Chapter 4: Glacier mapping and monitoring based on spectral data

Andreas Kääb\textsuperscript{1}, Tobias Bolch\textsuperscript{2}, Kimberly Casey\textsuperscript{1}, Torborg Heid\textsuperscript{1}, Jeff Kargel\textsuperscript{3}, Greg Leonard\textsuperscript{3}, Frank Paul\textsuperscript{2}, Bruce Raup\textsuperscript{4}

\textsuperscript{1} (Department of Geosciences, University of Oslo, PO Box 1047 Blindern, 0316 Oslo, Norway, kaeaeb@geo.uio.no)

\textsuperscript{2} (Department of Geography, University of Zurich, Winterthurerstrasse 190, 8057 Zurich, Switzerland, frank.paul@geo.uzh.ch, tobias.bolch@geo.uzh.ch)

\textsuperscript{3} (Department of Hydrology and Water Resources, University of Arizona, PO Box 210011, Tucson AZ 85721-0011, USA, kargel@hwr.arizona.edu)

\textsuperscript{4} (National Snow and Ice Data Center, University of Colorado, 449 UCB, Boulder Colorado 80309-0449, USA, braup@nsidc.org)
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Abstract

Spectral, and not least multi-spectral satellite data represent the backbone of spaceborne glacier mapping and monitoring, and have allowed for substantial progress of global glacier observations in recent years. In this chapter we give an overview of the information contained in, for the most part, ASTER or Landsat type spectral data, and of methods to qualitatively and quantitatively analyze this information for glacier studies. Besides multispectral techniques based on the visible, and near- and short-wave infrared sections of the spectrum, we also shortly discuss methods based on thermal and radar data, with special emphasis on the mapping of debris-covered glacier ice. A further focus is on spectral change detection techniques applied to multitemporal data over glaciers, with special attention to a novel image differencing technique. Finally, we give an overview of satellite-image based measurement of glacier flow, a group of methods that we view as a category of spectrally-based change detection.

4.1 Introduction

This chapter gives an overview of mono- and multitemporal approaches to map and monitor glaciers from space based on spectral data, of the kind of information that can be retrieved, and of the information characteristics and accuracy obtained. Specifically, we consider in this chapter:

- image segmentation and classification of mono- and multispectral data for mapping glacier outlines and glacier zones;
- spectral detection of changes in glacier boundaries and zones over time using multitemporal data;
- geometric detection of ice displacements (ice flow) using repeat data.

These three groups of glacier-related information represent, together with the production of glacier topography and the detection of elevation changes over time, the backbone of glacier observation from space. Geometric analysis of stereo data for derivation of digital elevation models (DEMs) is not considered in this chapter (see Chapter 5). Further, the main focus of this chapter is on the visible to short-wave infrared section of the electromagnetic spectrum. Thermal and microwave data are only covered in brief.

In general, spectral remote sensing of glaciers is greatly facilitated by the large difference in snow and ice reflectance from high values in the visible (VIS) and near infrared (NIR) (combined: VNIR) to low values in the short-wave infrared (SWIR) section of the spectrum. This specific feature in the optical spectrum represents the core for most multi-spectral glacier mapping. On the other hand, spectral remote sensing of glaciers is complicated by the fact that
glacier areas other than snow, firn and clean ice can be spectrally very similar to the surrounding of a glacier (e.g. debris-covered ice). In radar images, the backscatter contrast between ice and snow, and other terrain can be small and temporally unstable, so that a corresponding image segmentation is usually not straight forward. Furthermore, a spectrally defined glacier will in many cases not be equivalent to its definition in terms of an ice-dynamical or mass-balance system (e.g. snow patches attached to a glacier, outlet glaciers draining from one single ice cap). Finally, whereas many image analysis methods result in sharp boundaries between different classes, nature may contain gradual transitions that are then not adequately captured in the digital data (e.g. gradual change of debris-cover percentage). These major opportunities and problems characterize most methods and attempts at glacier mapping and monitoring using spectral data.

4.2 Image preprocessing

In most cases, the remotely sensed data used for glacier mapping and monitoring will have to undergo radiometric and geometric pre-processing. Radiometric pre-processing concerns pixel values, while geometric pre-processing concerns pixel locations. Radiometric pre-processing can include corrections for instrumental gain and offset, illumination conditions, as well as atmospheric absorption and scattering. Geometric pre-processing can include geo-location, registration and or re-projection of image geometries.

4.2.1 Radiometric preprocessing

A first step in radiometric preprocessing is the correction of systematic differences and variations in the sensitivity of detectors. In pushbroom imagery, such as ASTER, these sensitivity differences lead in raw imagery to along-track stripes. The necessary radiometric correction coefficients (gain and offset, or higher-order polynomials) are provided with the raw image data (ASTER Level 1A) or already applied (Level 1B and up). Scanning instruments, such as Landsat, may have comparable effects resulting from the cross-track scanning (Crippen, 1989).

Further major steps of radiometric preprocessing are atmospheric correction and correction of topographically-induced illumination variations. These corrections are covered in section 4.3.3 under ‘Calculation of reflectance’. A number of techniques however try to avoid atmospheric and topographic illumination corrections or unwanted atmospheric and topographic effects through the algorithms applied, such as band ratios, normalized differences, or normalizations within image matching that avoid or reduce such effects. It has been shown that in particular in mountains with their complex topographic and atmospheric conditions, errors in according corrections can be substantial and do not necessary improve uncorrected data as a whole (Paul, 2001).

Multi-angular or multitemporal applications may also be affected by the variation of the bidirectional reflectance distribution (Figure 4.1). Such effects are difficult to correct, but can in some cases be avoided by comparing data from similar acquisition positions and under similar illumination conditions (see section 4.7.2).
In addition to the above radiometric preprocessing, the construction of false color composites is useful, in particular for manual glacier delineations or for manually correcting automatic delineations (see 4.3.3).

Figure 4.1  Left: section of an ASTER 3N image over Svalbard, near Longyearbyen. Right: Normalized difference index image between the orthorectified 3N and 3B. Green colours indicate no difference between both images, red and blue indicate differences in digital numbers. Differences are due to reflectance differences under different viewing directions, i.e. effects from the bidirectional reflectance distribution function (BRDF) of the targets. Certain landforms, e.g. glaciers and flood planes, can be especially well distinguished in the difference image, indicating strong BRDF effects for these surface types in the NIR. Topographic distortions and occlusions in the 3B image also contribute to the image differences (e.g. steep north-facing flanks, shadows).

4.2.2 Geometric preprocessing

Here, we do not cover band-to-band or sensor-to-sensor co-registrations, which are usually done at an early processing level of the satellite data. After this, the two most important types of geometric pre-processing are the (i) transformation of the image data to a map projection, and (ii) removal of topographic distortions. Depending on the processing level at which the base data are provided, the image data may come in raw swath geometry, georeferenced (data in raw geometry, but transformation information to map geometry given), or geocoded (transformed to map geometry using a reference surface, usually the ellipsoid). Different data providers usually have slightly different terminologies for their processing levels, or hybrid levels might exist (e.g. ASTER L1B, which is georeferenced, and Earth rotation during overflight is already corrected for).
Removal of topographic distortions is usually done as orthoprojection (or orthorectification), sometimes also as terrain correction applied to swath geometry data. This processing step requires a DEM. The quality of the resulting orthoimages depends on

- the quality of the spacecraft position and attitude information (i.e. of the pointing direction);
- the quality of ground control points (GCPs) in case such are used for defining the image orientation, or for refining the latter as obtained from the sensor pointing data;
- the quality of the DEM used.

It is important to keep in mind the error propagation from vertical DEM errors into horizontal position errors in the resulting orthoimage. For a point with cross-track distance $R$ from the nadir track (orthogonal projection of the satellite path to the ellipsoid), an elevation error $\Delta h$ causes for a flying height above ground $H$ a cross-track offset $\Delta r$:

$$\Delta r = \Delta h \frac{R}{H}$$

For scanners and pushbroom sensors the resulting offset is in cross-track direction. For frame cameras, for instance, $R$ and $\Delta r$ are in radial direction from the image nadir point.

Whereas errors in map transformation can be roughly solved by co-registration of data to a reference data set, errors in the topographic correction cannot be easily corrected due to the usually non-systematic variations of DEM errors over a scene. Stereo sensors such as ASTER offer the possibility to closely examine errors in orthoprojection (Kääb, 2004). Higher-order geometric distortions may exist in the image data (Leprince et al., 2007; Nuth and Kääb, 2011), but will for many applications not be corrected for.

For many glacier mapping applications, a final geolocation accuracy of the orthorectified data of about one pixel will be sufficient, i.e. 30 m for the widely used Landsat TM/ETM data or ASTER when including SWIR bands. Glacier changes to be observed have to exceed this accuracy level roughly, which defines for a given rate in glacier-boundary change the time interval at which those changes can be mapped at a statistically significant level.

For measuring glacier displacements using offset tracking between repeat image data, sometimes a co-registration accuracy higher than one pixel is desirable, in particular for small movements that require sub-pixel precision image-matching (section 4.8).
4.3 Multispectral methods

4.3.1 Spectral response of typical glacial surfaces

The spectral signature of the ground cover determines the possibilities for their spectral separability. Here, we focus on the VNIR and SWIR spectrum (Figure 4.2). Thermal infrared (TIR) and the ground response of microwaves are briefly covered below in sections 4.4. and 4.5.

Schematic reflectance curves as a function of wavelength are given in Figure 4.3.

Snow
Fresh snow diffusely reflects up to 95% of the incoming VIS and about 50–80% of the NIR radiation. In the VIS spectrum, snow reflectance decreases with particulate inclusions (e.g. dust, soot, biota) (Warren and Wiscombe, 1980; Warren, 1982; Hall et al., 1989; Hall et al., 1990; Painter et al., 2001; Takeuchi, 2009; Casey et al., 2012). In the near infrared the corresponding influence of dust contamination decreases, and increasing snow grain size reduces snow reflectance (Painter, 2011). In the shortwave infrared, the reflectance of snow is very low, with a marked dependency on grain size, but a low one on snow contamination (Dozier, 1989; Bourdelles and Fily, 1993). This large contrast between the VIS and SWIR spectral signature is exploited for snow classification (e.g. Rott, 1976; Dozier, 1989). Under else similar emissivity factors, the TIR and passive microwave emission of snow and ice is, in comparison to other materials, limited by the fact that the surface temperature is at or below 0°C.

