Quality information for radars and radar data

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Contents

Chapter 1

Introduction

The workplan of the second phase of the EUMETNET OPERA program (2004-2006) contains a work package 1.2 on "Quality information for radars and radar data". A consortium of four different National Meteorological Institutes has worked on this project and has addressed this complex project theme. In addition a wide European support for the outcome of the project has been obtained.

The increasing interest from the hydrological and NWP modeling communities in weather radar has initiated a change from mainly a qualitative use to a more quantitative use of radar data. For the traditional use in nowcasting mainly qualitative requirements have to be fulfilled, but for quantitative precipitation estimation (QPE) or assimilation in a NWP model stringent quantitative requirements are usually in force.

In the previous OPERA program, the project members have been responsible for a project on the "Definition of Product Quality Descriptors" (Holleman et al., 2002). In this project a review of the physical problems of the observation technique was performed, ways to account for inherent limitations in the technique like clutter and beam shadows were proposed, and a set of BUFR-descriptors to encode the recommended quality information were defined. Only global (static) quality descriptors, i.e., descriptors that are valid for all data in a product, have been dealt with in this project. Daniel Michelson and Iwan Holleman have worked on the data quality project in COST-717 that was concerned with quality characterization and control weather radar data with a focus on the requirements from hydrology and NWP.

This OPERA project has built on the achievements of the previous OPERA program and the COST-717 action. This had the advantage that input and expertise from a wide community of radar experts, hydrologists, and NWP modelers have been incorporated in the project outcome. In addition, this approach has saved a lot of work and has strengthened the international support for the project results. The objectives of this work package 1.2 were:

1. Definition of usable information to characterize the achieved data quality
2. Address truly local quality characterization issues, i.e., down to the level of individual bins and pixels
3. Promotion of incorporation of the quality information in the exchanged radar products and polar data
4. Support the potential users of the new quality information from, e.g., the hydrological and NWP communities, in the application of this information

To fulfill the objectives the project work has been divided into the following five subpackages:

A. Quality information for radar system. Issues regarding radar hardware, signal processing and siting will be revisited.

B. Quality information for volume data of reflectivity and radial velocity. Issues of (permanent) clutter, attenuation, beam filling, non-hydrometeor identification, dealiasing, etc

C. Quality information for surface rainfall (accumulation) product. Issues like height of observation above ground level, Z-R relationship, particle phase, etc. How to include quality information in dynamical maps?

D. Quality information for wind profiles and radial wind super-observations. Issues like wind model, VAD or VVP, horizontal and vertical resolution, error correlation, statistics to be included, etc. Dynamical quality information for each vertical level or super observation?

E. Application of quality information. Issues like the definition of a common framework to incorporate the quality information from subpackages (A-D) and the provision of guidelines for end-users on usage of the quality information will be considered

Regarding the actual incorporation of the new-defined quality information in the exchanged radar data, a synergy with work package 2.1 "New data representation formats" is expected.

Chapter 2

Previous work

In the framework of the previous OPERA program (1999-2003) projects covering the "Production of radar data" and the "development and standardization of appropriate quality control procedures" were performed. This project was split into three subprojects:

1. Description of the currently applied quality-ensuring procedures, see Divjak et al. (1999)

2. Set-up of a library (database) describing calibration methods used for each radar

3. Definition of a list of quality descriptors, see Holleman et al. (2002)

The purpose of the last subproject was to come up with a review of how the physical problems of the observation technique impinge on our ability to accurately measure the observed quantity. It proposed ways to account for inherent limitations in the technique like clutter and beam shadows as well as the variable behavior of the technique for things like bright band and anomalous propagation. It has also dealt with the variable performance of the equipment and algorithms used to generate different data products. Finally, a set of appropriate BUFR-parameters to encode the current and recommended/standardized quality information into the BUFR-message for international exchange was defined.

Apart from being of general interest, the quality description indicators can be used during the production of radar composites and the assimilation of radar data in hydrological and atmospheric models. This subproject, therefore, had an evident connection with the activities of the former COST-717 action on "Use of Radar Observations in Hydrological and NWP Models".

In this subproject a review of all aspects of "quality" and how certain performance factors impinge on the "quality" of the final products has been performed. It was recognized that there are different factors that have bearing on performance. There are, for instance, static factors that relate to permanent conditions. These can be global, and relate to the fundamental technique (deficiencies in choice of operating frequency, i.e. attenuation, etc.), and/or they can relate to the particular installation (local interference, both physical and electrical, and the particular hardware employed). There are also changing factors that relate to variable performance of the equipment and the ability of the technique to cope with changes in the environment that it is trying to sample. These can be long-term trend type changes or very rapid dynamic changes.

From the review of the quality aspects, quality descriptors were deduced for basedata, surface rainfall product, and the wind profile product. The quality descriptors have been divided into global static, local static, global dynamic, and local dynamic descriptors. "Global" refers to descriptors that are valid for all data points, and "local" refers to descriptors which are given per pixel or altitude. "Static" is used to denote descriptors that are constant and only depend on the radar equipment, radar siting, or product algorithm, while "dynamic" descriptors vary for each observation.

From the obtained quality descriptors a list of proposed BUFR quality descriptors has been deduced by Holleman et al. (2002). Only global static quality descriptors are proposed, because it was not feasible to implement more complicated quality description within the lifetime of the previous OPERA program.

2.1 Quality Description Framework proposed by previous OPERA

The proposed quality descriptors were divided in the following way by Holleman et al. (2002):

- Static global descriptors. These indicators remain unchanged during most of the time and are constant in space. They are not influenced by changing external factors like environmental parameters, e.g., the weather

- Static local descriptors. These indicators remain unchanged during most of the time, but do vary in space. A good example of a static global descriptor is a static clutter map

- Dynamic global descriptors. These indicators are time and situation dependent and thus they can change from one product to the following in time. They are, however, considered valid during a whole scan sequence and are associated to all data points contained in a given product.

- Dynamic local descriptors. These indicators are also time and situation dependent. In addition, these indicators may change within a given product from one data point to the next one.

Chapter 3

Application of quality information

3.1 Summary

A framework is presented to facilitate the propagation of uncertainty information at the interface between weather radar and meteorological and hydrological applications. The underlying principle is to make maximum use of both:

1. the knowledge of the data provider on the sources of uncertainty, and,

2. the knowledge of the user about the sensitivity of his application to errors in the data.

Uncertainty information propagates from the observer to the end user, whereas sensitivity information propagates in the opposite direction from the user to the observer. Maximum benefit is only obtained if both information trains are well established.

3.2 Objective

The presented framework will facilitate the communication about uncertainty between data providers (here radar experts) and data users (for instance meteorologists and hydrologists). The goal is to improve the propagation of uncertainty and sensitivity information and thus maximize the practical benefit of applications using weather radar measurements as input.

3.3 Introduction

Many studies were made to describe the quality associated with weather radar measurements and products. There are two main approaches:

1. simulation of errors and limitations of the instrument, and,

2. comparison with ground truth.

In the first approach uncertainty is simulated based on conceptual models and detailed knowledge about the sources of error. An example is the simulation of the uncertainty that results from ignoring small-scale variability of vertical reflectivity gradients in common operational profile correction algorithms. Another example is the three-dimensional map of the radar visibility that can be simulated with a digital terrain map and a model of the propagation of the radar beam in the atmosphere. The visibility map shows regions of partial or total shielding of the radar beam by mountains and the horizon. It is a fundamental limitation of a weather radar and has direct impact on the uncertainty of radar estimates of rainfall rates at the ground. A third example is the clutter likelihood obtained with a conceptual model and measurements of the signal fluctuations, Doppler spectrum width, Doppler velocity, vertical gradients, spatial continuity and residual clutter during clear sky.

In the second approach we do not make assumptions on the origin of uncertainty. Here, uncertainty is quantified at the outcome by comparison of radar products (e.g. radar rainfall estimates) with ground truth (e.g. rain gauge measurements), see for instance Germann et al. (2006b). Although there is still work to be done along these two approaches, we already have enough information to make a first-order description of radar quality.

The critical point is the next step: The conversion from this instrument-oriented type of uncertainty information into measures that can be used in meteorological and hydrological applications. This step requires an intensive dialog and a clear definition of the interface between the provider (here radar expert) and the user (meteorologist or hydrologist). This is the missing part in current implementations of operational applications.

It is often proposed that the data provider needs to define a generally valid quality index between 0 (bad) and 1 (good). Although appealing from the user point of view, because there is not much work for him, this approach is doomed to fail for a simple reason: It does not take into account the specific sensitivities of the application to the various types of uncertainty in the data. This step requires detailed knowhow of the application, its sensitivities to errors in the input data and the propagation of uncertainty

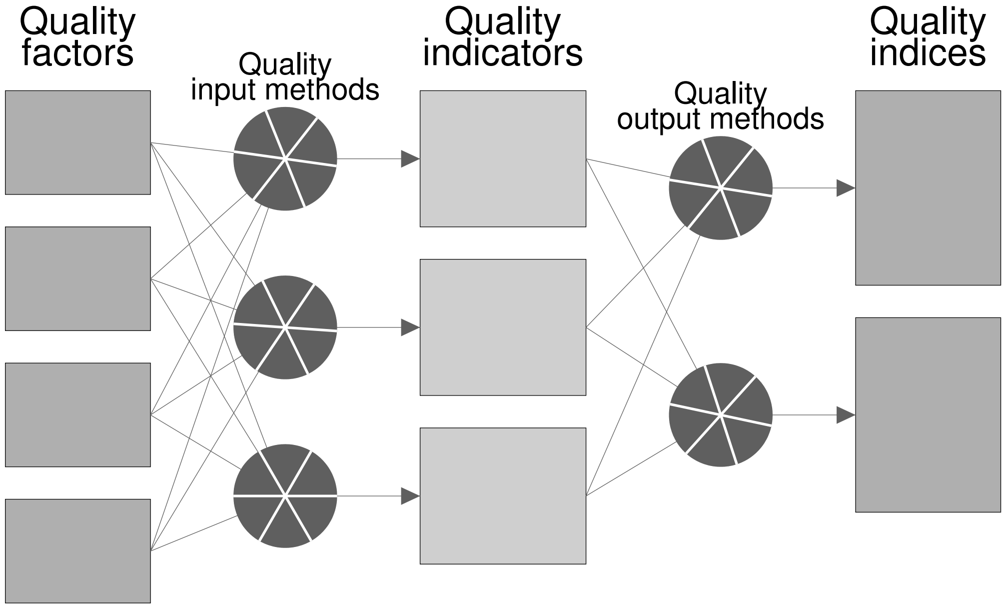

Figure 3.1: Illustration of the framework.

through the system to the output. The data provider does definitely not have this type of detailed knowhow. On the other hand, it is not sufficient either if the user gets from the data provider a large number of instrument-specific quality figures which are difficult to understand without the help of the technician of the instrument.

