whether the system can be used to achieve some desired goal"* [35]. This term could be further broken down into *utility* and *usability*, where the former describes whether the implemented functionality of the system covers the initial requirements and the latter describes how the users can utilize the functionality. We focus on these two terms in order to assess the usability of the implemented application. In the following subsections, we provide a detailed overview of the study process and results.

5.1 Participants

Nielsen and Molich [36] found that on average six participants can find up to 80% of all usability issues. Moreover, Isenberg et al. [26] showed that on average 1–5 participants are used in the visualization community when conducting evaluations. It is therefore not uncommon to have a low number of participants when conducting domain-specific qualitative studies, as qualitative research is not concerned with making statistically significant statements [25]. Hence, five participants (one female), with a median age of 27 (range 23 to 42) took part in this study. All participants were from the department of geography at the local university and work with the data sets from the Mendel station. All participants reported to have normal or corrected-to-normal vision and where to some degree familiar with the visual representations used in the application but had no further visualization knowledge. No compensation was provided.

5.2 Tasks

To explore and discover interesting findings, an overview of the data, as well as opportunities to further investigate specific parts of the data, was required (**R5**). The participants of the pilot study highlighted specific tasks that could be used to ensure guidance and that the domain experts participating in the final study would fully explore the data. The tasks were split into three categories, inspired by [4]:

Value. Tasks regarding the identification of variable values, e.g., *On a given month, what is the snow level around stick X?* Here the variable value is the target the expert is interested in (**R5**).

Range. Tasks regarding the identification of behaviour of variables in a certain range in time, e.g., *In given two months, what is the snow level for stick X?* With this type of task, the variable value within this time range is the target of interest for the expert (**R3**).

Correlation. Tasks regarding the analysis of correlations between variables, e.g., *In a given month, what is the relationship between X and Y for stick Z?* This type of task could be considered as an overview task, which fulfils one of the initial requirements of the experts. The goal is to find a correlation between given variables (**R2**).

For each task, the participants were required to interact with the application and explore the data. Since the focus of the study was to understand whether the application could be used by the experts to explore their data, make discoveries, and/or draw conclusions, we performed a qualitative study. We were, therefore, not interested in quantitative measures, such as time and accuracy but rather the overall user experience since all categories were important for the experts. For each participant, two tasks per category were asked, resulting in a total of six tasks per participant. To avoid any order effects, the tasks were balanced after the 6×6 Latin Square.

5.3 Apparatus and Viewing Conditions

During the study, a 17” Alienware laptop with NVIDIA GeForce GTX 1080 graphics card set at a resolution of 1920x1080 pixels with Windows 10 was used. The application was implemented using C++ and Qt5, and interaction with the application was provided by means of a computer mouse.

5.4 Procedure

Each session started with the instructor welcoming the participant and explaining the aim of the study followed by them signing a consent form and filling in a form collecting demographic information. Then, a training session presenting the application and making the participant familiar with the study process was commenced, taking approximately ten minutes. During this session, the participant was also welcomed to ask any questions. To prevent learning effects, synthetic data was used during this training session. The tasks used during the training session mimicked the tasks used during the actual experimental session.

When the participant felt comfortable with the study process and familiar with the application, the experimental session started. The participant was instructed to read each task out loud in order to fully understand and remember the task during the trial. Moreover, think-aloud protocol [30] was used as they performed the tasks. When the participant felt they had answered the task, the next trial began. After finishing all tasks, a debriefing session commenced where they were asked to fill in a questionnaire regarding their subjective ratings. To avoid any bias in their answers, the participant was asked to first fill in the questionnaire before further discussion regarding their replies continued for further collection of their feedback, followed by a debriefing. Each session was audio and screen recorded and took approximately 45 minutes to complete.

5.5 Data Analysis

Thematic content analysis [11], was used to analyze the collected data (audio and screen recording, post-study questionnaire, as well as semi-structured interviews) which resulted in four categories: *Acceptance, Application, Time,* and *Limitations*. To address the validity issue of qualitative evaluation methods [11], one of the authors conducted the study and analyzed the collected data. The results were then validated by the other authors. Overall, all participants were quite positive and pleased with the application (Figure 8).

The *Acceptance* of the application consisted of questions regarding satisfaction, expectancy, usage, easiness, as one participant noted that “*[the application] is really good because usually the software tools we use can either analyze and compare the temperature well in detail or can analyze the wind, or the snow [separately]*”, and another participant stated that “*It was quite easy to operate with [the application]*”. This is reflected in their survey responses (Figure 8). On the other hand, the application was seen as an additional tool that simplified their usual analysis process, as one participant said “*I would need to calculate further statistical analysis [to ensure correlations]* ” suggesting that the application could be beneficial in getting the first overview of the data.

The *Application* category consisted of questions regarding the visual representations and interaction with the application (Figure 8). Here the participants found the interaction simple and intuitive (**R1**) as one participant noted “*I was satisfied with the interaction of the application, the graphics, and from my point of view, it is quite different and easy to work with it*”. Here, we see signs of the functionality (utility) covering their requirements. Then again, since their focus is on the analytics, some participants found it difficult to interpret the values on the line graph, as one participant stated “*If we are talking about max values then ... but if it is the average then ...*”. This could be decoded as better clarifications in the application.