Ice
As a consequence of the reflectance properties of snow, bare glacier ice has a lower reflectance than snow in the VIS spectrum due to the accumulation of optical active contaminants (Warren and Brandt, 2008). This effect increases towards dirty glacier ice (Qunzhu et al., 1983; Koelemeijer et al., 1993). In the NIR and SWIR, the dependency of reflectance on increasing grain sizes from snow towards ice is effective. In addition, the presence of liquid water on the ice surface might lead to reduced reflectivity in the NIR (Rott, 1976; Paul, 2004). For debris-covered ice, the spectral signature of debris may prevail over the ice signature depending on the percentage of debris-covered surface area within a pixel (Casey et al., 2012). If a glacier pixel is covered with more than about 80 percents of a pixel by debris it cannot be separated from periglacial debris pixels or surrounding bedrock by spectral methods alone.

Rock
Unlike snow and ice, rock or debris-covered surfaces show a significantly different reflectance in the VNIR, SWIR and TIR. This fact usually allows for good spectral separability of such surfaces against clean snow and ice. The highly variable reflectance of different mineral and rock types in the VNIR, SWIR and TIR forms the base for lithology mapping from multi- and hyperspectral imagery (e.g. Clark, 1999; Sabins, 1999; Rowan and Mars, 2003; Volesky et al., 2003; Casey et al., 2012). Knowledge of the geology of a high mountain area supports geomorphological and geomorphodynamical analyses in various ways (e.g. erosion processes) (Casey et al., 2012). There are also direct applications for glaciological investigations. Detecting the spatial distribution and the type of surface debris on glaciers, for instance, allows the
identification of material origin and transport paths (Kääb, 2005b; Casey et al., 2012), and therefore conclusions on present and past dynamics can be drawn.

**Water**

Reflection of open water in the VIS is highly variable depending on its turbidity. In the NIR and SWIR, water strongly absorbs radiation, independent of its turbidity. NIR and SWIR reflection of water is similar to snow and ice which can lead to misclassifications. Inclusion of the VIS is, then, able to separate both categories (Huggel et al., 2002; Paul, 2004). Turbidity and temperature of glacial lakes, important information for their characterization, can be derived from VIS and thermal infrared data (Wessels et al., 2002).

**Vegetation**

Much research on multi- and hyperspectral remote sensing of vegetation is available (Liang, 2004; Jensen, 2007). Vegetation mapping usually takes advantage of high reflectivity in the NIR. In glaciological research, the existence of vegetation itself might be the most interesting result since it potentially points to, for instance, comparably stable surfaces, plant succession or lack of surface abrasion. First-order vegetation mapping may be applied for excluding distinct areas from further analyses or removing misclassifications, although in some rare cases, vegetation is known to grow in soils overlying stagnant glacier ice.

![Figure 4.2](image-url)  
Figure 4.2  Atmospheric transmission, sections of the optical and microwave spectrum, and spectral range of Landsat ETM+, ASTER, and active microwave sensor bands. UV: ultraviolet; VIS: visible; NIR: near infrared; SWIR: short-wave infrared; MIR: middle infrared; TIR: thermal infrared, radar bands.
4.3.2 Principles of classification approaches

The surface signature in the spectral domain is used to describe and distinguish surface types and conditions. Such classifications may be characterized (Schowengerdt, 2007) by terms such as: hard / soft classification, manual / supervised / unsupervised classification, parametric / non-parametric classification, spatial / spectral segmentation, pixel / subpixel classification, and multispectral / hyperspectral classification.

Hard versus soft classification

The result of a hard classification assigns exactly one category to a terrain point, providing sharp boundaries between classes. In soft classification only likelihood values are given for a pixel to belong to certain classes. In glacial environments, both discrete (hard) and fuzzy (soft) transitions exist, thus, suggesting application of both classification types. In nature, the boundaries between, for instance, glacier and rock, or snow and bare soil are in general very sharp, while its detectability in remote sensing depends on the spatial image resolution. The classification goal is, then, to determine the boundary position as accurately as possible. On the other hand, the transitions, for instance, between stagnant ice and moraine, or gradually decreasing vegetation coverage are smooth, so that a change in class likelihood might better reflect the conditions in nature.

The choice of hard versus soft classification strategies depends not only on the natural characteristics of the boundary between two surface categories, but also on the spectral properties and spatial resolution of the sensor applied, and the scale considered. A category transition in nature might be discrete in one part of the spectrum, but fuzzy in another part. If the spatial resolution of a sensor (ground-projected instantaneous field of view, GIFOV) is significantly larger than the spatial variations of a category, a resulting pixel contains a mixed signal of more than one ground category (mixed pixel), independent of whether the category transitions are discrete or fuzzy. Such mixed pixels can be classified hard (e.g. threshold) or soft (e.g. category percentages).
Manual, supervised and unsupervised classification

Manual delineation of categories is done by combination of human interpretation and digitizing. Manual delineation is used for simple classifications, but also for accuracy assessments, ground truth acquisition, or completion or correction of other classifications. Supervised classification is an application-driven method. Training areas of the categories to be mapped are operator-selected in order to develop the spectral signatures of these classes. Separability analysis is applied to test if the selected categories can be distinguished at a statistically significant level from another. Overlapping signatures are separated. The spectral signatures are then used to automatically segment the entire image. During unsupervised classification the image is automatically segmented in concentrations of spectral vectors, with the number of classes assigned selected by the spectral analyst. These clusters of data classes represent artificial categories. Unsupervised classification is, therefore, a data-driven method. The automatic clusters must then be assigned to classes of user-interest. All three classification-strategies may be combined.

Parametric versus non-parametric classification

Parametric classification assumes a certain statistical distribution of a particular class (e.g. mean spectral vector and covariance). The statistical class parameters are estimated from training areas within the image under analysis or inferred from other sources. An individual pixel is assigned to a certain class according to its statistical proximity to the class parameters (e.g. nearest mean, or maximum-likelihood). For non-parametric classification, the class-membership is decided not on statistical parameters but on simple boundaries (e.g. boxes) in the spectral space defined around training data, or on Euclidean distance to training pixels. Artificial neural networks (ANN) are non-parametric classifications where the decision boundaries between the classes are determined iteratively by minimizing an error criterion on the given training data (Jensen, 2005).

Spatial and spectral segmentation

Supervised and unsupervised, parametric and non-parametric classifications primarily rely on the spectral characteristics of individual pixels. Image segmentation can also be done using neighborhood relations of pixels (spatial segmentation). Edge detection or feature extraction algorithms can be used to detect class boundaries. Areas of the same class membership may be aggregated by region growing algorithms where individual pixels are joint according to algebraic rules (e.g. based on spectral characteristics). Some spatial algorithms work also for panchromatic imagery. The spectral and spatial approaches can be combined to spatial-spectral segmentation, for instance, by applying spectral classification to pixel areas aggregated beforehand, by spatially filtering the classification results, or – more advanced – by integrated object-oriented image classifications (Jensen, 2005; Schowengerdt, 2007)

Subpixel classification

Hard classification methods assign each pixel to exactly one category. Quantifying the categories contributing to the spectral signature of a mixed pixel leads to sub-pixel classification. With subpixel accuracy a distinction must be made between spectral sub-pixel resolution (which categories contribute, and how much?) and geometric sub-pixel resolution (where are the categories?). In principle, it can not be resolved from a mixed pixel where the contributing categories are located. Corresponding assumptions might, however, be drawn including the
spatial context of a pixel or external knowledge, for instance, about the typical characteristics of a boundary. Some kind of such geometric sub-pixel precision may be achieved by post-classification editing of class boundaries that were originally determined with pixel-precision. Simple approaches of that type consist of interpolation or smoothing of classification results. For instance, the pixel-wise (i.e. horizontally stepped) classification between glacier ice and adjacent bedrock might be better represented by interpolating a smooth horizontal curve separating both classes. In practice, however, such procedure is often complicated by a number of classification problems, and might require knowledge-based interpolation algorithms; success of the approach depends on the ratio between GIFOV and spatial resolution at which the category boundaries should be mapped, among others.

**Linear unmixing** tries to determine for individual pixels the fraction of idealized pure signatures (endmembers) contributing to its actual spectral composition. The endmember signatures can be derived from extreme pixels assumed to consist only of one endmember class (i.e. pure unmixed) or inferred from other data (Klein and Isacks, 1999; Painter et al., 2003). **Fuzzy set classification** follows the opposite approach to the linear mixing concept by allowing one pixel to be member of multiple categories with a certain probability connected to each membership (Binaghi et al., 1997).

**Combinations and others**

The classification approaches listed here can be applied on *multispectral* data with a small number of comparably broad bands as well as on *hyperspectral* data with a large number of narrow bands. However, some of them are especially suited for hyperspectral data (e.g. linear unmixing), and a number of additional algorithms exist for hyperspectral data (Lillesand and Kieffer, 2000; Schowengerdt, 2007).

Classification approaches can be combined or applied sequentially. Instead of using only spectral data, some classification algorithms also allow inclusion of spectral derivatives (e.g. band ratios instead of bands themselves, or multitemporal data) or non-spectral data (e.g. DEM) (Brown et al., 1998).

### 4.3.3 Image processing techniques for glaciers

Here, we summarize selected classification procedures in the optical spectrum that have already been tested for glaciological applications, in particular mountain glaciers (cf. Sidjak and Wheate, 1999; Paul, 2001; Albert, 2002; Paul et al., 2002).

**Manual delineation**

Manual delineation of panchromatic or multispectral image features might be useful for highly complex classifications where expert-knowledge is needed, for instance, for separating rockglaciers, dead ice, debris-covered ice and periglacial debris from each other. An analyst is able to include experience, knowledge and complex logical rules in the decision process, also relying on non-spectral, i.e. multidimensional data or knowledge. Manual delineation is often needed to complement and correct automatic classifications. (e.g. Rott and Markl, 1989; Hall et al., 1992; Williams et al., 1997; Paul, 2002; Andreassen et al., 2008), but especially for older
panchromatic data like air photos, Hexagon or Corona reconnaissance satellite images (e.g. Bolch et al., 2010b; Narama et al., 2010) and those data without SWIR band (e.g. Landsat MSS, Ikonos, Quickbird, ALOS AVNIR, etc.)