In short, we need a framework to facilitate the communication on data quality.

3.4 The framework

The core of the framework presented here (Fig. 3.1) is a clearly defined interface that consists of a set of generic and physically meaningful parameters *(quality indicators)*. This is the simplest way to make best use from both i) the knowledge of the data provider on the sources of uncertainty, and, ii) the knowledge of the user about the sensitivity of his application to errors in the data. The set of quality indicators contains neither instrument-specific nor application-specific peculiarities.

The conversion *(quality input method)* from instrument-specific quality information *(quality factors)* into generic and physically meaningful quality information *(quality indicators)* requires detailed knowledge of the instru-

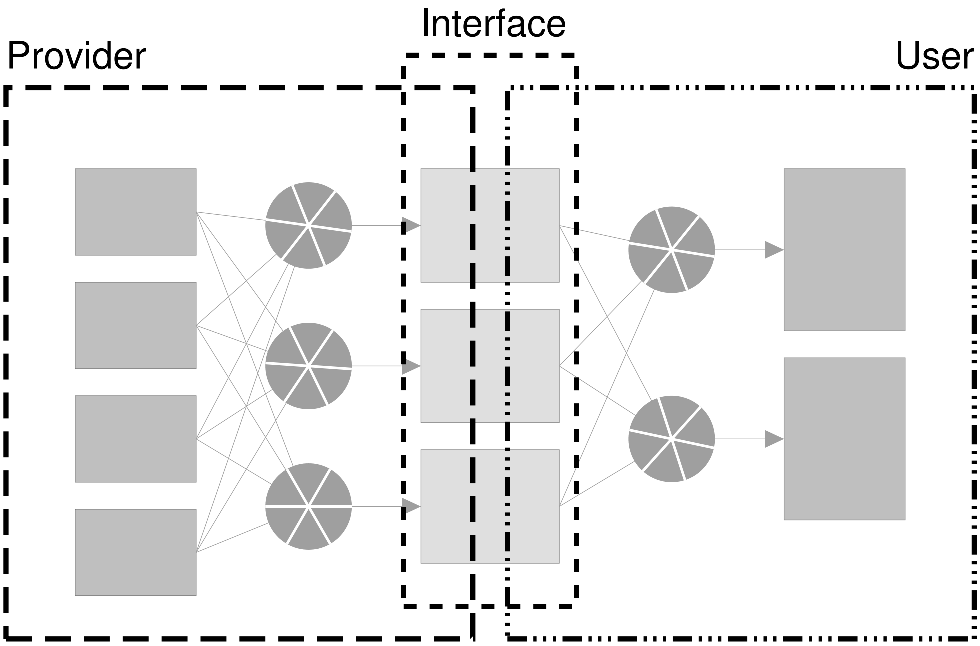

Figure 3.2: Provider, interface, and user.

ment, the measurement techniques, the data processing, and is thus clearly a task for the data provider (here radar expert). The wavelength of the radar, for instance, is a quality factor. The root mean squared error of horizontal wind speed expressed in [m/s] of a wind profile product, on the other hand, is an example of a quality indicator.

The conversion *(quality output method)* from the quality indicators into a form of quality information that can be used in the application *(quality index)*, on the other hand, requires detailed knowledge of the application and its sensitivity to uncertainty in the data, and is thus clearly a task for the user (meteorologist or hydrologist).

Both steps, the quality input and output methods, are only possible if the quality indicators at the interface are defined in a generic way using common physical and statistical definitions.

The flow of quality information from the data provider *(provider unit)* to the user *(user unit)* goes through the interface *(interface unit)* which consists of a set of quality indicators (Fig. 3.2). The number and type of quality indicators is open. The only requirement is that any user can read and correctly interpret the quality indicators without detailed knowledge of the provider unit.

3.4.1 Terminology

Here we give a short definition including some examples of the terms introduced in the previous section. See also Figs. 3.2 and 3.3.

Provider: the instance producing the data (e.g. radar system)

Quality factor: a factor that affects the quality of the data (e.g. wavelength)

Quality input method: method to convert quality factors into quality indicators

Quality indicator: generic physically meaningful descriptor of the data quality [1] (e.g. root mean square error of wind speed expressed in [m/s]).

Interface: instance that holds the set of quality indicators

Quality output method: method to convert quality indicators into quality indices

Quality index: way of using quality information in the application (e.g. a weight between 0 and 1, good data having larger weights)

User: instance of the application that uses the quality information

3.5 Example

Here, an example is given to illustrate how the above scheme can be applied in practice.

Context: A hydrologist is developing a real-time system for short-term prediction of river runoff of several catchments in the Swiss Alps. The size of the catchments is of the order of 1000 km^2. The model predicts the probability that the runoff exceeds a predefined threshold in the following 2 hours. The only rainfall input is a radar map of surface rainfall rates at a resolution of 1 km and 5 min available with a delay of 1 min.

Step 1: The hydrologist (user unit) goes through the list of quality indicators (interface unit) provided by the radar experts (provider unit), and selects those quality indicators that seem useful in the given context. These are:

[1] We prefer the term "quality indicator" rather than "quality descriptor" because the latter is already used in the context of metadata in OPERA BUFR messages.

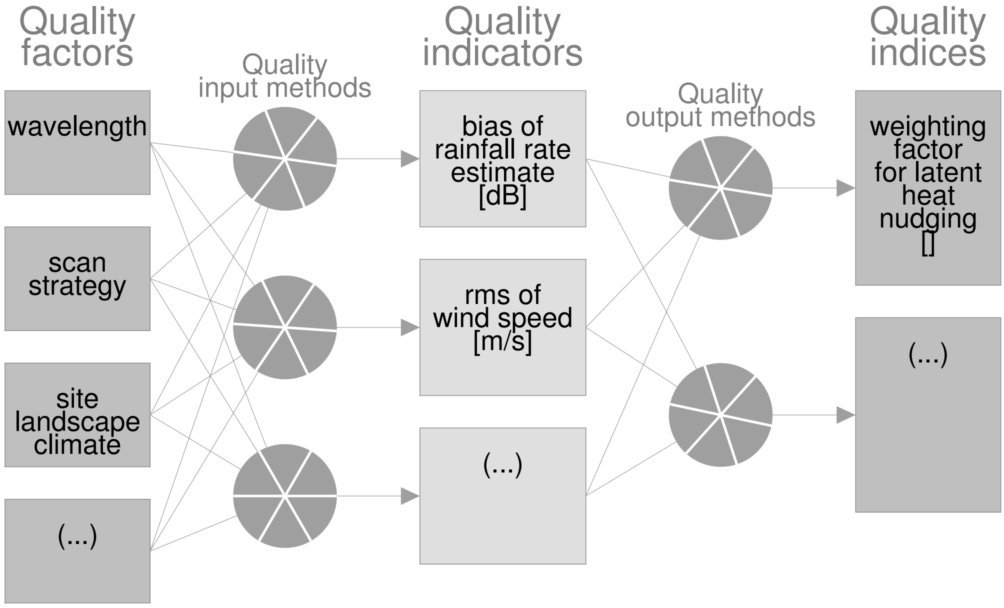

Figure 3.3: Examples of quality factors, indicators and indices.

1. RCF: A map that indicates for each season and 1 km pixel the frequency of residual clutter; in % of time.

2. RB: A static map that indicates for each 1 km pixel the residual bias of the radar rainfall estimate, in dB.

3. RS: A static map that indicates for 9 subregions of Switzerland a measure of the spread of radar errors, in dB.

4. CI: A static map that indicates for each 1 km pixel the average intensity of clutter when clutter elimination is switched off, in dBZ.

Step 2: The hydrologist defines the quality output method to convert the information of the selected quality indicators into quality indices to be applied in the runoff prediction system. The quality output methods are based on i) knowledge on the sensitivity of hydrological runoff modeling for a 1000 km^2 catchments in the Alps, and, ii) the detailed description of the quality indicators provided by the radar expert. A possible solution may be:

1. A binary mask to use only those 1 km pixels with RCF<3% AND |RB| <5dB AND RS<3dB AND CI<15dB.

2. A correction factor derived from RB to correct rainfall rates of accepted pixels.

3. A confidence index derived from RS to be associated with the runoff forecast: high for RS<1.5dB; medium for 1.5dB<RS<2.5dB; low for RS>2.5dB.

Step 3: Cross-check of quality output method by radar expert from provider unit.

Step 4: Implementation, verification, education.

In the above approach the uncertainty of radar precipitation estimates is taken into account using the static map of radar error spread (quality indicator RS). This way we do not consider space-time correlation of radar errors. There is a more sophisticated approach if an estimate of the full error covariance matrix including space-time correlation is available: In this case we can generate an ensemble of radar precipitation fields, each member of which is a possible realization of the true field and is in agreement with our best knowledge on radar uncertainties (Germann et al., 2006a). Here, the error covariance matrix is the quality indicator, the ensemble generator the output method, and the ensemble itself the "quality index". The hydrological model can then simply be run several times each time with a different radar input. that is, a different ensemble member. A crucial point in this approach is the selection of a small ensemble out of a large number of generated members. The selection practice, which is also part of the output method, obviously depends on the sensitivity of the application and thus requires knowledge from the user unit.

3.6 Harmonized representation of *quality indicators*

This section outlines a means for representing *quality indicators* in a harmonized way, with a focus on their international exchange in a way which the receiver can anticipate. The quality framework presented earlier in this chapter uses the term *indicator* in a specific way, and the term *index* in another. Although we will see that the harmonization procedure presented below is designed as a conventional index [0-1], in this context it is intended only as a scaling method for representing a *quality indicator*[2]. In other words, the reader should not consider the harmonization process to be analogous to a *quality output method* which results in a *quality index*. Instead, the scaling process is simply intended to represent the *quality indicator* in a predictable way which can thus facilitate its exchange and use in various applications.

[2]Note, however, that international exchange of *quality indices* as defined in this quality framework, or their provision to users, is by no means prohibited.