Saving *Time* when exploring the data was something the experts requested as well. We hypothesize that the application saves their time for data exploration because it fulfils their requirements (**R1**-**R7**). Additionally, it prevents them from manual processing the data and jumping between multiple software tools for the data analysis, as they are doing now. One participant noted “*I did not have any specific expectations on the application [before seeing it], I only wanted to easily view the data and multiple types of data in one application. [After using it] I think it meets my requirements quite well*”. Another participant said “*[It saves me time because of] the way the application is viewed because I can easily compare different parameters, and I do not have to use more programs*” (**R2**). However, conducting a detailed analysis with the application might result in the participants spending more time with the application

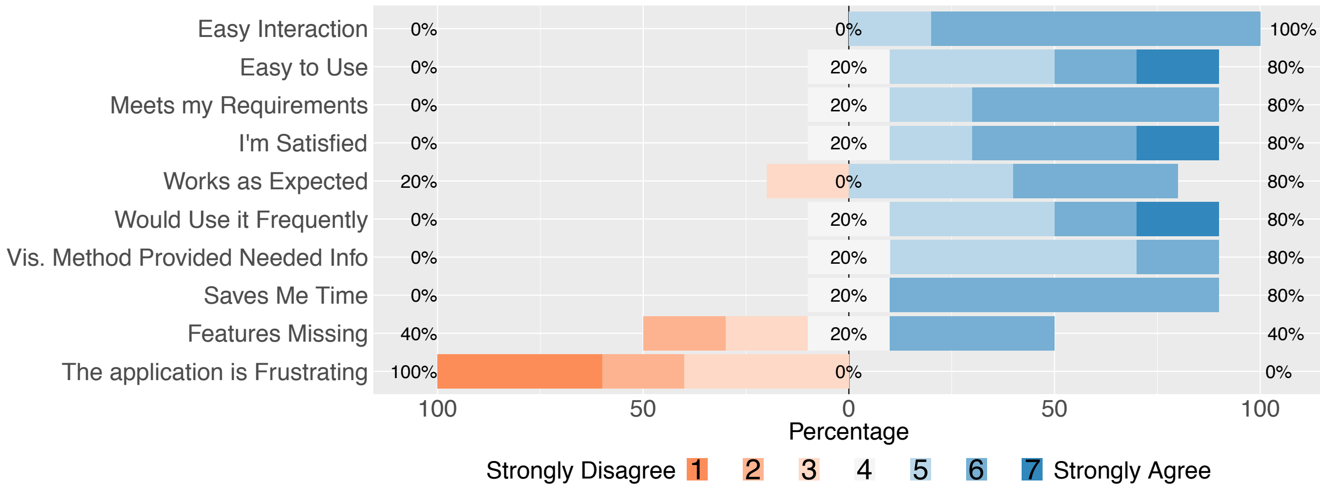

Figure 8: Participants' answers from the post-study questionnaire. Each question was ranked on a 7–point Likert scale with 1 being *strongly disagree* and 7 being *strongly agree*. The two questions at the bottom were reversed meaning the lower the score the better result.

as one participant noted "*For some things it does save me time, but for other things, such as selecting [exact time span], filtering, correlation analysis it could take longer*". This observation, however, is not surprising since such tasks are by nature demanding and would take time to perform regardless of the software used.

The *Limitations* of the application, consisting of missing features and frustration, were discussed during the semi-structured interview after the participants filled in the post-study questionnaire. While the overall experience was positive (Figure 8), the participants discovered further features to be implemented to simplify the analysis.

One essential feature was to combine a simple line graph in the Chart View with the Wind Rose diagram to separate wind speed to be able to extract specific details and compare the variables with others. One participant noted "*A line graph for the wind speed is missing because from the Wind Rose diagram you cannot see all the details [for the wind variable]*". This can also be seen in the question asked in the post-study questionnaire regarding missing features (Figure 8). This combination would help the user to better analyze the data and minimize the cognitive overload as one participant noted "*It is not so easy for me to remember all the data for individual months*".

The desired goal of the domain experts was to have a simple and intuitive application that would ease their daily work. Reflecting back on the Nielsen's definition of *Usefulness—whether the system can be used to achieve some desired goal*, we can state that the application would be useful for the domain experts as one of the participants noted "*I will work with this [application] quite a lot, that [the ability to combine multiple data sets] is really what is important for us*" (**R2**).

5.6 After Final Study

After the transcription and analysis of the feedback from the final study, we informally iterated the application with the experts one more time. Based on the study, several missing features were addressed:

- Representation of wind speed in a line chart.
- Manual setting of precise time using a calendar widget pop-up window combined with time selector(**R3**).
- Selection of several sticks at the same time and visualization of their snow level in the multiple bar chart, enabling the user to switch between showing the minimal, average, or maximal values (**R7**).