**False color composites**

False color composites (FCC) may take advantage of differences between the spectral signatures of the categories prevailing in the multispectral image (Figure 4.4). For instance, in a Landsat ETM+ 543 RGB-composite (red: channel 5, green: channel 4, blue: channel 3) snow and ice are clearly separated from clouds, debris, rock or vegetation due to the significant step in reflectance for ice and snow between VNIR and SWIR compared to the other materials. FCCs can be used for facilitating manual delineation or for automatic classifications. They work well for clean ice and snow (e.g. Della Ventura et al., 1983; Williams et al., 1991). Instead of FCCs also IHS-transforms or decorrelation stretches might be helpful.

![Figure 4.4 Landsat TM color composites over Tordrillo Mountains, Alaska. Left: TM channels 3-2-1 red-gree-blue true color composite; middle: 432 false color composite; right: 543 false color composite.](image)

**Calculation of reflectance**

Derivation of the ground reflectance at each pixel requires three steps (Bishop et al., 2004):

(1), calculation of the effective planetary reflectance at sensor \( \rho \) from the raw DNs of the image. Calculation of planetary reflectance normalizes the at-sensor radiance \( L_{\text{sensor}} \) for exoatmospheric solar irradiance \( L_{\text{top-of-atmosphere}} \) and depends thus for a given sensor on the solar zenith angle and the Earth-Sun distance at acquisition time \( \rho = \frac{L_{\text{sensor}}}{L_{\text{top-of-atmosphere}}} \). The DNs have to be transformed into radiance at the sensor using the calibration coefficients gain and offset (Markham and Barker, 1985).

(2), atmospheric correction of the reflectance due to aerosol content (Vermote et al., 1997), which improves the correspondence of satellite with in situ measurements.

(3), topographic correction to account for varying illuminations caused by different solar incident angles, slope and aspect effects (Hugli and Frei, 1983; Sandmeier and Itten, 1997).
Comparing the remote-sensing derived reflectance to that obtained from in situ measurements, or to theoretical predictions from spectral signatures, allows to some extent for surface interpretation from the corrected image. This approach has been used mostly to characterize snow and ice facies, or their albedo, respectively (Hall et al., 1988; Gratton et al., 1990; Hall et al., 1990; Gratton et al., 1993; Koelemeijer et al., 1993; Winther, 1993; Knap et al., 1999; Paul, 2001, 2004; Casey et al., 2012).

**Spectral transforms**

*Intensity-hue-saturation transformation (IHS):* For visual interpretation and further classification or processing, a transformation of RGB images (i.e. three-band imagery) into another color space might be useful (Figure 4.5). The most often applied color space in that context is the IHS color space. The IHS components of a RGB image are, for instance, obtained from geometric projections of a color vector in the RGB space (Schowengerdt, 2007). The IHS components of an image might be manipulated (e.g. replacement of intensity component by a higher resolution I component, or stretching) and then inversely transformed to the RGB space. Also, the components I, H or S might be used in a classification individually (Paul, 2004).

*Principle component transformation (PC):* Multispectral image bands are often highly correlated due to the spectral similarity of the material within an entire wavelength range, due to topographic effects (e.g. shading) and due to the spectral resolution of the applied sensor. Principle component transformation (PCT) aims at transforming the original image linearly to minimise the inter-band correlation (Richards, 1993; Schowengerdt, 2007):

By reducing the spectral image redundancy, PCs are able to facilitate classification from visual inspection or other automatic approaches (Sidjak and Wheate, 1999). Direct assignment of PCT-results to classes of glaciological interest is, however, difficult (Paul, 2004) (Figure 4.6). PCs can be useful for ice displacement measurements based on offset tracking in order to optimally exploit all intensity variations contained in a multispectral data set (Ahn and Howat, 2011)(section 4.8). A disadvantage of this method is that the result varies with the spectral classes present in an image.

*Decorrelation stretching* is an application of the PC or IHS transforms to reduce correlated and, thus, redundant information of multispectral imagery (Gillespie et al., 1986; Schowengerdt, 2007). It allows for better visual exploitation of multispectral imagery and, thus, aids manual delineation, and preparation and selection of further classification methods (Figure 4.9). For decorrelation stretching the multispectral bands are PC transformed. The respective PCs are then stretched to optimally fill the color-space, and transformed into the RGB color space (Figure 4.7). Decorrelation stretches are, for instance, available as ASTER Level 2 products.
Figure 4.5  IHS transform of the Landsat TM 321 composite of Figure 4.4. Left: intensity (brightness), middle: hue (color), right: saturation (amount of white).

Figure 4.6  The first three principle components (PC1, PC2, PC3, from left to right) of the Landsat scene of Figure 4.4. All VIS, NIR and SWIR bands included in the transform.
Figure 4.7  Decorrelation stretch of the Landsat scene of Figure 4.6, computed as the histogram stretch of the PC1-PC2-PC3 red-green-blue composite.

Image algebra and segmentation
Different algebraic algorithms may be applied on spectral bands, among which band ratios \( R_{ij} = \frac{DN_i}{DN_j} \), or
\[
R_{ij} = \frac{(DN_i - DN_{\text{min}(i)})}{(DN_j - DN_{\text{min}(j)})},
\]
and normalized differences indices (NDI, or modulation ratios) are the most widespread (Schowengerdt, 2007)
\[
NDI_{ij} = \frac{R_{ij} - 1}{R_{ij} + 1} = \frac{(DN_i - DN_j)}{(DN_i + DN_j)},
\]
where
\( DN_i \) and \( DN_j \) are digital numbers of two bands \( i \) and \( j \) that show high separability for the category to be classified with respect to other categories in the image, and
\( DN_{\text{min}} \) are the minimum (i.e. darkest) DNs of an individual band.

For band ratios, subtraction of the minimum DN for each band applied reduces the illumination effects from atmospheric scattering (Crippen, 1988). Similarly, the results of normalized differences might be improved by subtraction of the band-specific minimum DNs. For ice and snow, usually bands in the VNIR and bands in the SWIR are used in the index (e.g. TM 2,3 or 4 versus TM 5 Bayr et al., 1994; Rott, 1994; Jacobs et al., 1997; Paul, 2001, 2002; Paul et al., 2002; , or ASTER 3 versus ASTER 4 Kääb et al., 2003a; Paul, 2004; Bolch and Kamp, 2006).

The normalized difference snow index (NDSI) is defined as (green–SWIR)/(green+SWIR) (Dozier, 1989; Hall et al., 1995a; Sidjak and Wheate, 1999). Water can be detected by the normalized difference water index (NDWI: (NIR–blue)/(NIR+blue), Huggel, 1998; Kääb et al., 2000a; Kääb et al., 2000b; Huggel et al., 2002), similar to the well-established NDVI for vegetation (e.g. (NIR-red)/(NIR+red), Hardy and Burgan, 1999). Classification of water or vegetation might be useful for eliminating misclassifications from the above band ratios for ice and snow (Paul et al., 2002; Bolch and Kamp, 2006). Band ratios and NDIs partly eliminate atmospheric and topographic influences that affect both bands applied in a similar way (e.g. Holben and Justice, 1981). For final segmentation or classification of the ratio or normalized difference image, thresholds have to be chosen. Image algebra and segmentation algorithms are especially robust (Paul, 2001). To gain better control on the results further terms might be added, possibly including additional bands.
Currently VIS/SWIR or NIR/SWIR band ratios are among the most often and most operationally used methods for mapping clean ice areas. A threshold on a visible channel is typically added to improve the algorithm performance in cast shadow. The ratio VIS/SWIR misclassifies dark shadow as glacier ice when using images with uncorrected path radiance. This can, however, be removed with a threshold in the blue band (e.g. TM1). When little glacier ice is present in the a scene the NIR/SWIR ratio is preferable (Paul and Kääb, 2005). A typical, ratio-based glacier mask might therefore be:

$$\frac{DN_{\text{VNIR}}}{DN_{\text{SWIR}}} > k \quad \text{AND} \quad DN_{\text{VIS}} > l$$

where

- $DN_{\text{VNIR}}$ are the digital numbers in visible or near-infrared channels, usually red or near-infrared (e.g. TM3 or TM4, or AST2 or AST3; the choice of red or near-infrared depends on the scene conditions);
- $DN_{\text{SWIR}}$ are the digital numbers in a short-wave infrared channel (e.g. TM5 or AST4);
- $k$ is the threshold applied to the ratio in order to obtain a binary glacier mask; typical values for $k$ are on the order of 1.5-2.5, but may be even smaller or bigger and depend much on the individual scene and imaging conditions;
- $l$ is the threshold on a short-wave visible channel ($DN_{\text{VIS}}$; e.g. TM1), with values that have to be adjusted to the actual scene and illumination conditions (Paul and Andreassen, 2009). Instead of $DN_{\text{VIS}}$ the intensity value of a IHS transform can be used (Paul, 2004).

**Unsupervised classification**

Unsupervised classifications tend to be successful for relatively homogeneous terrain with few categories (e.g. clean-ice glaciers), whereas problems occur often for variable terrain with many classes (e.g. clean ice, dirty ice, debris-covered ice, or clean ice in cast shadow, Paul, 2001, 2004). The unsupervised categories have to be assigned to classes of user-interest, which leaves the major classification problems for terrain with low separability (e.g. the above ice types) still to the analyst. Unsupervised ISODATA classification was applied by Aniya (1996) for glacier inventorying of the Southern Patagonia Icefield using Landsat TM bands 1, 4 and 5.

**Supervised classification**

Supervised classification (e.g. maximum-likelihood, spectral angle mapper) works often accurately for high mountain terrain with reasonable spectral separability. As for all spectral classifications, debris-covered ice mapping remains challenging. Best results with supervised classification can be achieved by including VIS, SWIR and TIR spectral bands as well as derivatives such as band ratios, principle components or normalized differences, or TIR derived silica weight percent (e.g. Bronge and Bronge, 1999; Sidjak and Wheate, 1999; Casey et al., 2012). The choice of training areas is especially crucial for inhomogeneous terrain as often found in alpine environments. Usually, the spectral class signatures trained from one scene cannot be applied for other scenes, which reduces the automation capability or requires radiometric adjustments. Further studies on supervised classification of mountain glaciers have been performed by (Gratton et al., 1990; Binaghi et al., 1993; Paul, 2001, 2004). Klein and Isacks

**Artificial Neural Networks (ANN)**

In ANN classification the decision boundaries are not fixed in a deterministic way from training signatures, but obtained in an iterative fashion by minimizing an error criterion on the labelling of the training data (Schowengerdt, 2007). ANN classification is not restricted to spectral data. Other input data, such as spatial relations of pixels, multitemporal data, DEMs or DEM derivatives can be used. For glacial and paraglacial terrain, ANN classifications from data of a single domain (spectral or DEM) have been tested (Brown et al., 1998; Bishop et al., 1999; Paul et al., 2004). The main potential of ANN application in glaciology might, however, lie in the integration of multidimensional data (Paul et al., 2004).