While users should, ideally, be conscious of the science behind a given *quality indicator* the scaling procedure does not demand such detailed knowledge. In fact, in reality, some users may simply appreciate having confidence in all *quality indicators* being available in a harmonized way, no matter what they represent. Towards the end of this section, after the principles are give, specific information is presented which is required to perform the harmonization.

For quality characterization to be meaningful, with quality information originating from many disparate sources, a generalized procedure must be defined and applied. In terms of the pure logistics involved in exchanging the relevant information internationally, such a generalized procedure becomes vital both in facilitating the exchange and in a given institute's ability to manage the information received from international sources. In the following, an attempt is made to use the proposed terminology defined in Chapter 3 of this report.

Quality characterization becomes "internationally relevant" when a *quality indicator* is defined. All steps preceding the definition of the *quality indicator* can be considered to be internal to the characterization algorithm. What is important is that the *quality indicator* is defined using a recognized physical quantity. The name of this *quality indicator* must therefore always be given in the package (file) which is exchanged internationally.

As long as the minimum and maximum values of the individual *quality indicator* are given (also in the package) then the *quality indicator* can be represented in a harmonized manner, e.g. for a Cartesian array in normalized form, as,

$$\hat{\mathrm{Qind}}_{(x,y)} = \frac{\mathrm{Qind}_{(x,y)} - \min(\mathrm{Qind})}{\max(\mathrm{Qind}) - \min(\mathrm{Qind})}, \tag{3.1}$$

thus always resulting in a *quality indicator* containing values between 0 and 1. Values lying outside this interval can be used to denote "no data" (unradiated areas) and "no echo" (radiated but no return) pixels or bins[3]. In cases where the *quality indicator* is categorical, e.g. "yes" or "no" information, it can easily be represented as no=0 and yes=1[4]. Although it may seem counter-intuitive to reformat a physical quantity in a given *quality indicator* using this harmonization procedure, doing so ensures that any *quality indicator* exchanged internationally will arrive in a harmonized, and therefore **predictable** fashion.

[3]It is therefore unwise to attempt to compress the contents of any continuous *quality indicator* to an 8-bit unsigned word using a linear transform, no matter how tempting it may be.

[4]If there are more categories than "yes" or "no", then care must be taken so that the categories can be normalized cleanly using this proposed harmonization.

Potential problems arise in this process if the *quality indicator* is not a linear quantity. However, as luck would have it, the radar community is comfortable using the decibel scale and so any *quality indicator*, such as radar reflectivity factor and precipitation intensity or accumulation, can easily be accommodated as such if required.

In summary, any given *quality indicator* can be packaged as a floating point array (per-pixel *quality indicator*) provided the following information is provided on the *quality indicator*:

- the physical entity contained in the *quality indicator*,
- accurate description of the physical entity,
- the maximum value in the *quality indicator*,
- the minimum value in the *quality indicator*,
- the value used to identify "no data",
- the value used to identify "no echo".

It might be advantageous to propose standard values of the latter two flags, e.g a value greater than one for "no data" and a negative value for "no echo".

This procedure provides a harmonized method of representing *quality indicator* information expressed as an **error**, a **correction**, and/or an **uncertainty**.

3.7 Combining of *quality indicators*

If all *quality indicators*, packaged according to Sec. 3.6, were made available for international exchange, and network capacity was sufficient to support the operational exchange of all this information, then it would not be necessary to address the issue of combining *quality indicators*. Instead, it would be up to each NMS to combine the *quality indicators* however it wishes, based on its own priorities and applications.

However, we do not yet have the luxury of being able to exchange all *quality indicators*, so the issue of combining them intelligently must be addressed. Generally, if two or more *quality indicators* are to be combined, the combination can be either:

- additive (arithmetic mean), or
- multiplicative (geometric mean),

where normalized weights are assigned to each *quality indicator* before the combination takes place. These weights can be determined in any of the following ways:

1. Each array is assigned a static weight.
2. A pixelwise weight is determined dynamically.
3. Any combination of 1 and 2.

Combination of information in this context is analogous to data **compression**, since the objective is to represent the same information much more efficiently.

It can be argued that additive combination is physically unmeaningful, since any given (normalized) *quality indicator* with zero quality should in principle make any remaining qualities irrelevant. In other words, an arithmetic average quality can be considered useless if any individual quality is zero. This issue is dealt with ruthlessly when calculating the geometric mean.

An important objective when combining *quality indicators* is in making the process **reversible**, ie. non-destructive compression. To enable this, all weights must be available as metadata along with the method used in applying them. If any of the weights have been determined at the pixel or bin level, then arrays of weights must be given for the process to be reversible. If any of the weights are zero when deriving the geometric mean, then it becomes impossible to retrieve the original *quality indicators*, according to the principle that "you can't get something from nothing"[5]. Therefore, in some cases, there may be no benefit in combining *quality indicators* compared to making them available individually, at least in terms of reversibility.

If making the individual *quality indicators* available is impossible, for whatever reason, then the combination process can only be considered analogous to destructive compression[6]. Nevertheless, in such cases, the international availability of an average *quality indicator* can still provide valuable information to the user on the quality of a given observable.

3.8 Fractality

So far the framework has been presented from the point of view of having a provider unit that covers the whole chain from the raw measurement made by a radar system to the final radar product that is ingested in a hydrological application.

The same framework may be applied at a smaller scale, for instance at the interface between a raw radar product with reflectivity in polar space

[5]This is like trying to perform an attenuation correction on an extinguished signal. . .

[6]A common form of destructive compression is Huffman coding used in creating JPEG files.

(provider unit) and an algorithm that makes the best radar estimate of surface rainfall rates (user unit). See Fig. 3.3. Here, the quality indicators describe the uncertainty of polar reflectivity, and the quality output method incorporates the sensitivity of the rainfall rate estimation algorithm to uncertainties in polar reflectivity.

Another example is the procedure of compositing images from single radars to produce a radar mosaic. Here the individual radar systems are the provider unit, and the compositing procedure is the user unit. The quality indicators in the interface unit describe the uncertainty of data of the single radar images.

The framework may be applied at a larger scale as well. The whole chain from the radar observation through numerical weather prediction modeling and hydrological modeling to a sea level prediction can be considered as the provider unit. The user unit is the civil protection who have to make a decision in case of a sea level prediction above a critical threshold. Here, the quality input method simulates the whole chain of uncertainty propagation from the observation to the sea level forecast. The quality indicator can be, for instance, the expected range of sea level, a reasonable way to express the uncertainty in the whole forecast system. In short, the same framework can be applied at different scales of details.

3.9 Conclusion

A framework is presented to provide a guideline to improve exchange of uncertainty and sensitivity information at the interface between a data provider (here radar community) and a user (here meteorologist or hydrologist). Its success depends among other factors on the acceptance by the data provider and user.

The presented framework is not anyhow strictly related to radar technology, meteorology or hydrology. It can be used as well at any other interface between a data provider and a data user, provided that uncertainty in the data is relevant for the given application.

Usually the selection of the quality indicators and the definition of the quality output method are static. Principally it is also possible to allow for dynamic adaptation of the quality output method to changes in either the sensitivity or the uncertainty or both. Obviously, this solution may easily become unstable and needs thus to be used with care.

Chapter 4

Quality information for radar systems

In this chapter, we discuss quality factors inherent in a radar system. Hence, the focus is on system properties which affect the quality of the measurement data. System independent properties - like weather - are discussed in the next chapter. However, it should be kept in mind that the distinction between these “internal” and “external” quality factors is somewhat vague as some of these factors interact: the sensitivity of a radar to some external quality factor often depends on an internal quality factor. Various radar system quality factors have already been introduced concisely in the earlier OPERA reports by Divjak et al. (1999) and Holleman et al. (2002). In this chapter, the goal is in defining quality factors and indicators that can be utilized in assessing quality of radar data (5) and further, in generating products (6, 7) such that quality information is taken into account.

4.1 Operating frequency

In setting up a weather radar system, one of the fundamental choices is the type of radar. The *operating frequency* is a central static system parameter. Defining quality in formal terms becomes a practical need for example in combining data from two radars with differing frequency. A typical weather radar operates in the C band (around 5 GHz) providing a good balance between sensitivity to precipitating droplets and attenuation. Weather radars exist also in the X-band (around 10 GHz) and the S-band (around 3 GHz). Relative performance of these bands is outlined in Fig. 4.1. Hence, operating frequency determines the compromise for sensitivity and attenuation. On the other hand, attenuation depend on weather: data quality is a function of distance and intensity of precipitation along the beam. Due to this dynamic aspect, we return to this topic in the next chapter.

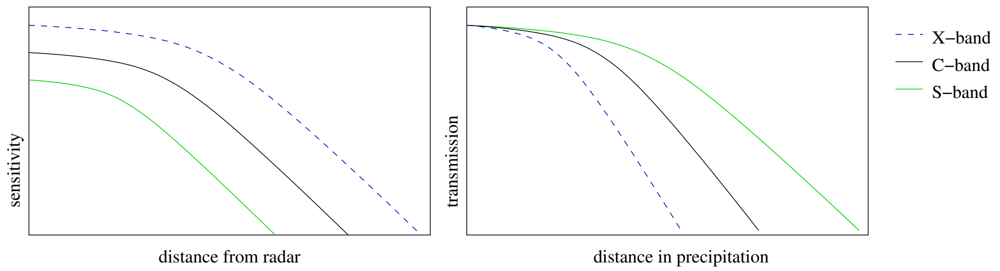

Figure 4.1: Schematic presentation of sensitivities of different frequency bands: increased sensitivity yields decreased transmission (ie. increased attenuation).

4.2 Beam width

The angular *beam width* is a fixed system property determined by antenna disc dimensions and frequency. As the beam diameter increases linearly with range, the spatial resolution decreases proportionally in the beam-perpendicular direction. This topic is also discussed in the next chapter. Formally, the beam with is often approximated as a Gaussian bell curve; hence beam width refers to the half-width of the beam power. Strictly speaking, power transmitted off the main beam sometimes hits targets of high reflectivity, especially ships and aircraft (see section 5.11). In addition, distinct maxima off the main beam, *sidelobes*, cause unwanted echoes that are sometimes hard to recognize.