The final application was presented to two of the senior domain experts that participated in the final study and had the most inspiring and critical comments. The participants appreciated and made immediate use of the calendar and time widget to adjust time intervals to a precise time. The participants commented on the fact that this feature is now available, given that though it was possible to set the time using the interval sliders, they found this approach more convenient. However, the sliders are still very useful for tasks where the precise selection of time interval is not crucial.

Among other improvements, we added the possibility to select several sticks at once. This helped them to easily compare the snow level at these sticks.

Even though the participants were familiar with reading the wind rose representation (**R1**), the addition of the wind speed into the line chart eased the temporal exploration of wind speed patterns.

One of the participants would appreciate the possibility to set the timeline interval by interacting directly with the Chart View. Last interesting suggestion was to change the displaying mode when selecting the interval in the Timeline View. Currently, the charts in the other views are updated once after the mouse interaction is done. The experts would prefer the immediate update of the charts. Both of these will be included in the next iteration of `PINGU`.

6 Results and Discussion

In the current state, our tool operates primarily with a dataset arising from a single year [22], i.e., 2017. Clearly, this amount of data is not sufficient for making any strong inferences concerning long-term trends or for verifying hypotheses. However, it was sufficient for designing a tool for the visual exploration of the currently available dataset and understanding the correlation between different measurements.

Having data from more years would be definitely beneficial for the experts and this is our plan for the future. However, already the visual analysis of the currently available data is very beneficial for the geographers. Waiting for more data in order to improve the design of the tool would cause the delay of possible consequences on the data-capturing plan for the next season by one year. Therefore, although we are currently working only with a one-year data set, our design decisions are made already with keeping in mind significant future extensions of the input datasets.

Except for the positive feedback on the proposed tool, its functionality and interaction options, the domain experts had for the first

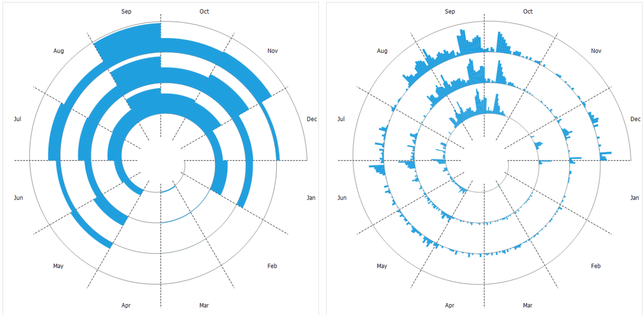

Figure 9: Two proposed spiral views for visualization of repeating patterns in data within several years. Here, synthetic data for three years are visualized.

time chance to look at the data about the snow level evolution, which is possible to get from the trail camera images. They agreed it finally gave them this information in details previously impossible to get and the visual representations available in our tool confirmed the expected correlation between the snow level and fluctuation of the ground temperature. One of the experts stated that: *PINGU provides us with an efficient solution for visualizing the spatial changes in snow cover and in an interplay with the other parameters, studied in climatology or geomorphology (e.g., air and soil temperature), it provides us with fast and effective analysis of mutual interactions between these parameters.*. They also concluded that our tool could serve them for assessing if the current positions and number of sticks and trail cameras are appropriate for correct capturing of snow level values.

In order to prepare the tool for its extension to operate with data from additional years, we also integrated a spiral-based visualization, inspired by [47], which aims to show the trends of a selected parameter over the years (Figure 9).

In the last informal discussion with the experts, we were discussing the feasibility and other future extensions of the tool in this direction. They admitted that this view is interesting but very novel for them, thus, they will need to test its feasibility in more detail within our future collaboration.

7 Conclusion and Future Work

In this paper, we introduced `PINGU`, an interactive visual analysis tool for understanding the series of data collected at the polar station in Antarctica. Our contribution consists of three main parts—data preparation and preprocessing, design and implementation of `PINGU`, and evaluation of its usability.

In the first part, we helped the experts with extracting the data about the snow level from a large series of images, taken by trail cameras. We designed a semi-automatic tool fastening the extraction process which enabled them for the first time process all images captured at the polar station.

In tight collaboration with the geographers, we compiled a set of initial requirements, leading to the implementation of the first prototype of `PINGU`, evaluated by the experts in the pilot study. The results influenced the functionality of the tool in the next development phase, which was thoroughly tested in the final study. The comments raised within this study were still incorporated to the final version of the tool, informally discussed again with the experts.

Based on the results of the conducted study, we can conclude that the domain experts were positive with getting introduced to such a visual analytics tool that can combine all their data into one application. Our approach and procedure can serve as a guideline not just for the presented domain, but also other domains working with similar tasks and data.

Although the experts were satisfied with the current status of the tool, we are planning to continue in its development. Possible directions for such future work include further feature implementation, such as selection and comparison of multiple variables (sticks and sensors), ability to filter multiple time-windows on the timeline, ability to show additional data such as “Albedo effect” (the ability of surfaces to reflect sunlight), and most importantly, enable to operate with data from more years. The experts also would like to add more measuring devices (i.e., trail cameras, sticks, and sensors). Within their next stay at the polar station, they are planning to gather the detailed terrain information using drones. Then, we will be able to change the Map View and extend its content, possibly also by integrating a 3D terrain view.

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