**Combinations**

Often, classification procedures can (or must) be combined either by fusing different approaches or by performing them sequentially. As mentioned for the supervised classification, spectral derivatives or results of other pre-processing classifications may be combined as input layers. Sidjak and Wheate (1999), for instance, achieved good results for glacier mapping from a supervised maximum-likelihood classification using the PCs 2–4 of TM bands 1–7, a TM4/TM5 band ratio, and the NDSI. The most often used chain of sequential classification approaches is to complete and correct automatic classifications manually. Such procedure is, for instance, so far unavoidable for mapping debris-covered ice. Band ratios for glacier mapping, for instance, may result in misclassifications for vegetation in shadow and turbid water, which in turn may be eliminated by applying a NDVI and NDWI (Paul, 2004; Bolch and Kamp, 2006).

**4.3.4 Post-processing and embedding in a GIS workflow**

Spatial-domain filters may follow automatic segmentations and classifications. For instance, a median filter on raw band ratio results is recommended (Paul et al., 2002). The filtered segmentation results, still in raster format, are then converted to vector data. A number of manual, semiautomatic or automatic steps has to follow in order to obtain glacier outlines from a clean ice/snow mask (Kääb et al., 2002; Paul et al., 2002):

- Separation of contiguous ice/snow areas into glaciers. For that step the preparation of glacier basin masks was proposed (Paul et al., 2002). This step can be automated to a high degree based on hydrological modeling using a DEM (Schiefer et al., 2008; Bolch et al., 2010a).

- Correction of the outlines for debris-covered ice, lakes (see above), and other misclassifications

- In case of repeat glacier inventorying, existing outlines can significantly facilitate the latter step (Bolch et al., 2010a)
Possibly, intersection of the glacier outlines with a DEM in order to derive topographic glacier parameters (Paul et al., 2009).

Possibly, generation of central flow lines and intersection with the glacier outlines in order to later derive glacier parameters related to this flow line (e.g. length) (Paul et al., 2002)

4.4 Mapping of debris-covered ice

Mapping of debris-covered glacier parts constitutes one of the, if not the major bottleneck of spectrally-based global-scale mapping of glacier areas. Before summarizing a number of attempts to this problem, we would like to recall that, first, debris-covered glacier parts cannot be sharply mapped in many cases even in principle, and that, second, debris-covered glacier parts should be treated separately from clean-ice glacier parts in climate related glacier analysis, due to the insulating properties of debris cover.

First, the transition from a debris-covered glacier part to debris-covered stagnant ice or to ice-cored moraines is ever-changing and often not sharp in nature. Possible definitions of this transition might involve

- **ice content**: A definition of the glacier boundary under debris might be deduced from the percentage ice content at depth and its characteristics. The determination of intra- and sub-debris ice is often the domain for in-situ geophysical surveys. Sub-surface ice content is not strictly visible at the surface, but might have an effect accessible at surface such as a thermal signal, distinct topography, or be detectable in repeat images;

- **ice ablation rates**: The amount of ice ablation might define the glacier boundary (Whalley, 1979; Haeberli and Epifani, 1986; Kääb et al., 1997). This ablation rate is not necessarily related to the ice content, e.g. it is zero for an ice-cored moraine under permafrost conditions where the supraglacial debris thickness exceeds the local active layer thickness; thermokarst features and related topography are one expression of these ablation rates;

- **kinematics** of the debris-mantled ice body and its *dynamic connection* to the main glacier. A deformation threshold would have to be set, which also implies the measurement precision of the method used.

The above three basic factors might either be directly observed, or only their, perhaps combined, expression at the surface, e.g. through topography, debris lithology, or velocity as detected in repeat imagery.

Second, debris-covered glacier parts should be treated separately from clean-ice glacier parts because of their potentially very different reaction to atmospheric forcing (Scherler et al., 2011). Very thin debris-cover (< a few cm; Østrem, 1959; Fukjii, 1977; Nakawo and Young, 1982; Mattson et al., 1993; Rana et al., 1997; Adhikary et al., 2000; Kayastha et al., 2000; Nicholson
and Benn, 2006)) increases ablation rates, whereas thicker debris-cover reduces ablation rates. Where, however, glacier surface roughness increases and supraglacial ponds develop as a consequence of the differential melt pattern and thermokarst processes induced by the debris-cover, the area-averaged ablation rates might well be again on the order of clean ice or perhaps even higher (Sakai et al., 2000; Bolch et al., 2011).

So far, attempts to map debris-covered glacier parts are based on topographic information, spectral information, combinations of both, and radar interferometry (Shukla et al., 2010).

Due to glacial transport, supraglacial debris often has sources different from the rock and sediments that are directly adjacent to a given position of supraglacial debris. In some cases, the spectrally characterized lithological variations may therefore exhibit differences between glacially transported or transformed debris and rock/debris from adjacent valley flanks (Kääb, 2005b; Casey et al., 2012). In by far most cases, however, VNIR and SWIR based spectral classification alone will not be sufficient to map debris-covered glacier sections. The idea that the thermal signal of debris and debris on ice could be different led to attempts to exploit TIR bands (see section 4.5).

A number of studies tried to map debris-covered ice from geomorphometric parameters and analysis, e.g. looking at distinct curvature changes at the glacier margin, DEM-based flow-paths, or combining a number of DEM-derived parameters (Bishop et al., 2001; Bolch and Kamp, 2006). Further studies combined above information types (VNIR/SWIR or TIR + geomorphometric parameters) (Paul et al., 2004). Other studies combined both VNIR and SWIR, TIR and geomorphometric parameters (Bolch et al., 2007; Shukla et al., 2010; Bhambri et al., 2011).

Another approach to mapping supraglacial debris is to compare elevation models of different times and view elevation change over time as an indicator for ice ablation or ice-dynamic processes (Kääb, 2005b). As yet, this approach is often hindered by the lack of available DEMs with sufficient resolution and accuracy.

Ice kinematics can be directly measured using image matching methods (see section below) or radar interferometry, thus potentially mapping the landscape units belonging to a, dynamically defined, glacier system (Kääb, 2005b, a; Bolch et al., 2008). In an extension of this idea, the loss of radar phase coherence over time indicates tiny ground movements and may surprisingly clear depict the dynamic boundaries of a glacier. This approach seems especially successful for L-band radar data with comparably robust phase coherence for the terrain surrounding the glaciers (Atwood et al., 2010; Strozzi et al., 2010) (Figure 4.8).

All above approaches proved to give useful results for particular regions and base data, but show also clear deficiencies when transferred to other regions, either for reasons of data availability or because of different glacier characteristics.

Manual digitizing of debris-covered glacier parts, thus so far still the most often used methods for delineating debris-covered parts of glaciers, combines, depending on the operator and the available data, a number of the above characteristics of glacier debris-cover, e.g. spectral, geometric and topographic ones.
4.5 Thermal imaging

So far the thermal infrared spectrum is little exploited for investigating mountain glaciers (Figure 4.8). Under incoming direct shortwave radiation, debris generally has stronger thermal emission than ice due to its higher temperatures, leading to a strong signal in the TIR bands (Warren and Brandt, 2008). It is presently under investigation, to what extent TIR data can be used to detect glacier ice under loose or thin debris-cover from respective cooling of the superimposed debris (Taschner and Ranzi, 2002; Kääb, 2005b; Mihalcea et al., 2008; Shukla et al., 2010; Casey et al., 2012), (cf. Lougeay, 1974, 1982). Figure 4.9 shows an example on how the inclusion of TIR in image interpretation and classification supports mapping of the geological composition of the surface. Taschner and Ranzi (2002) show that differences in thermal infrared emission exist between a debris-covered glacier and its surrounding, and how these differences can facilitate glacier outline delineation. Shukla et al. (2010) and Bhamibi et al. (2011) combine TIR data with other spectral data and geomorphometric information for mapping debris-covered ice. In general, mapping debris-covered ice from thermal data has the shortcoming that the recorded thermal emission on such a surface is not strictly dependent on the ice underneath, but rather on a number
of factors contributing to the energy balance such as roughness, incoming shortwave radiation (see following paragraph), thermals emissivity of the surface layer, meteorological conditions, etc. Kääb (2005b), and in more detail Casey et al. (2012), explore lithological variations on supraglacial debris through TIR data, and how these results can be exploited glaciologically. TIR based silica percent mapping may be used to indicate weathering and active turnover of glacier debris (Casey et al., 2012). One disadvantage of TIR methods is TIR’s typically coarse spatial resolution compared to VNIR and SWIR bands (ASTER: 90m, Landsat ETM: 60m).

During daytime, the longwave radiation emitted from the terrain surface is to a large extent dependant on the shortwave incoming radiation (e.g. Mittaz et al., 2000; Hoelzle et al., 2001). Therefore, nocturnal or early morning TIR imagery might potentially better indicate the thermal differences of the ground material (Figure 4.8).

TIR data has also been used to map thermal resistance of debris cover (Suzuki et al., 2007).

In large-scale applications, low-resolution TIR data with high revisit times (in particular MODIS) are operationally used for mapping the melt extent and its temporal variations over large ice bodies (e.g. Greenland) (e.g. Hall et al., 2006).