4.3 Doppler filtering

A central radar property is the support of *Doppler speed measurements* providing beam-directional velocity components of target particles. Speed measurements are input for meteorological end products (Ch. 7) but also serve as an important means for anomaly detection and removal. In Doppler radars, the *maximum unambiguous velocity*, is constrained by frequency f by $V_{Nyquist} = \mathrm{PRF} \cdot c/4f$. where PRF is the pulse repetition frequency. The *maximum unambiguous range* is limited trough $R_{Nyquist} = c/2\mathrm{PRF}$.

Technically, unlike operating frequency f, maximum unambiguous velocity and range are not static system properties as PRF can be altered. Thus, scanning routines may involve dual-PRF or vary PRF between subsequent tasks. In designing quality indicators (Ch. 3), instead of PRF, it is more informative to use maximum unambiguous velocity and range which are more likely physically meaningful quantities to end users.

4.4 Calibration errors

As radars consist of real mechanical and electronic parts, various kinds of losses and distortions occur. Calibration is an unavoidable procedure to get measurement data to match with ideal, theoretical models. Various calibration procedures can be applied to optimize hardware accuracy (Divjak et al. (1999),Huuskonen and Hohti (2004),Puhakka and Puhakka (2004), Huuskonen and Holleman (2006)). Calibration itself is a non-ideal procedure, and remaining errors will decrease the measurement quality. Since calibration errors are intrinsically unknown, they cannot be communicated and applied in data processing unlike many other quality indicators.

Pointing errors are mechanical calibration errors resulting from inaccuracies in initial calibration or from biased position sensors. Especially in the lowest elevation angles, one-tenth degree errors will cause significant problems. In addition to static, bias-like calibration errors, fluctuations may occur for example due to radar tower oscillations in wind or bending due to asymmetric heating caused by the sun.

Electromagnetic calibration errors originate from hardware components involved in a measurement cycle of a radar: the transmitter, waveguide, antenna mirror, and receiver. All these components are potential causes of signal loss. For various practical reasons one typically satisfies with a calibration error (reflectivity measurement bias) of 2-3 dBZ. In addition, there are fluctuations that are sometimes hard to detect. For example, sensitivity decreases gradually with receiver age.

4.5 Radar siting

Deciding the location of a radar is a complex task. Firstly, target applications and customers must be considered; public forecasting, hydrology, and aviation for example have different needs. Second, one should consider a radar as a component of larger (radar) observation network: current and future stations affect the location of a new site. Third, there are often various geographical constraints for potential locations of a radar station: accessibility, orography, public land use and regulations.

As a quality factor, radar siting is one of the most static ones. Failure in these produces problems which cannot be corrected by other parts of data processing or can only be corrected to a limited extent. Adding radars to a non-optimally designed network or moving radars to better locations are sometimes solutions to consider but require large expenses.

For an established radar station, local orography, at least the *radar horizon*, is a quality factor to be communicated in the data processing. (See Sec. 5.4)

4.6 Summary

The quality factors discussed above have been collected in Table 4.1. Basically, there are three types of factors deteriorating data quality: biases, fluctuations and probabilistic quantities. In principle, biases are the easiest ones: they can be canceled by good calibration. Fluctuations are inaccuracies of which the magnitudes are unknown in single measurements, but statistical properties may be available. For example, approximated error limits can be communicated as $\pm\Delta$ type accuracy information. Further, subsequent or multi-source errors (limits) can be treated in a mathematically disciplined manner (see Peura et al. (2006)). Probabilistic quantities are needed in describing occurrences (frequencies) of events that affect quality. More quantities of this type are introduced in the next chapter.

Table 4.1: Summary of quality indicators of a radar system. Typical values are rough estimates. See also Saltikoff et al. (2004).

Quality factor	Quality indicator	Notation		Typical value	Affects
Operating frequency	?	f	[Hz]	3, 5, 10 GHz	Sensitivity, attenuation
PRF	Max unamb. velocity	V_{Nyq}	[m/s]	5–30 m/s	Wind products
	Max unamb. range	R_{Nyq}	[m]	50–250 km	Range
Beam width		β	[deg]	$1°$	Spatial resolution
Pointing acc., elevation		$\Delta\theta$	[deg]	$< 0.1°$	Spatial resolution
Pointing acc., azimuth		$\Delta\phi$	[deg]	$< 0.5°$	Spatial resolution
Radar horizon	Max range at altitude h	r_h	[m]	$< 5°$	Range
Clutter	Statistical cl. maps, Doppler-filtered signal		[dBZ]		Data reliability
Sensitivity	Min. detectable signal at 1000m	MDS	[dBZ]	< -40 dBZ	Detection of snow and drizzle
Overall uptime reliability	Data availability	P_{data}	[%]	$90 - 99\%$ dBZ	Everything

Chapter 5

Quality information for volume data

In this chapter, we discuss quality associated with weather radar measurements: reflectivity (Z), Doppler velocity data (V), and velocity spectrum width (W). Besides the system related error sources discussed in the previous chapter, radar data frequently suffers from external errors such as aircraft, buildings, electromagnetic interference and other factors illustrated in Figure 5.1. We start by discussing the general geometrical properties of weather radar data as quality information often conforms to that geometry. As this chapter focuses on the volume data, not on products generated from the data, only basic products (PPI and CAPPI) are introduced for the purposes of illustration.

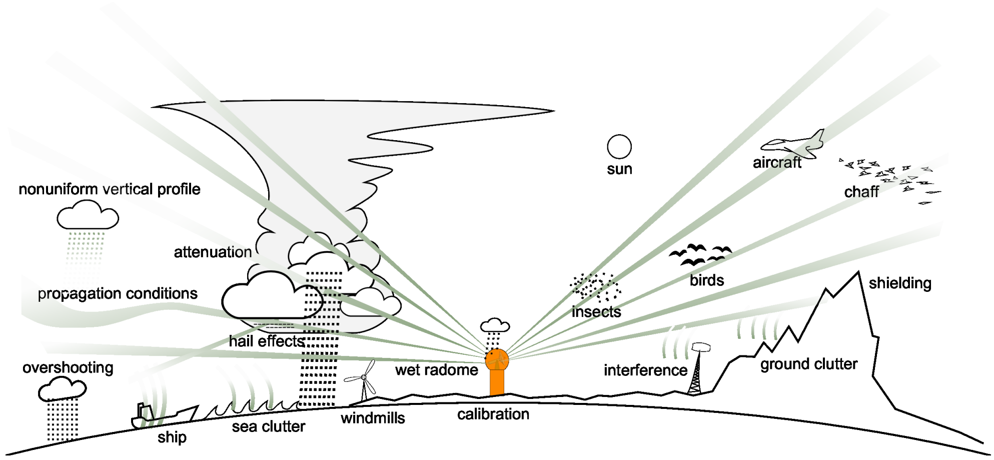

Figure 5.1: Phenomena affecting radar data quality.

5.1 Measurement geometry

In operational weather radars, the measurements are mostly carried out as azimuthal *sweeps* or *elevation scans*, that is, antenna rotations with a constant elevation angle. Measurements are operationally configured as *tasks*, each of which typically consisting of several sweeps, producing a set of nesting conical surfaces. The obtained three-dimensional measurement dataset is called a *volume scan* or briefly, a volume.

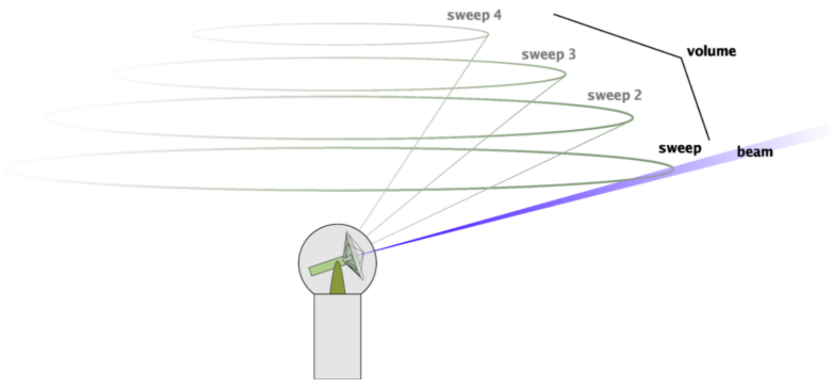

Figure 5.2: A typical scanning strategy of an operational weather radar.

Sweep data, measured in the polar coordinates, can be presented in a two-dimensional array (Fig. 5.3). This so called *b-scope* format is not suited to meteorological monitoring but is useful in tracking anomalies. As it is the complete presentation of the measurement, prior to geographical projections and data compositions, it is often most efficient to design data correction procedures in this format (Peura, 2002).

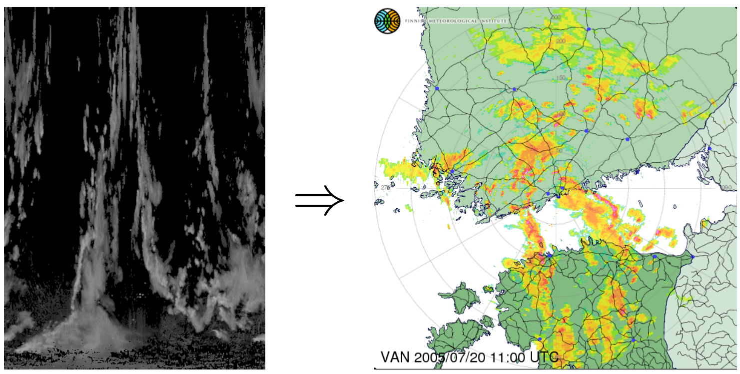

Figure 5.3: The b-scope image of the lowest elevation (0.5°) (left) and the corresponding Cartesian image product (right).

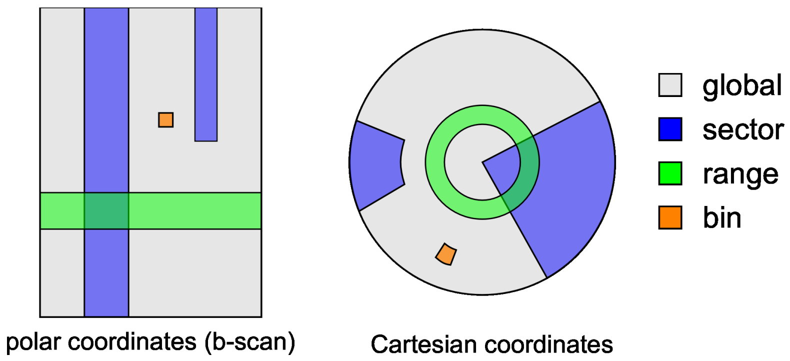

Figure 5.4: Possible geometries of quality information.