Figure 4.9  Thermal infrared images over Tordrillo Mountains, Alaska, during the same day. Left: daytime TIR from Landsat ETM, right: nighttime TIR from ASTER. During day (left), longwave emission is modulated by topography due to incoming shortwave radiation. This effect is largely reduced in the nighttime image (right) in which elevation-dependency of longwave emission is more pronounced in addition to the emission contrasts due to surface type. The difference between both data sets is also related to the ground thermal inertia.
4.6 Microwave/SAR methods

Active microwave radar methods, where a beam of electromagnetic radiation is transmitted at an oblique angle to the ground and the returned beam is captured and analyzed, can be used for glacier mapping as well. In the microwave spectrum, the ground response is a function of the applied wavelength, polarisation, incidence angle, ground roughness, microwave penetration (volume scattering) and the complex dielectric constant of the surface (Lillesand and Kieffer, 2000). The latter describes the reflectivity and conductivity of the terrain material. The reflectivity depends among other influences on the surface roughness in relation to the applied wavelength and volume scattering. While centimeter-scale roughness appears rough for K-band ($\lambda \approx 2\text{cm}$) (i.e., large fraction of diffuse reflection), it appears smooth in the L-band ($\lambda \approx 20\text{ cm}$) (i.e., large fraction of specular reflection). The material conductivity in the microwave spectrum is mainly dependent on the liquid water content. A cold and dry snow pack may be invisible for microwaves so that the main reflection happens at the underlying material, whereas the penetration into wet firn or ice is very small and surface reflectivity is high (Marshall et al., 1995; Kelley et al., 1997; Engeset, 1999; Nagler and Rott, 2000; Zahnén et al., 2003; Warren and Brandt, 2008). Small mountain lakes often represent a relatively smooth surface, thus, leading to specular reflection and a dark signature in the SAR image (Pietroniro and Leconte, 2000). Polarisation of the emitted and received radar signal (H: horizontal, V: vertical) is also able to add to the separability of different categories in the SAR image, because different geometric
properties of scatterers on and within the snow, firn and ice pack may lead to either preservation, 90\degree change or diffusion (de-polarisation) of polarized incoming radar waves with respect to the backscattered ones (Figure 4.11, Figure 4.12).

**Figure 4.11** Color composite of HH (sent H, received H) and HV channels (sent H, received V) of an ALOS PALSAR winter scene over Kronebreen, Ny Ålesund, Salbard. HH: yellow, HV: blue. Color differences in the composite occur due to changes in the degree to which surface or near surface backscattering mechanisms change the polarization of the incoming radar signal. Dominant co-polarization (here: HH) points to corner reflection and ice lenses or layers, dominant cross-polarization (here: HV) points to volume scattering, e.g. in the homogenous ice. North to the top.
Figure 4.12  Color composite of a fully polarized ALOS PALSAR winter scene over Ny Ålesund, Svalbard (Kronebreen to the lower right). North approx. to the right.
Figure 4.13 Envisat ASAR backscatter over Ny Ålesund/Kronebreen, Svalbard. Upper right: 13 June 2008, middle left: 29 February 2008, middle right: 26 September 2008. The February data are taken after a cold and snowy period (lower panel), the June data after a period of slightly positive temperature with little precipitation, and the September data after a period of strong rainfall. Whereas glacier delineation is difficult on single dates due to the different
ground conditions, glacier edges become better visible in the multitemporal false color composite of all the scenes (upper left). Lower panel: blue bars: precipitation, red line: air temperature in Ny Ålesund (data from met.no). North to the top.

The penetration of radar waves into the snow, firn and ice pack, though unwanted for a number of applications, may also be exploited, e.g. for the detection and mapping of crevasses covered by snow (Figure 4.13).

Radar interferometry (interferometric synthetic aperture radar, or InSAR) for extraction of DEMs is not covered in this chapter, but differential radar interferometry (DInSAR) for measurement of glacier flow is briefly discussed in section 4.8.

Optical and microwave data for glacier remote sensing are in a number of aspects complementary, so that their combination might offer new insights and approaches. These topics are treated in the final section.

Figure 4.14  ALOS PALSAR winter backscatter data over Kronebreen, Ny Ålesund, Svalbard. Upper image (PALSAR scene, cf. Figure 4.10), lower left: section of the same scene, lower right: summer ASTER VNIR data over the same section as the lower left panel. Even through
snow cover, crevasse zones (visible in the summer ASTER data) become clearly detectable as high backscatter in the radar images.

4.7 Spectral change detection; multitemporal data merging

4.7.1 Overview

We term merging of either spectral or spatial domain data of different acquisition times as multitemporal data merging. Two important multitemporal merging methods are: measurement of elevation changes (Chapter 5) and terrain displacements (section 4.8). Merging of these two categories of multitemporal geometry data allows for understanding and modelling of glacier dynamics. Vertical changes and horizontal displacements are quantitatively combined with the kinematic boundary condition at the surface (e.g. Kääb et al., 1998; Gudmundsson and Bauder, 1999; Kääb and Funk, 1999; Kääb, 2001).

A basic multitemporal merging in the spectral domain consists in the overlay of repeated image data, most often applied for digital change detection (Singh, 1989; Mouat et al., 1993; Lillesand and Kieffer, 2000). Change detection techniques include:

- postclassification comparison,
- multitemporal classification,
- multitemporal principal component analysis,
- multitemporal false colour composites,
- algebraic expressions,
- change vector analysis, and
- change axis analysis.

Although mainly designed for application in the spectral domain, some of the above strategies can also be applied for other data types.

Common spectral (and also non-spectral) classification procedures may be applied separately on data sets of different times, and the classification results compared thereafter (postclassification comparison). For instance, glacier-covered areas can be detected by multispectral classification from a satellite image of time 1, and again from a satellite image of time 2. By simple algebraic expressions the areas of glacier change can be extracted and quantified.

Instead of comparing results after the classification, terrain change may also be detected by merging the multitemporal data within one classification procedure by defining change classes and non-change classes (multitemporal classification).

The individual bands (or layers) of multitemporal data may be combined into one new multilayer data set (Fujimura and Kiyasu, 1999). Principal component analysis of this new data set may
then enable to detect changed terrain parts as little correlated components of the multilayer data set. Such an approach is of special use when change has to be extracted from a large number of data (Marshall et al., 1995).

**Multitemporal false colour composites (FCCs)** represent a powerful tool for visualising change between two or three images (Figure 4.13, Figure 4.15, Figure 4.17). Such FCCs might directly form the basis for mapping, or serve as preparation and evaluation of other change detection algorithms. The number of data acquisition dates included in a multitemporal FCC is restricted to three unless PCA is used beforehand to extract the most dominant changes from the data stack. Multitemporal FCCs may also be used to visualize and investigate results of other change detection techniques. (See separate section 4.7.2)

**Algebraic expressions** such as subtraction, ratios or normalized difference indexes between two or more multitemporal data sets or derivatives of them are often used for change detection (Figure 4.16, Figure 4.17). Detecting elevation differences from repeated DEMs is a simple example for temporal data subtraction. Spectral differences between repeated imagery indicate terrain changes, but are also affected by different illumination and atmospheric conditions. Under some circumstances, ratios of multitemporal imagery tend to normalise for some effects such as cast shadow (cf. Crippen, 1988). Figure 4.16 shows an example for detecting glacier movement from repeated ASTER imagery from a multitemporal band ratio. Thereby, change was detected from the displacement of individual terrain features such as crevasses (*spatial change*). Change may also be detected from the general change in spectral signature, for instance when an area becomes ice-free due to glacier retreat (*spectral change*) (Paul et al., 2004).

The above change detection approaches may be applied on the raw image data, but also on corrected (e.g. for illumination and atmosphere), or further transformed or processed products (e.g. orthoimagery, filter products, PCs). Application of change detection algorithms can also be restricted to certain areas masked by some previous classification (Lillesand and Kieffer, 2000).

For a given pixel of a multispectral image or multilayer data set, two or more (spectral) variables can be plotted against each other for individual acquisition dates. A *change vector* connects the resulting points in the chosen variable space. The magnitude and direction of this vector (or vector cluster for a group of pixels) may be characteristic for a certain type of change, for instance plant succession in glacier forefields, development of the snow pack or glacier retreat. (Lillesand and Kieffer, 2000).

A two- (or more-) dimensional scatter plot of a spectral band at time 1 versus the same band at time 2 approximates the plot diagonal in case of no changes between the two acquisition dates. For significantly changed pixels the respective plot points lie apart from this diagonal, forming typical clusters for individual change types. *Change axis analysis* defines a non-change axis (the above diagonal, or a parallel or slightly rotated axis) and perpendicular change axes. Threshold coordinates in the change-axes space are then used to classify individual changed, or non-changed, respectively, pixels (Lillesand and Kieffer, 2000). The method is also sensitive to changes that the detection does not aim at, such as changes in shadow.

For all change detection approaches, accurate uniform geometry for the repeated data sets is crucial. Such techniques are, thus, usually applied using imagery of the same sensor and same
sensor position (e.g. repeat tracks) or orthoimages. Location differences between the compared data sets might influence the change detection procedures heavily (Figure 4.16). Similarly, illumination differences due to different sun positions may create significant apparent changes (Figure 4.15, Figure 4.17).

**Figure 4.15** Deposits of the 20 September 2002 rock/ice-avalanche at Karmadon, North Ossetian Caucasus. Change detection is done by a multitemporal RGB-composite. R: ASTER band 3 of 22 July 2001; G and B: ASTER band 3 of 13 October 2002. Avalanche track and deposits, as well as lakes dammed by the deposits become well visible. Red-colored changes in northern slopes are due to different shadow/illumination conditions between the acquisition dates.

**Figure 4.16** Normalized difference index image (right panel) of two ASTER images over a glacier in Bhutan (20 January and 20 November 2001; left panel). Largest differences (black and white colors) occur at crevasses due to their movement from left to right (black-and-white pattern) and at the retreating calving front of the glacier. Differences at the lateral
moraines point to errors in the orthorectification, presumably from DEM errors (SRTM) propagating into horizontal orthoprojection errors.

Figure 4.17  Left: section of a RGB normalized difference index (NDI) of two Landsat scenes (22 Sep 1992 and 31 Oct 2009). R: NDI of bands 5, G: NDI of bands 4, B: NDI of bands 2. Right: section of the 2009 scene. The different dates of the year (> 1 month difference) lead to illumination differences that become visible as apparent change (cf. section 4.7.2). Glacier retreat, e.g. becomes visible as red colors. The white ring around the lake in the middle (lake Sabai) reflects the reduction in lake area from the lake outburst on 3 Sep 1998.