A Cartesian image of sweep data — often projected on geographical image layers — is called a *planar position indicator* (PPI). Mostly, the lowest-elevation sweep is considered only; hence this kind of image is sometimes called a *base product*. A *constant-altitude planar position indicator* (CAPPI) is a horizontal intersection of radar data. A typical altitude of the intersecting plane is 500 m or 1000 m.

If the intersecting plane is between (under, over) the beams, measurement values have to be interpolated. Often, one applies a Gaussian model for the beam power, obtaining for example a weighted sum of the lower/upper beam intensities to each image point.

Optimally, interpolation or extrapolation schemes - like those applied in surface precipitation products (Ch. 6) utilize approximated vertical profiles of reflectivity to recover from sparse or missing measurements.

5.2 Beam broadening and filling

As illustrated in Fig. 5.5, the physical width of an atmospheric volume corresponding to a measurement bin expands with distance from the radar. In Cartesian products, this *beam broadening* effect means that the spatial resolution varies drastically (Fig. 5.5). This geometrical property is apparently a static quality factor. However, the extent of information loss depends dynamically on weather: in a convective event details are more likely missed than in widespread, smoothly varying precipitation. In radar image composites, variable input resolutions can be used as quality indicators such that the radar with the best spatial resolution dominates over other radars Peura et al. (2006); Fornasiero et al. (2006).

The sixth power mathematics in radar combined to beam broadening yields a further problem called *beam filling*, which means that an intensive phenomenon at a periphery of a measurement volume dominates in the whole measurement volume. Inversely, if target fills only 50% of the bin volume, only about 3 dB is missed.

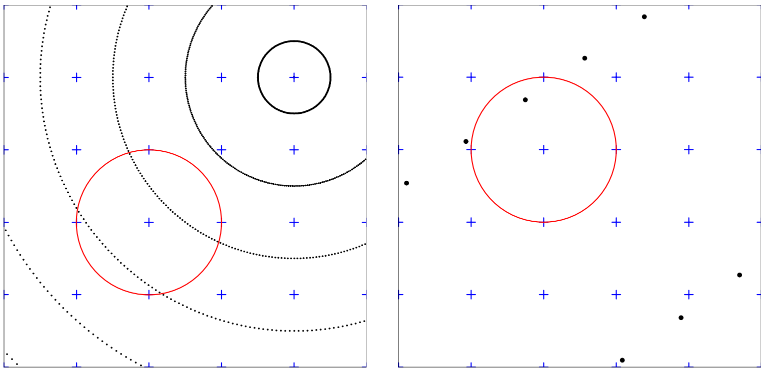

Figure 5.5: Geometrical disparities in resampling radar data ($\cdots$) to target pixels ($+$) in a Cartesian image product Henja and Michelson (1999). Close to the radar (left) several measurements contribute to an image pixel - and vice versa in distant locations (right).

5.3 Beam overshooting

The curvature of the Earth means that even the lowest radar beams are relatively high (1000 m at 150 kms, 3000 m at 200 kms), making estimations of surface rain less reliable. Hence, this causes faulty estimations in the case of overhanging precipitation (altostratus, see Figure 5.6) and in low-initiating snowing (Koistinen et al., 2003). Similar problems occur also due to beam blocking caused by mountains.

One can say that Earth curvature itself is not an"anomaly" or error. In some applications, like in data assimilation applied in numerical weather prediction (NWP) models, the three-dimensional volume data can be applied using the native polar geometry. Hence, strictly speaking this problem should not be seen as volume data quality issue. It however dominates in many central products like in surface rainfall products (Ch. 6).

5.4 Beam blocking

In mountainous regions, terrain elevation limits the radar horizon: due to *beam blocking*, precipitation behind the horizon remains undetected. As discussed in 4.5, radar horizon is one of the major issues to be taken into account

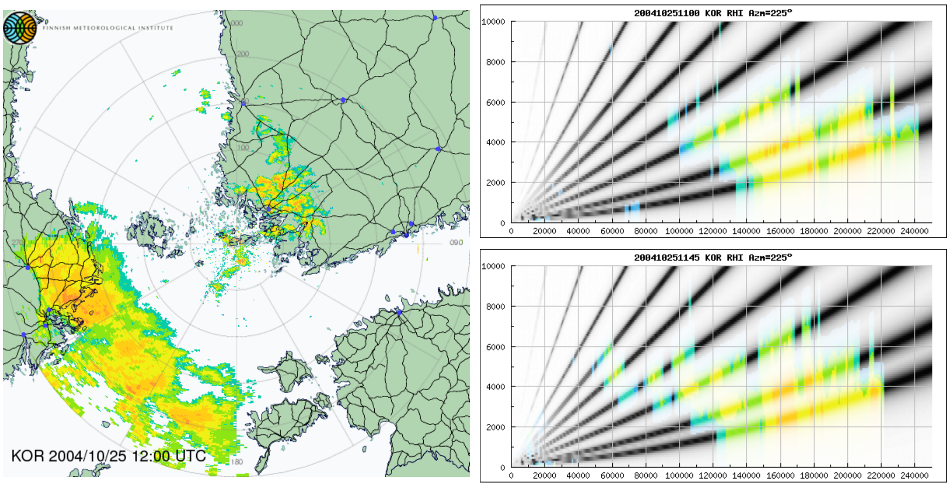

Figure 5.6: Overhanging precipitation approaching from the South-West (225°). In distant observations, precipitation-free areas remain under the radar beams.

in siting. (One may also argue that a radar horizon belongs to the radar "system".) Radar horizon elevation in degrees or meters can be communicated as a function of azimuth and range. Alternatively, it can be given for each radar elevation angle, like the map shown in Figure 5.7 or for certain altitude(s) (Table 4.1).

5.5 Ground clutter

As radars are very often used for approximating surface precipitation, the lowest sweeps are targeted as close to the Earth surface as possible. As a compromise, radar data is sometimes contaminated by strong peak-like echoes – *ground clutter* – originating from buildings, masts and natural targets like tall trees. Doppler filtering carried out by radar signal processors is an established technique to remove such anomalies; the practical hypothesis is that only hydrometeors move. However, some non-precipitating targets – like wet tree tops in wind – do move.

On the other hand, also the removal of valid false echoes produces holes in the image products. As a possible solution, one could mark the altered bins with the probability of an anomaly (that is, confidence on the validity of the applied removal) and use that information in re-generating missing data from, say, neighboring bins.

As not all operational radars are equipped with Doppler filters, there are many ground clutter detection algorithms reported in the literature. The

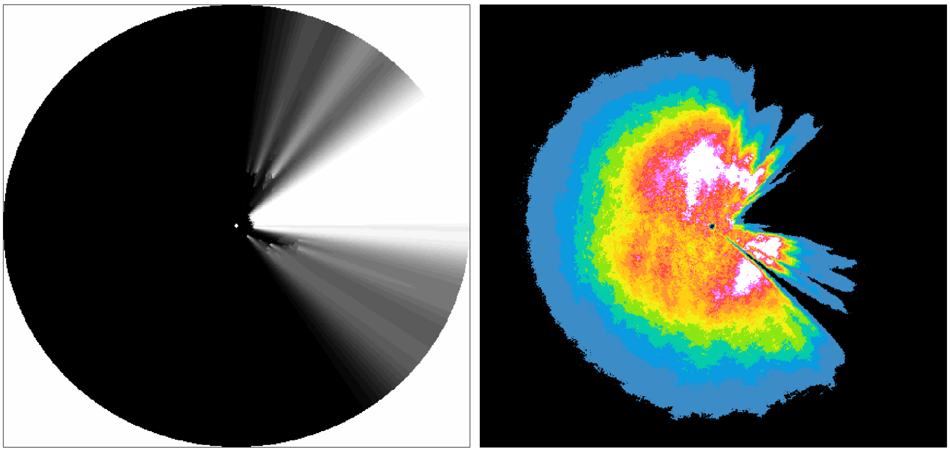

Figure 5.7: Beam blockage image and precipitation image suffering from missing sectors. Increasing pixel intensities indicate decreasing quality. (Courtesy of Uta Gjertsen, met.no .)

algorithms output errors as reflectances and/or probabilities.

5.6 Sea clutter

One of the most critical and yet unresolved anomalies is the so-called *sea clutter*. It occurs typically when warm air layer located over cold sea refracts radar beams downwards, making them hit sea weaves. An example is shown in Figure 5.8.

The sea clutter problem is rather serious because the contaminated areas are large and echo powers (dBZ's) are relatively high, producing severe errors in estimated rain rates. On the other hand, the problem is hard to tackle, because the shape of echo patterns appearing in radar images resemble those of true precipitation — a challenge for both duty meteorologists and automated correction schemes. Even the motion of the waves produce Doppler speeds similar to those of true precipitation, leaving Doppler filters inapplicable.

The spatial and temporal resolution of SYNOP observations in sea areas is poor, making physical, beam propagation model based correction methods inapplicable.

One general strategy is to approximate temperature and humidity conditions to estimate the probability of surface precipitation. For example, one may try surface temperature and cloud top height and proceed towards deriving vertical cloud structures by applying temperature and humidity pro-

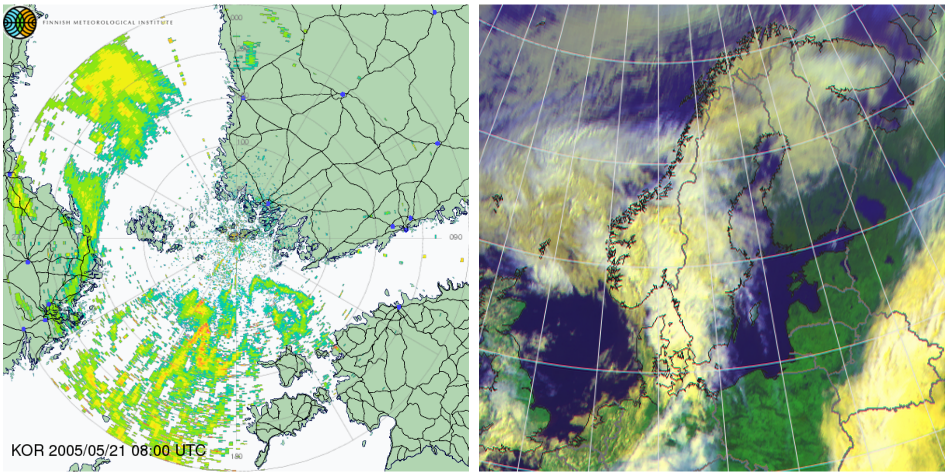

Figure 5.8: Left: Weather radar image containing both sea echo (south-west) and precipitation (west, north-west). Right: corresponding METEOSAT image supporting the recognition of sea clutter by revealing cloud-free sea in the respective area.

files. Practically, one may use a numerical weather prediction model for approximating air temperature and hence, probability of rain. Also thermal information from satellite data can be applied Bovith et al. (2006).

5.7 Beam attenuation

As explained in Chapter 4, the atmospheric attenuation of a radar beam depends on operating frequency. Further, attenuation is highly sensitive to intensity of precipitation: in moderate rain, radar beams can easily penetrate through hundreds of kilometers without remarkable loss while relatively small areas of heavy (over 45 dBZ) rain or hail block the beam quickly. An example is shown in Figure 5.9. Principally, attenuation can be estimated by accumulating it in subsequent bins, but due to intrinsic sensitivity of this process the obtained values are prone to large errors. However, one can more easily *determine* the probable sectors of attenuation which means that measurements from another radar (or rain gauges) can be adaptively used in recovering from the attenuation (see Figure 5.9, right, and compositing examples in Section 8.3).

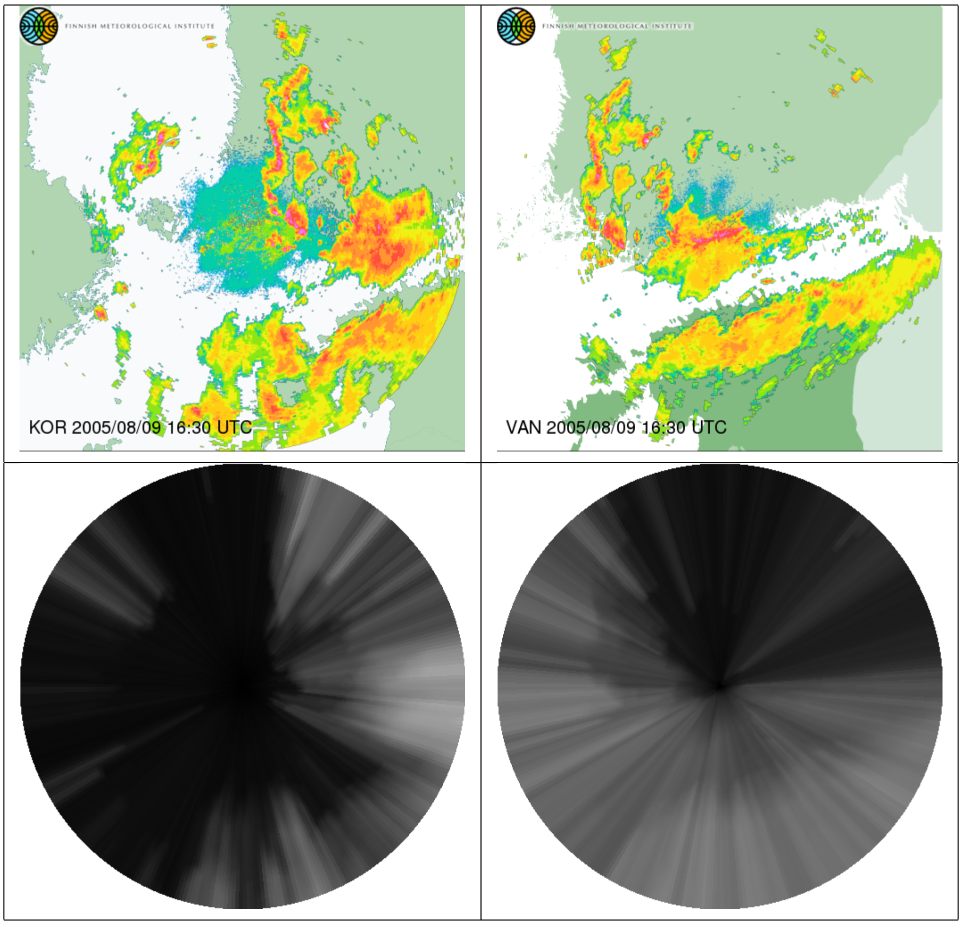

Figure 5.9: Attenuation problem at Vantaa radar (top right) appearing in undetected precipitation over Estonian islands Saaremaa and Hiiumaa (South). Bottom: respective probabilistic attenuation images.

5.8 Wet radome attenuation

As explained in Ch.4, the radome of a weather radar causes some attenuation, even though its form and materials are designed to be permissive for the applied radar frequency (Germann, 1999). On a "normal" (dirty) radome, the two-way attenuation may be of order 3 dB at the rain intensity of 15 mm/h. On a waxed radome, the respective attenuation is of order 1.5 dB (Kurri and Huuskonen, 2006). The attenuation effect increases in the case of sleet, which sometimes builds a sticky layer on the radome. This is a challenge for radome designers — and also for detection designers trying to model the expected layer shape and thickness on the radome.

5.9 Wind turbines

Generally, actively moving — translating, rotating, vibrating — targets cause quality problems in both dBZ and Doppler data. Moreover, they cannot be removed by Doppler filters designed to detect zero-velocity targets. *Wind turbines* are a problem of this category. Recently, OPERA has formulated recommendations for the siting of wind turbines so that these problems can be avoided or at least decreased; see the related OPERA project report (Chéze et al., 2006) and recommendations (Chéze et al., 2006).

5.10 Insects and birds

Radar data is often contaminated by insects flying or drifting at altitudes up to one kilometer. As their water content is small, they do not cause severe errors in dBZ but nevertheless cause some biases in cumulative rainfall products. The bias dominates near the radar because of radar sensitivity and relatively low altitudes. An example is shown in Figure 5.10.

To some extent, birds and insects can be recognized by the constant low-intensity dBZ field near the radar. Birds are bigger and more independent movers, causing increased variance in Doppler speeds: in spectrum width detected by the signal processor as well as in speed discontinuities in neighboring bins of measured data. In precipitation, the changes in velocities of neighboring bins are smoother — interrupted only by aliasing i.e. "jumps" at the ends of the unambiguous range. These jumps can be filtered out by appropriate processing. One of the detection challenges is in that also extreme weather events such as gusts, microbursts and tornadoes cause similar jumps in Doppler speeds.

It should be kept in mind that existence of insects is actually desired in Doppler measurements, especially in precipitation-free situations ie. clear air echoes.

Sometimes one may apply "cross-filtering", that is, flagging/removing erroneous measurements in Doppler data based on quality indications obtained from intensity data, and vice versa.

5.11 Ships and aircraft

Ships and aircrafts appear as distinct peaks in the dBZ data. The intensity of a peak is comparable or larger to that of convective cells including hail. The intensity decreases rapidly towards the neighboring bins. The strongest echoes are caused by ships. Often, the peaks originating from ships have

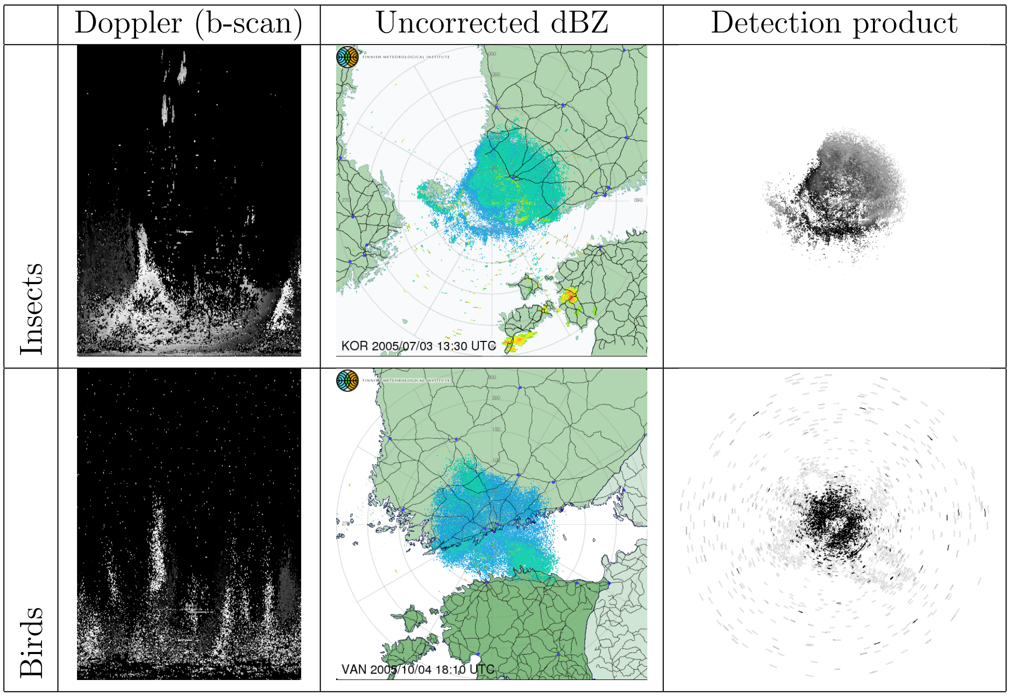

Figure 5.10: Birds and insects in radar data. The Doppler velocity field contains more variations in the case of birds; the detection product for birds is based on this property. The detection product for insects actually detects both insects and birds; it is based on fuzzy rules of proximity and reflectivity.

"sidelobes" perpendicular to the radar beams because ships can reside a few degrees off the radar beam and still return strong echoes. These "sidelobes" can be used in detection and removal (Peura, 2002).