4.7.2 Image Change Evaluation by Subtraction of Multispectral Anniversary Pairs (ICESMAP)

Many chapters in this book show the results of change detection and landcover characterization using multispectral images. Image differencing is a general processing technique developed to identify uncorrelated zones within multitemporal image sets (Singh, 1989; Jensen, 2005), that is, where surface changes have occurred during the time between image pair acquisitions. This per-pixel image algebraic method simply involves subtraction of one digital image from another to produce a third difference (or change) image. This can be expressed as,

\[ D_{x_{ki}} = D_{x_{ki}(t_2)} - D_{x_{ki}(t_1)} + C \]
where \( x \) = pixel value for sensor band \( k \); \( i \) and \( j \) are image line and column values respectively, \( t_2 \) refers to the later image; \( t_1 \) refers to the earlier image; and \( C \) is a constant for rescaling to unsigned 8-bit image values (although radiometric bit depths may vary dependent upon sensor characteristics). For multispectral imagery, the image spectral bands, \( k \), will vary by choice of the user, but for our work with ASTER imagery \( k \) includes the three VNIR bands (band3-NIR, band2-red, band1-green) composited into RGB color space. Adequate change detection by image differencing can be extremely challenging to do quantitatively if the images were acquired under different illumination or sensor view conditions. Widely disparate shadowing and complex scattering phase functions can be the most difficult or impossible challenges to remedy (Figure 4.17).

Here we provide background to one method, **Image Change Evaluation by Subtraction of Multispectral Anniversary Pairs** (ICESMAP), which was developed for GLIMS by the University of Arizona group (J.S. Kargel and G. Leonard) in order to circumvent the need for complex radiometric and geometric transformations of images over rugged surfaces. For this book, ICESMAP has been applied to glaciers in the Chugach Mountains, Alaska (chapters XX & XX); Hoodoo Mountain, British Columbia (chapter XX); Mount Rainier, Cascades (chapter XX); the Mount Everest, Himalaya area (chapter XX); and the Mount Cook area, New Zealand (chapter XX). This section is the first detailed presentation of the methodology. However, the first published application of the ICESMAP methodology was for an image pair acquired over Central East Greenland (Kargel et al., 2012).

Alpine glaciers and adjacent terrains typically undergo satellite-discernible surface changes due to weather events, discrete geomorphological events, and seasonal and interannual fluctuations. Some of these changes integrate effects of climate changes, ice motion, phase state, and mass movements on glacier surfaces. Notable changes seen in differenced anniversary image pairs may reveal changes in glacier extent and texture/microrelief; surface patterns and area density of crevasses, debris, meltwater ponds and streams; snow distribution, and grain size of snow, firn, and ice; melting or freezing of wet snow; snow and rock avalanches; and changes in vegetation types and density on debris covered glaciers, moraines, and beds of drained glacier lakes. All of these material or topographic changes may potentially be resolved spatially, spectrally, and/or radiometrically, which is the core premise of image change detection: that surface variations result in changes in radiance intensities which are larger in magnitude with respect to radiance changes resultant from other sources unrelated to changes in the surface (Ingram et al., 1981).

Other sources in this case refer to relative changes in image-pair radiometry due primarily to changes with little relation to surface changes. These may include variable view geometry and scattering phase function of the surface; different sensor gains, shifting solar position in the sky related to time of year and day, and differing atmospheric attenuation conditions related to humidity and temperature, optically thin condensation clouds, and dust (Jensen, 1983). The minimization or removal of these extraneous effects is required to see and quantify actual surface changes; the approach of ICESMAP is simply to minimize these effects rather than correct for them, noting that in practice, it is very difficult and often impossible to make an accurate correction for all these variables. The problem with corrective approaches is that usually not enough is known, or uncertainties are too great, to allow quantitative correction and isolation of effects of actual changes. The ICESMAP solution is simple control of non-surface changes so
that there is little or nothing to correct. If the sun is in the same position in the sky and the sensor view of the surface remains the same, then there is no need to correct differences in solar angle and differential effects of shadowing and hillshading, differential pathlength of photons through the atmosphere, differential sensor gains, scattering phase functions, and so on. With these factors controlled, it is better than having to correct for them. The limitation, of course, is that images must be acquired on or near anniversary dates (or, as we explain below, otherwise have the sun in the same place in the sky) with the same sensor and with the same view of the surface. The trick is proper selection of adequate image pairs, which commonly but do not always exist for a given area.

In some cases, *single band* image differencing may be sufficient to indicate where surface changes have occurred, for example using either visible or NIR bands to identify surface brightness and vegetation changes respectively. In this method, threshold DN values within the difference image histogram are selected by the user to highlight areas of significant change (e.g. statistically selected ‘area-change’ values: $\geq 2\sigma$ or $\leq -2\sigma$). Note in this example that areas of change are represented within the tails of the histogram; whereas values clustering on or near the mean of the difference image histogram represent areas of little to no change. Whilst slightly more complex, the differencing of *multispectral* image pairs can lead to a richer portrayal of user-identifiable change features. This is true since multispectral data can better capture the unique compositional information contained within the variable surface spectral responses detected by the different channels of the sensor. The resultant change image may subsequently contain information related to changing surface material compositions and their distributions. The resulting difference image then requires post-differencing classification or coding of the surface changes by an expert familiar with the terrain. Compared to single-band differencing analysis, often based on thresholding, it may also be more complicated to segment specific features of change in multiband differencing, and it may be necessary to identify what combination of image bands are responsible for indicating a particular surface change before additional thresholds or band ratios are applied. The interpretation can be but is not always intuitive; if one image or both images contain saturated bands (where the upper range of recorded radiance is limited by gains sensitivity), then the colors represented in the change image may look dramatic but in fact can become difficult or impossible to interpret. This potential problem underscores the importance of applying images that have been acquired with optimal GLIMS gain settings (i.e., gain settings set to maximize optimal image quality for the glaciers and features of interest for the particular area of study), or ignoring or very carefully dealing with areas of the difference image where image saturation is problematic.

Principle factors affecting image quality needed for image differencing include atmospheric conditions, cloud cover, sensor gain settings, and sun-target-sensor viewing geometry. For some purposes, such as multitemporal mapping of the calving front extent of a glacier, there is little preprocessing one must do to an image series except to assure proper image coregistration. In many other cases, such as the mapping of more subtle landcover units or seeking to identify a wide range of changing landcover / land use phenomena between images, it becomes necessary to correct for various parameters of the changing observing geometry within the image pair including sensor-solar azimuth angle and solar zenith angle, scattering phase functions, atmospheric absorptions, differing sensor gain settings, and inter-instrument calibrations. This can be done, but is sometimes a complex process that may ultimately prove futile if the images
were acquired under conditions that are too disparate from one another. Subsequently, isolation of seasonal versus interannual, versus long-term trends can be difficult. Therefore, for purposes of assessment of interannual and long-term glaciological trends, change assessment is ideally done with images acquired by the same imaging system in sun-synchronous orbits, using the same instrument settings (e.g. gain) and viewing geometry, and acquired on (or near) anniversary dates, and with the same atmospheric conditions. For these conditions, the solar-sensor azimuth and solar zenith angle parameters are nearly identical; consequently observing geometry and scene illumination are the same. If atmospheric conditions also are similar and ground features are unchanged, then the same spectral reflectance image will be recorded, because illumination, viewing, absorption, and scattering functions are the same. Furthermore, if the instrument drift is known and corrected, then if one image is subtracted from the other, a black field will be obtained (zero difference). Normally, of course, this is not the case as surfaces are changing, and we are interested in these actual surface changes. In short, near-anniversary date image pairs better insure that spurious signals and artifacts, potentially resultant from differing diurnal and seasonal sun angle effects, and seasonal vegetation phenological differences are minimized.

For the current generation of orbiting Earth observing sensors, exact anniversary dates are rarely acquired, but images acquired within a few days of the first image acquisition anniversary are fairly common for more frequently imaged areas of Earth. Importantly, image pairs should be selected for the season and or annual date(s) that may optimally capture the changing phenomena of interest to the user. For satellite glacier studies, this may include images acquired at the end of the regional ablation season. Secondly yet also importantly, seasonality is important for image date selections. Winter images may be relatively darker, contain significant shadowing, and be hindered by increased snowcover. The former two problems may in part be mitigated by acquiring image data from sun-synchronous sensors which collect scene data during local mid-day times. In addition, there is wider tolerance for non-exact anniversary date image pairs collected near the solstices compared to the equinoxes, this because the sun’s observed path through the sky is at a minimum during the solstices, and maximum during the equinoxes. As a result, an image pair differing by one week collected near the solstice will show far less shadowing differences than a similar one-week pair acquired near an equinox. Another approach may include selection of images acquired over an equivalent number of days before and after a solstice, so that the sun again is at the same place in the sky (though seasonal changes may become significant). Shadows and surface scattering are not identical but are similar, and with the same look direction the total solar radiative path length is also similar.

The success of image change assessment by this method is keyed to accurate image pair coregistration. Serious mis-registration can produce ghosting and false indications of change, and even mis-registration by a few tenths of a pixel can produce false outlining of features, typically revealed where material contacts are highlighted by a pair of lines of differing colors representing erroneous indications of change. If the registration is very precise, the generally unchanging features (over time spans of years to decades) such as hills, valleys, mountains peaks, and other relief features and various material units that are visually prominent in the source images, virtually disappear as muted grayscale features in the change image. As a quality minimum, image coregistration should produce RMSEs of less than or equal to ½ pixel, a precision possible with a variety of commercial image processing software programs, or
otherwise with user-generated image processing code. Georeferencing may also be required if one or both images are not yet georeferenced and if it is important to assign geospatial values to input and output products.

The following steps summarize the generalized approach for applying ICESMAP. Different users may find that they can modify or eliminate some steps, depending upon the image data type and quality used, the software or code applied, and the desired final products.

**Generalized ICESMAP processing steps (e.g. ASTER VNIR):**

Selection of VNIR multispectral image pair / series. Ideal images are cloud and haze free, apply identical sensor gains, and are acquired on the anniversary date. However, images a few days off the anniversary date usually provide useful results. Appendix 25.1 provides an error analysis for one example of image differencing applied to an ASTER image pair acquired near Mount Everest. ASTER Level 1B image data are well suited, with DN values in terms of scaled (8-bit) radiance (Abrams et al., 1999).