5.12 Summary of quality indicators for radar data.

In this chapter, we have presented dynamic quality indicators for weather radar data. A summary is shown in Table 5.1. Most of the presented problems in data quality actually result from the combination of system parameters and targets measured. Some indicators are analogous to measurement accuracies while some are of probabilistic nature. In the latter case the quality indicator can be used as an index as well.

dBZ	Detection: SHIP	Detection: EMITTER

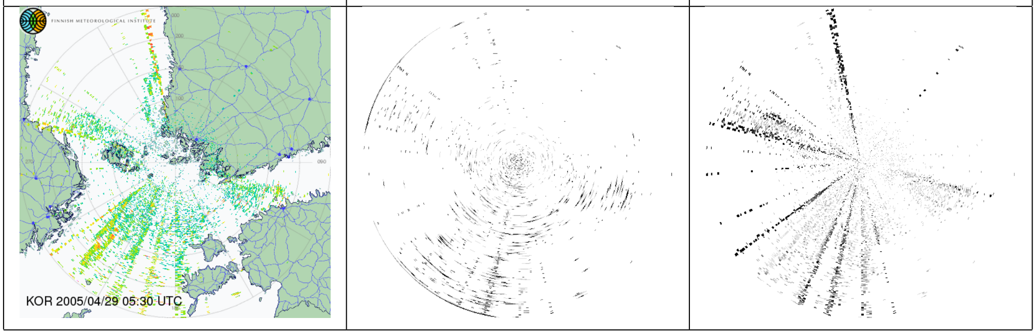

Figure 5.11: Ships and electromagnetic interference (dBZ).

Table 5.1: Suggestions of quality indicators and indices for radar data. Most of the indicators typically imply designing challenging detection schemes. "Non-meteorological echoes" include land and sea clutter, speckle noise, electromagnetic interference, aircraft, birds etc. The quality indicators requiring vertical profile of reflectivity (VPR) relate more to problems beyond the "plain" volume data; see Ch. 6.

Quality factor	Quality indicator	Quality index
Beam broadening	(Dynamic detail loss analysis?)	Spatial resolution inversed [$1/m^2$]
Beam overshooting	VPR analysis (near-radar measurements, models, soundings)	Probability [%]
Overhanging precipitation		Probability [%]
Non-meteorological echoes	Odd values in data [Z],[m/s]	Probability [%]
Wet/snowy radome attenuation	Echo loss in all or some directions [Z]	Probability [%]
Attenuation in precipitation	Path-integrated attenuation (PIA) [Z]	Probability [%]

Chapter 6

Quality information for precipitation at the surface

This Chapter addresses quality issues related to the representation of data and quality information of radar reflectivity factor and precipitation at the Earth's surface. Rainfall can be instantaneous or accumulated.

The foundation upon which this work is conducted is the Data Quality Report produced as a part of COST 717 (Michelson et al., 2005a). Since surface estimates are dependent on the radar set and its original measurements, the content of this subpackage is dependent on other elements of this Work Package, namely subpackages A and B (Chapters 4-5). Input data quality to the task of estimating surface variables will also fundamentally affect the surface estimate.

In this Chapter, the ways in which contemporary methods used to estimate surface reflectivity and rainfall can interface with the task of deriving quality information are addressed.

6.1 Methods based on the Vertical Profile of Reflectivity (VPR)

VPR-correction techniques are, similarly to gauge-adjustment techniques presented below, designed to make radar observations made aloft representative at the surface. Since the input to a VPR correction can be the same as the input to gauge adjustment, the magnitude of the necessary correction will be the same for both. However, some processing chains use these two methods sequentially, such that the VPR correction first accounts for most of the correction, and then gauge adjustment acts to minimize the residual bias against gauge observations. Gauge adjustment is addressed in the next section.

The underlying principle in conducting a VPR correction is that the knowledge of the vertical distribution of radar reflectivity can be used to determine a correction applicable to a measurement made aloft. In other words, the difference between the reflectivity at the surface (bottom) of a profile and the reflectivity at any given height along the profile can be used as a correction for radar data measured at that height.

Despite the simplicity of the VPR correction principle, there are a number of important limitations and uncertainties involved in making the principle work in practice. The most important challenge is in deriving a VPR, the basis for the correction, which is representative in both time and space. A radar can generate a complete VPR only rarely. This VPR is generated using data at short ranges, e.g. <40 km, and it may not be representative in more distant areas. The profile may also be contaminated by random or systematic errors, so it may not even be representative for the area from which the data used to generate it were taken. Therefore, a climatological profile can play an important role, since it can always be used as a fallback in cases where the local profile fails. Temporal averaging of profiles, with or without the climatological profile, is also useful in deriving more widely-applicable profiles (e.g. Germann and Joss, 2002). Numerous techniques have been developed mostly within the last few years, yet there is no recognized reference publication which reviews them. The background provided in Michelson et al. (2005b) builds upon that given in Germann and Joss (2002) and might serve as a useful starting point.

Networking VPR corrections adds to the complexity of deriving a representative VPR upon which a correction can be based. If each radar in a network produces an operational VPR, and the radar network density is low (e.g. around 200 km between pairs), then spatial interpolation of these profiles may still give improved results compared to using local profiles for each radar (Pohjola and Koistinen, 2007). Nevertheless, spatial interpolation of VPRs risks introducing artificial gradients in the horizontal distribution of the derived profiles. Little can be done about such artifacts, yet both producers and users of data corrected using such profiles should be aware of the artifact's potential existence.

A major uncertainty in conducting any VPR correction is the existence of overhanging precipitation. Such precipitation does not reach the surface, due to evaporation, yet it is easily detected by radar. The problem becomes serious where an echo becomes stronger as a result of correction, yet no precipitation reaches the surface; the "correction" leads to worse results in such cases. Diagnosis and treatment of overhanging precipitation presents a major challenge at present. At the other end of the profile, total beam overshooting (no radar echo) cannot be corrected because there is nothing there to correct.

The VPR is a simple product which should be made available for international exchange, either alone or as part of the corresponding wind profile (WRWP). If VPRs are available internationally in real time, then interested NMSes can use them to perform VPR corrections themselves, according to their own priorities, instead of receiving e.g. a CAPPI product which has already been corrected. Similarly, if VPRs are to be made internationally available, they should not be subject to any temporal or spatial interpolation beforehand. Quality control of individual VPRs should, however, be conducted and documented.

If a surface radar estimate has been derived using a VPR correction, and this product is made internationally available, then the VPR used for the correction becomes this product's *quality indicator*. This is the most efficient way to package this information, since the product's metadata (antenna height, scan strategy) together with the VPR can be used to determine the correction applied to the original data and even reconstruct the original data if wanted. If the surface product was generated using dynamic corrections based on spatial interpolation of two or more VPRs, then the correction applied to each pixel becomes the product's *quality indicator* and this *quality indicator* can then easily be harmonized according to Sec. 3.6.

6.2 Gauge adjustment

Using observations from precipitation gauge measurements to adjust the quantities provided by radar is a well-established statistical framework for improving the quality of radar information. A proper review of gauge adjustment, both techniques and practices in Europe, has been produced in COST 717 (Gjertsen et al., 2004) and should be consulted for more detail.

The objective of gauge adjustment is to *correct* radar data measured aloft using surface measurements, the result being a radar-based surface estimate. Since radar makes it measurements at increasing altitudes with increasing range, gauge adjustment most often deals with correcting radar's systematic underestimation. Corrections can, however, be negative in highly convective precipitation climates or in summer conditions out to relatively short ranges. While the simplest form of correction is a bulk correction (adjustment using a single global value), gauge adjustment is most effective when applied spatially. A simple spatial adjustment involves applying a correction based only on range. A fully spatial correction involves deriving and applying a pixelwise correction. Such methods are commonplace in Europe today.

Primitive forms of gauge adjustment consider the gauge observations as representing "the truth", and the radar data are forced to agree with them. More intelligent techniques attempt to consider the errors to both gauge measurements and radar estimates in the adjustment procedure. Gauge errors in this context deal with determining the gauge measurements' spatial representativeness. Gauge measurements suffer from several fundamental error sources, some of which can be extreme but which are correctable (e.g. Michelson, 2004). While both producers and users of gauge-adjusted radar data must be aware of such gauge-measurement errors, addressing them directly lies outside the scope of this work package.

There are different families of gauge-adjustment techniques. A widespread family of methods involves using the gauge-to-radar ratio as the basis for adjustment. This is an intuitive approach, since adjustments can easily be expressed in terms of dB. Another family of methods involves the use of gauge observations to dynamically tune the Z-R relation at the pixel level. The output of such procedures can be expressed in terms of coefficients A and b. Other approaches may output results in other ways.

Radar's underestimation at distant ranges (increasing heights) can be extreme, involving corrections of several thousand percent. This is normal radar behavior and nothing to be alarmed about. It is therefore appropriate that corrections be expressed in terms of dBZ for reflectivity and in dBR (mm/nh) for precipitation. It is therefore also appropriate that errors and uncertainties be expressed in these quantities as well. This is straight-forward for gauge-to-radar-based adjustment techniques. It should also be fairly easy to modify techniques based on the Z-R relation to output results in these quantities.

If results from gauge-adjustment can be output in a harmonized way, then we can identify a useful *quality indicator* which can be easily normalized according to Sec. 3.6. This would enable the packaging and international exchange of quality information related to gauge adjustment.

6.3 Multisource methods

With the exception of gauge adjustment, this section deals with how radar data quality may be characterized through the use of information from external (relative to the radar) information sources for the purposes of determining surface estimates.

Multisource methods are slowly emerging to give us the ability to improve the quality of radar observables. While such methods have been used operationally for over a decade in the United Kingdom (e.g. Kitchen et al., 1994), they are relatively uncommon elsewhere. So far, they seem to be most useful in solving problems in relatively uncomplicated ways. For example, NWP model fields have been found to provide fairly accurate information on the height of the melting layer (Mittermaier and Illingworth, 2003); such information can be useful when treating the bright band in radar data. Since newer NWP model configurations can better resolve precipitation systems than previous models, we have the potential to better resolve the spatial distribution of factors influencing precipitation observed by radar. The first attempts at achieving a VPR-like correction using NWP, analyzed fields, and model physics were only partly successful (Michelson et al., 2005b), yet this kind of approach shows promise. Similarly, several attempts have been made to use NWP or extrapolated surface measurements to determine the precipitation phase and thus apply corresponding Z-R relations, yet none of these methods have reported any success. Polarization techniques at typing precipitation particles appear to be useful at short ranges, yet their operational usefulness to full range is still uncertain.

One of the areas where multisource methods may become useful in the short term is in the identification and treatment of overhanging precipitation and evaporation in the boundary layer. As mentioned in Sec 6.1, VPR corrections cannot properly deal with evaporation. This is probably one of the more important reasons why VPR correction techniques today do not succeed in significantly reducing the random error in validations against gauge observations. Multisource treatment of evaporation could be a useful method following a VPR correction which stops at the cloud base. Similarly, correcting radar for the effects of wind drift on snow is a current issue of concern, especially in temperate and colder climates. This is being addressed constructively (Mittermaier et al., 2004), and can also help reduce the random error against gauge data.