1. Optional: Atmospheric correction or dark object subtraction from all bands (Chavez, 1975)
2. Produce 3-band image stacks (e.g. AST3-AST2-AST1 → RGB)
3. Subset images if necessary (i.e. reduce to area of interest)
4. Co-register image pair / series (< ½ pixel RMSE$_{xy}$)
5. Subtract earlier image from the later image
6. Re-scale to unsigned image format (full dynamic range of original imagery, e.g. 8-bit, 16-bit). Note: this step may occur automatically depending on the software applied, or design of the algorithm.
7. Render difference image into RGB space
8. Post-differencing, user-assignment of change features. User defines what all anomalous change features represent.
9. Optional: Threshold individual or multiple difference image band(s) to segment and quantify desired change features or apply a higher-level customized classifier or a clustering algorithm such as Fuzzy C Means.

The change image from a pair of differenced 3-band images is also rendered as an RGB image although the DN values are rescaled so that the lowest negative value is set to zero, and the maximum change value is rescaled to DN = 255 (for 8-bit images). In this case, unchanging features become a neutral gray, and changed surfaces become brighter or darker or colored. However, there are usually portions of the difference image that show residual features that cannot be completely removed, such as small variations on the surface where shadows have shifted slightly, where differential slopes have slight illumination differences (especially when sloping near grazing solar incidence). Changes in vegetation or soil or snow moisture can be of interest, but differences in leaf moisture or slight differences in soil moisture and other fairly insignificant changes can have large effects on a difference image. Typically though the change features above are rather minor, against which more dramatic surface changes will stand out boldly, particularly if the chosen image pair is of high quality. Real changes will be highlighted in image brightness or color against a background of non-changing surfaces that appear relatively subdued in the change image.
In the chapters mentioned above, examples of difference image results and their interpretations are given. The Himalayan image pair used for Chapter 25 has an extended explanation in terms of method for that specific pair, interpretation, and some sources of error and artifacts. Other chapters provide briefer explanations. In general, and not considering areas where one or another image is saturated in one or more bands, areas where the differenced image is blue represent a surface that has become bluer (or less red), such as formation of a pond; where reddish, they have become more reddish (or less blue), such as drainage of a pond; and where greenish, band 2 has become brighter relative to bands 1 and 3. Where the image is black, it has become darker in all bands; and white areas have become brighter in all bands. Recall one of the chief caveats that when one or both of the images are saturated in one or more bands, the colors represented in the change image are more difficult to interpret because some information is lacking in those pixels. This most commonly occurs within areas that are highly reflective across all VNIR bands, such as within or proximal to snowfields in the accumulation zones. Although such areas may appear in a multitude of different hues, it is often still possible to identify the transient snowline (e.g. ELA) especially if only one of the images in the image pair is less saturated or unsaturated. Table X shows 13 typical cases of changing surface features within glaciated terrains, from the perspective of how these features would appear in the before image and subsequently in the difference image.

*Table 4.1 Examples of ICESMAP image difference characteristics*
4.8 Ice flow

The kinematic boundary condition at the surface (Kääb and Funk, 1999) or the mass conservation relation (Cogley et al., 2011) expresses that a change in terrain elevation over time at a certain location and the vertical component of a three-dimensional displacement of an individual particle at the surface describe different kinematic quantities. A change in elevation at a defined glacier location may be the effect of mass balance, three-dimensional straining and/or mass advection, the latter of which is again a function of glacier displacement and geometry.

Glacier displacements can be determined by different methods, though most of them only deliver single components of the three-dimensional velocity vector:

- vertical differences between multitemporal DEMs (see Chapter 5),
- qualitative analysis of movements, such as from terrestrial indicators (e.g. lack of vegetation; degree of lichen coverage and lichen size; surface weathering), change
detection techniques (see above) or repeat image animation (flickering) (entire topic not covered here) (Kääb et al., 2003b; Paul et al., 2007)

- digital matching of repeated optical imagery (see below),
- differential radar interferometry (DInSAR) (see below),
- repeated terrestrial and satellite geodesy, i.e. repeat survey of natural or artificial markers (not covered here),
- analogue and analytical photogrammetric methods (not covered here),
- DEM matching, i.e. digital matching of repeat DEM grids, similar to image matching (not explicitly covered here, but implicitly under image matching)
- terrestrial real or synthetic aperture radar (not covered here), and
- mechanical methods such as strain wires (not covered here).

4.8.1 Image choice and pre-processing for image matching

A highly efficient method for measuring terrain displacements is the comparison of repeated optical imagery. If original imagery is used, the obtained displacements have to be rectified using the corresponding sensor model and orientation parameters (Kääb, 1996; Kääb et al., 1997; Kääb and Funk, 1999; Kaufmann and Ladstädter, 2002). If orthoimages are used, the image comparison directly delivers the horizontal components of the displacement vector. The approach is, in principle, applicable to terrestrial, aerial, and spaceborne imagery.

The choice of images to be used for matching has to fulfill, or balance, the following conditions:

- the time difference between the images used has to be large enough that the displacements exceed the accuracy of the matches. The matching accuracy is mainly, but not only (see section 4.8.4) a function of the image resolution and the precision of the matching algorithm.

- The time difference between the images has to be small enough that surface transformations (melt, shearing, etc.) do not inhibit the finding of corresponding features in the multitemporal images. Corresponding features may be destroyed after weeks for fast-flowing glaciers under temperate climate conditions, or may last several years for cold regions and/or slowly deforming debris-cover.

- The larger the time difference between the images the better is the signal-to-noise ratio in the estimated ice velocities.

- The images have to be co-registered at an accuracy higher than the targeted measurement accuracy or displacements. This co-registration can be part of the geometric pre-processing (e.g. orthorectification with common tie or ground control points) or a
separate pre-processing step (i.e. co-registration using stable-ground points). Alternatively, stable-ground offsets can be measured as part of the image matching process, correction parameters estimated from these, and the displacements on glaciers corrected accordingly. Note also remarks on orthoprojection in section 4.2.2, not least the error propagation from DEMs into orthoimages.

Besides the geometric pre-processing of images to be matched (mainly co-registration), radiometric pre-processing might be useful. In case the matching algorithm has no in-built normalization between the gray values of the image, such processing will generally much improve the results. Instead of a raster-based image matching process, points of interest with sufficient gray-value variations around them can be detected and the matchings performed at these locations only. Improved image matching results are reported if derivatives of the original images are used, instead of the originals themselves, for instance gradient images (usually called orientation images) or principal components (Frezzotti et al., 1998; Haug et al., 2010; Ahn and Howat, 2011; Heid and Kääb, 2012a).

4.8.2 Image matching techniques

The digital comparison between multitemporal images, termed image matching, or intensity matching/tracking or texture matching/tracking may be accomplished by area-based matching techniques (also called block matching), or feature-based matching techniques. Block matching compares complete grey-value arrays, i.e. image sections, to each other, feature-based matching compares geometric forms such as edges or polygons that are extracted from the imagery and converted to vector features. For measuring glacier movement, area-based methods seem preferable due the fact that the reflectance variations to be tracked are often smooth, at least for medium- and low-resolution data, and would thus not allow extraction of distinct vector features. Algorithms for area-based matching operate in the spatial domain or in the frequency domain, or a combination of both.

Among the spatial-domain techniques most suitable for glacier flow are double cross-correlation and least-squares matching (Grün and Baltsavias, 1987; Scambos et al., 1992; Kääb and Vollmer, 2000; Kaufmann and Ladstädter, 2002; Kääb, 2002; Debella-Gilo and Kääb, 2011a), among the frequency-domain techniques are Fourier- and wavelet-based algorithms (Leprince et al., 2007; Haug et al., 2010). All these area-based methods rely on extracting an image section (reference template) from the reference image (e.g. time 1) and searching within a search window the most similar search template in the search image (time 2). For frequency-domain methods, the search window is equivalent to the search template.

A detailed list, explanation and comparison of the most commonly used matching methods in glaciology is given by (Heid and Kääb, 2012a).

The size of the search window has to be chosen according to the expected maximum displacement, such that the search template that corresponds with the reference template can, in fact, be found in the search window. The size of the reference- and search templates have to be chosen according to the textural characteristics of the ground surface. If the reference template size is too small, the similarity surface has no clear maximum; if the reference template size is
too large, computing time soars up, and deformations within the template area degrade the matching accuracy or in extreme cases cause mismatches.

Some matching algorithms are inherently of sub-pixel precision such as least-squares or Fourier-transform based ones. For other algorithms such as cross-correlation, sub-pixel accuracy can be achieved by either interpolating the images or templates to higher resolution (oversampling), or by peak fitting to the similarity surface at its maximum (Debella-Gilo and Kääb, 2011a). In cases where the observed displacement greatly exceeds the spatial resolution, sub-pixel precision might not be necessary.

Digital motion measurements from repeated optical imagery have been applied

- for ice sheets using satellite imagery (e.g. Scambos et al., 1992; Whillans and Tseng, 1995; Frezzotti et al., 1998; Haug et al., 2010; Ahn and Howat, 2011),
- for arctic glaciers using satellite imagery (e.g. Lefauconnier et al., 1994; Rolstad et al., 1997; Dowdeswell and Benham, 2003; Kääb et al., 2006) (Figure 4.18),
- for mountain glaciers using satellite, aerial or terrestrial imagery (e.g., Seko et al., 1998; Nakawo et al., 1999; Evans, 2000; Kääb and Vollmer, 2001; Kääb, 2002; Kääb et al., 2003a; Skvarca et al., 2003; Kääb, 2005a, b; Bolch et al., 2008; Scherler et al., 2008; Copland et al., 2009; Quincey et al., 2009a; Quincey and Glasser, 2009; Heid and Kääb, 2012a, b).

Matching of orthoimages combined with repeated DEMs provides the horizontal displacements and surface elevation changes. The vertical component of the displacement can be estimated from the DEM gradients if surface-parallel displacement is assumed (Kääb and Funk, 1999). The accuracy of this approximation is determined by the representativeness of the DEM used compared to the actual terrain topography.

A combination of simultaneous multitemporal and multiangle image matching where a surface particle is measured in all overlapping images of all image acquisition dates is, in fact, able to deliver the three-dimensional surface particle displacements. Such procedure can be substantially simplified by introducing approximated orthoimages (i.e., orthoimages computed from a coarse DEM; also called pseudo-orthoimages) instead of the original imagery (Kaufmann and Ladstädter, 2002; Leprince et al., 2007). The latter procedure and the above combined orthoimage/DEM-gradient approach converge if DEMs with sufficiently high spatial resolution are available. Repeat ASTER stereo-imagery, i.e. stereoscopic channels 3N and 3B, open up for the possibility of simultaneous matching in both multitemporal and multiangular data for direct measurement of three-dimensional displacements.

4.8.3 Post-processing and analysis

Any image matching results will contain inaccurate measurements or mismatches. If the probability of such errors is not much reduced by pre-processing steps such as point-of-interest
operators (Förstner, 2000; Kaufmann and Ladstädter, 2002; Debella-Gilo and Kääb, 2011b), a number of post-processing steps are available to detect and remove erroneous measurements.

- Minimum and maximum speeds (i.e. velocity magnitudes) to be accepted can be set.
- Most matching algorithms provide also a measure of the matching quality, such as the cross-correlation coefficients or signal-to-noise ratios. A threshold can be set to eliminate results below a certain quality measure.
- For single glaciers a directional slice (range of direction angles) can be chosen for velocity vectors to be accepted. Similarly, a maximum directional offset set can be chosen between the original displacement vectors and those from other sources, for instance the aspect from a DEM.
- Simple filters can be used to identify potentially erroneous measurements such as a running vector median or RMS windows.
- The original measurements can be compared to a low-pass filtered version of the displacement field and a threshold set on the respective difference for measurements to be accepted (Heid and Kääb, 2012a). A similar procedure can be built in into the matching process itself to limit matching positions to most probable positions (Evans, 2000).
- The original image 1 can be compared to a simulated image 1S that is obtained by interpolating image 2 using the reverse displacements matched between 1 and 2. The correlation between 1 and 1S is an indicator of the matching success, though only a relative one, because the overall correlation level between 1 and 1S depends not only on the displacement between times 1 and 2, but also different imaging conditions etc. The method is thus particularly useful for algorithm comparisons (Debella-Gilo and Kääb, 2011b).
- Instead of applying image matching to a single pair of raw or preprocessed images, a number of versions of the input images can be matched (PCs, directional filtered, etc.) and from the stack of results the most probably correct match be selected (Ahn and Howat, 2011).

Glacier velocity fields from image matching can be analyzed in various ways, such as transverse and longitudinal profiles, spatial gradients (i.e. ice deformation), temporal variations, stream line and relative age calculations, direct inclusion in numerical flow models, etc. (Kääb, 2005b).

### 4.8.4 Accuracy

The total error budget of displacement vectors matched from repeat images contains

- the pure precision of the matching algorithm, which may be on the order of up to 10-20% of a pixel;
• the representativeness of a match for the matching window area covered: The measured
displacements are often assigned to the center pixel of the window, but can in theory
originate from anywhere inside the window, depending on the visual contrast and the
algorithm used. If the window contains deformation, this also introduces an error

• the geolocation accuracy of individual pixels, which might be on the same order of
magnitude as the pixel size itself, and stems from instabilities within the sensor (e.g.
topographic phase), (ii) the phase difference due to actual topography above the ellipsoid (topographic
phases), (iii) the displacement phase due to any terrain shifts between the two acquisition times,
(iv) atmospheric phase distortions, and (v) noise (Figure 4.19). Removal of the curved Earth
phase from an interferogram, and subtraction of the topographic phase from the total phase
difference gives a differential interferogram with only displacement remaining apart from
atmospheric effects and noise (differential SAR interferometry, DInSAR). The topographic
phase can either be simulated from a DEM, or inferred from multiple interferograms the
difference between which is able to eliminate a constant displacement term (Bamler and Hartl,
1998).

Radar interferometry requires phase coherence between the acquisition times of the individual
SAR images. Such coherence over ice and snow is usually lost within hours or days, a fact that
limits the applicability of satellite radar interferometry usually to the 1-day tandem phase of ERS
1 and ERS 2 during 1995 and 1996, and the occasional 3-day repeat cycle orbits of ERS (e.g. 1991), and a coordinated ERS-ENVISAT campaign. Longer periods of phase coherence of up to one orbit cycle of typically several weeks or even longer are usually only found for ice bodies in particularly stable cold and dry conditions (e.g. Canadian Arctic during winter, Antarctica, etc.). New opportunities for radar interferometry over glaciers can be expected from the ESA Sentinel-1 mission.

Radar interferometry provides only the line-of-sight component of the displacement. Other components have to be projected, for instance assuming movement along the direction of steepest descent as calculated from a DEM. Combination of interferograms from ascending and descending orbits is thus able to provide two components of a three-dimensional displacement vector, in particular for high latitudes with large azimuth differences between the two orbit directions (Kwok and Fahnestock, 1996).

Numerous ice flow studies using radar interferometry exist, mainly in polar regions, but less under typical mountain topography, for smaller glaciers, and in lower latitudes (e.g., Luckman et al., 2007; Quincey et al., 2009b).

A totally different technique applicable to repeat SAR data is offset tracking (in principle equivalent to above matching between optical images). Backscatter intensity or radar phase texture is tracked between multitemporal SAR images using image matching techniques as described above. As all image matching techniques, SAR offset tracking provides two-dimensional displacements in the image plane. In case of phase coherence (see above) phase texture can be tracked with high accuracy (radar speckle tracking). In case of coherence loss, i.e. where radar interferometry is not anymore possible, there might still be sufficient SAR intensity texture to be matched between the repeat images. The main differences between SAR offset tracking and matching of repeat optical data consist (i) in the potential of SAR images to contain backscatter intensity texture even in cases where optical images would not contain sufficient texture (e.g. snow areas) and (ii) in the much higher noise level of SAR data (radar speckle). This high noise level requires matching algorithms that are particularly robust against noise, and much larger matching templates compared to optical data have to be employed. The latter requirement limits the application of the method to larger glaciers. New high-resolution SAR sensors such as Radarsat-2 or TerraSAR-X, however, allow glacier flow to be studied also for smaller glaciers by reducing the geographic area of the matching templates (not the template size in number of pixels), and by often showing more scene details to be potentially matched over time (Figure 4.20).
Figure 4.18  Surface velocity field for a section of Kronebreen, derived from ASTER imagery of 26 June and 6 August 2001. Isolines indicate ice speed in meters per year. The surface velocities of Kongsvegen are too small to be measured from repeated satellite imagery of 15 m resolution over a few weeks. Underlying ASTER image of 6 August 2001.

Figure 4.19  Radar interferogramme between an ERS 1/2 tandem pair of 5 and 6 Apr 1996. Perpendicular baseline is 12 m, so that the topographic phase contribution is small and
most visible color fringes due to ice movement. Kronebreen to the middle left shows coherence loss due to the large velocities (cf. Figure 4.18). The large fringes to the middle right indicate slowly deforming sea ice.

Figure 4.20 Surface displacements on Kronebreen derived from SAR offset tracking using Radarsat2 finebeam data of 6 and 30 Apr 2009. Speeds increase from zero (lightblue/cyan) over pink, yellow to blue (1.3 m/day).

4.9 Challenges, conclusions and perspectives

Classification approaches based on multispectral imagery are thoroughly developed and well established. Significant progress can, however, be expected from newly developed combinations of input layers and combinations of classification algorithms. For ice and snow applications, inclusion of thermal bands is little tested and should be further investigated.

Paul (2002) and Paul (2004) found band ratios to be an especially simple, robust and fast method for glacier mapping over large areas. Manual adjustment of the necessary threshold seems to be preferable to thresholds automatically optimized from training areas (Rott and Markl, 1989). For complicated situations adaptive threshold variations over one scene depending on variations of the ground or illumination properties might be investigated.

There is still much potential in using spectral data and its derivatives alone, but multidimensional classification including, for instance, DEMs may be most promising since they best reflect the nature of high-mountain phenomena and processes. The increasing availability of suitable DEMs supports this trend. The manual application of expert knowledge for delineation will be more and more reduced but never become redundant (Rott and Markl, 1989).

Hyperspectral analysis of the glacial, peri- and paraglacial environment could provide new advantages for classification, but also for understanding numerous phenomena and processes.
While promising results are already available for geological applications, only little is known about the hyperspectral response of alpine environments with rugged topography (Keller et al., 1998; Schläpfer et al., 2000; Gruber et al., 2003; Casey et al., 2012). In contrast to multispectral applications, hyperspectral ones have a large potential to lead much further beyond the human ability for visual interpretation.

Microwave sensors respond especially sensitively to snow and ice and their physical properties due to a varying liquid water content and varying penetration depths. However, much research is still needed on the complex dielectric properties of snow and ice under various conditions to allow for linking the recorded microwave response to geophysical characteristics of ground materials.

Optical and microwave data for glacier remote sensing are in a number of aspects complementary, so that their combination might offer new insights and approaches. In principle, the combination of both spectral sections is possible within

- **DEM generation and elevation change detection:** A major shortcoming of optical stereo DEMs is their dependency on visual contrast. InSAR DEM generation is not affected by that problem but rather relies on the (often sensitive) phase coherence. Optical DEMs can serve as initial solution for an InSAR DEM by solving the modulo $2\pi$ ambiguity during phase unwrapping, in particular over low-coherence areas. Such a DEM gets its overall vertical scale from the auxiliary DEM and the details from radar interferometry. Similarly, the absolute vertical scale of an InSAR DEM that is usually uncertain due to baseline uncertainty can be refined by fitting the InSAR DEM to an auxiliary, e.g. optical DEM or altimetry data (Moholdt and Kääb, 2012).

- **Quantification of glacier movement:** Optimal conditions for differential radar interferometry, radar offset tracking, and repeat optical image matching differ significantly from each other, and may vary even over one scene at one point in time. Radar interferometry requires phase coherence which is among others limited to small displacements and deformations. Radar offset tracking does not suffer from such problems, but is still more sensitive to ground changes than repeat optical data and requires much larger matching windows. On the other hand, sufficient contrast of backscatter features necessary for SAR offset tracking is usually found over much larger areas than the visual contrast necessary for optical matching.

- **Spectral analysis of glaciers:** Spectral fusion of optical and SAR data might be especially promising for spectral analysis of glaciers (Rott and Strobl, 1992; Rott, 1994; Hall et al., 1995b; König et al., 2001; Hall et al., 2009)(Warren and Brandt, 2008)

**Acknowledgements**

The contribution was supported by the ESA Climate Change Initiative project Glaciers_cci (4000101778/10/I-AM), ESA GlobGlacier (21088/07/I-EC), and The Research Council of Norway through the CORRIA project (No. 185906/V30).
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