Despite the advances made over the last few years, multisource methods are still in their infancy and need time to mature. Consequently, it may be too early to formulate harmonized procedures for deriving *quality indicator*s, unless the net result to be represented as a *quality indicator* is expressed in a way which is always related to the physical quantity observed by the radar.

6.4 An example QPE quality indicator

Operational quantitative precipitation estimation (QPE) in Sweden is performed using a simplified version of the BALTRAD gauge-adjustment technique (Michelson et al., 2000). This algorithm will be the basis for exemplifying how a *quality indicator* may be formulated which follows the quality

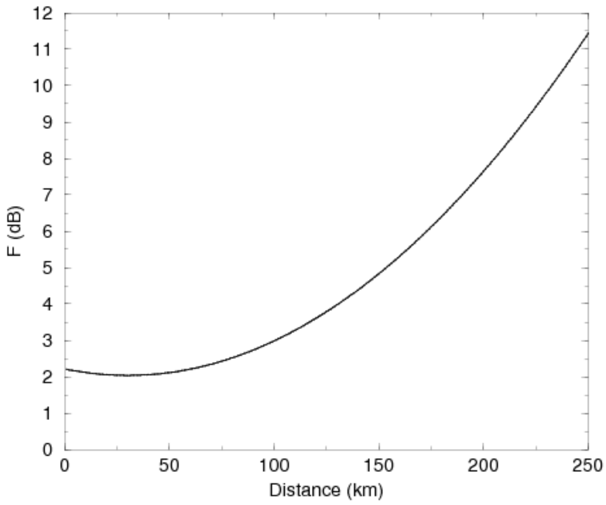

Figure 6.1: Operational gauge-adjustment correction factor as a function of surface distance, derived for May 25, 2006, at 6:00 UTC.

framework set out in this report. For the sake of simplicity, we can state that no other quality-control methods are applied to the data prior to gauge adjustment.

This gauge-adjustment technique is based on the gauge-to-radar ratio, specifically:

$$F = 10 \times \log \frac{G}{R}. \tag{6.1}$$

Originally, the algorithm makes use of data assimilation methods for deriving a fully spatial adjustment-factor field. The basis for this is correction factor F as a function of surface distance from the radar, which is used as a first guess. This first guess is derived using a second-order polynomial. Then, individual F points are spatially interpolated, and, based on the qualities of individual F points, the spatially interpolated field is weighted against the first guess to derive the final adjustment factor for each pixel. In practice, it has been found that the density of real-time SYNOP observations is so low that the spatial analysis has almost no impact on the final result. So, the real-time implementation uses only the first guess.

The real-time implementation generates one-hour accumulated precipitation products on the full Nordic network coverage area. SYNOP observations are available for 6 and 18 UTC. Additionally, the second-order relation is based on all F point pairs available over a ten-day moving window. This means that the first guess will not be subject to abrupt changes over time.

A case from May 25, 2006, at 9:00 UTC illustrates this product and its

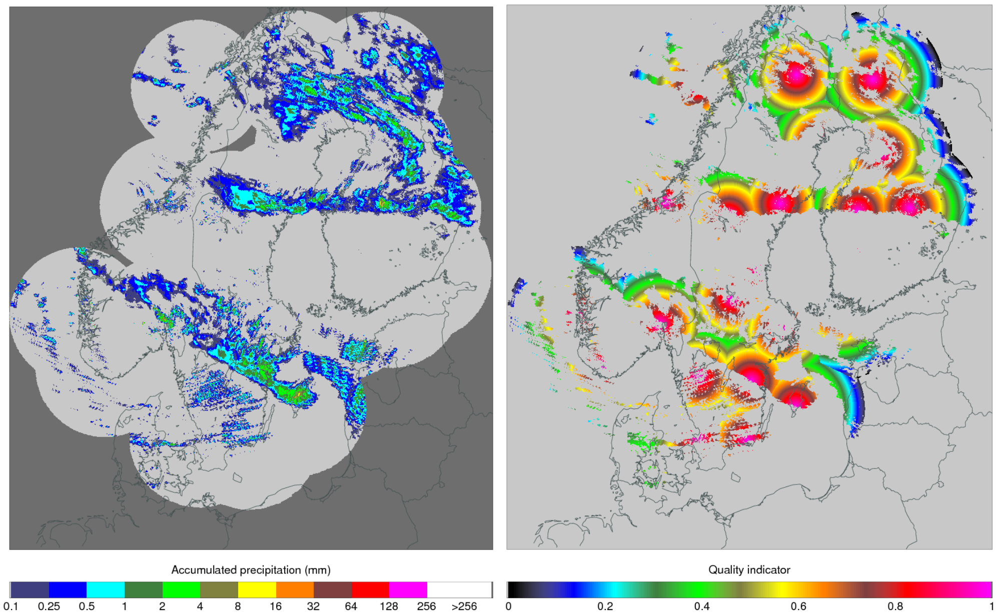

Figure 6.2: The left image shows a one-hour gauge-adjusted accumulated precipitation ending on May 25, 2006, at 9:00 UTC. Quality indicator corresponding to the left image is shown in the right image where quality ranges from 0 (lowest) to 1 (highest).

quality indicator. Figure 6.1 shows the correction factor as a function of surface distance from the radar. This correction is applied to each pixel in the radar-based precipitation accumulation which is derived from Nordic composites. The one-hour gauge-adjusted precipitation accumulation is shown in Figure 6.2 (left image).

In order to package the *quality indicator* according to the proposed framework, a couple of constants are needed; these are the minimum and maximum surface distances from the radar in the whole product domain (0 and 250 km, respectively). The three coefficients used in deriving the correction factor shown in Figure 6.1 are also needed. These values are all stored as metadata in the product file. The application of this information using Equation 3.1 is also provided as metadata in the product file. The *quality indicator* itself is stored in the product file as a separate image, illustrated in Figure 6.2 (right image), with 32-bit floating point depth just like the accumulation image. Note that this image is scaled according to Equation 3.1. Note also that this image is little more than a spatial representation of Figure 6.1, applied to the precipitation accumulation composite, *if* all data from all radars are present for the integration period. If a radar dropped out during the integration period, other radars covering the same area will contribute instead, and then the *quality indicator* image can be described as semi-dynamic.

The availability of this information in the product file implies that the *quality indicator* image, together with the associated metadata, can be used to reverse the gauge-adjustment. This means that it becomes possible to determine the correction applied to any given pixel. And this means that it becomes possible to formulate criteria for accepting/rejecting the precipitation accumulation based on the correction factor and/or surface distance. In fact, we have everything we need to formulate a *quality output method* and derive a *quality index* for a given application.

It should be noted that this application of the quality framework is a relatively trivial one, as the framework allows for multiple quality indicators of different dimensions. It nevertheless represents an early operational implementation of the quality framework which can evolve over time. With increased amounts of quality information, and more dynamic information available at the per-pixel level, the issues related to the combination of the information, outlined in Section 3.7 of this report, become relevant.

Chapter 7

Quality information for wind data

This chapter will deal with quality information for weather radar wind profiles, radial wind super-observations, and raw radial wind data. The weather radar wind profiles which can be considered a special kind of super-observations will be discussed in detail. It is concluded that the radial wind standard deviation is a useful and commonly available quality indicator for weather radar wind data. The following items will be described in this chapter:

- Review of quality factors for weather radar wind data
- Retrieval and quality evaluation of weather radar wind profiles
- Derivation of radial wind super-observations
- Analysis of raw velocity data
- Recognition of bird migration contamination
- Proposal for quality indicators

7.1 Quality factors for wind data

A detailed overview of quality factors for wind (profile) data is given in an OPERA working document (Holleman et al., 2002). In chapters 4 and 5 some quality factors influencing the radar systems and radar base data are discussed. A resume is given below.

7.1.1 Velocity Aliasing

Because a Doppler radar uses phase differences to determine the radial velocity, there is a maximum velocity that can be determined unambiguously. This maximum velocity is called the Nyquist velocity and it can be expressed as (Doviak and Zrnić, 1993):

$$V_{Nyquist} = \frac{\mathrm{PRF} \cdot \lambda}{4} \tag{7.1}$$

where PRF is the Pulse Repetition Frequency of the radar pulses and λ is the wavelength of the radar (5 cm for C-band). The timelag between two successive radar pulses, and thus the PRF, also determines the maximum range that can be resolved unambiguously. This leads to the fundamental equation for the maximum (Nyquist) range and maximum velocity of a Doppler radar:

$$R_{Nyquist} \cdot V_{Nyquist} = \frac{c \cdot \lambda}{8} \tag{7.2}$$

where c is the speed of light. For measurements with a Doppler radar, a trade-off, therefore, has to be made between the maximum velocity and the maximum range. Velocity aliasing can usually be identified in radar images by detecting abrupt velocity changes of about $2 \cdot V_{Nyquist}$ between neighboring measurements. In this case, the basic assumption is that the true wind field is sufficiently smooth and regular; this is true for the greater part of the weather situations with the exception of mesocyclones, tornado vortices or highly sheared environments.

Aliasing problems can largely be circumvented by applying different measurement techniques, like dual-PRF or staggered PRT (Pulse Repetition Time). Many operational Doppler radars in Europe have the capability of using the dual-PRF technique. During a dual-PRF measurement, radial winds are measured with alternating high and low PRFs. By combining the measured velocities at low and high PRF, the maximum unambiguous velocity can be extended by about a factor of three. Recently several publications of analysis and correction of dual-PRF velocity data have appeared (Joe and May, 2003; Holleman and Beekhuis, 2003; Tabary et al., 2005). Alternatively, dealiased wind profiles can be obtained from the azimuthal derivative of the velocities (Tabary et al., 2001) or by mapping the velocity data on a Torus (Haase and Landelius, 2004). In a second step the dealiased wind profiles can be used to dealiase the radial velocity data.

To be able to interpret Doppler velocity data information on the applied PRF(s) and on the measurement technique, e.g., single-PRF, dual-PRF, staggered PRT, should be given in the BUFR message. Furthermore, (additional) de-aliasing during post-processing of the velocity data or calculation of the wind profile should be indicated.

7.1.2 Clutter and anomalous propagation

Radial wind measurements can be heavily affected by normal or anomalous propagation clutter. Clutter signal can be suppressed to a large extent from the reflectivity and radial wind data by reducing the echo power around zero radial velocity using discrete filtering techniques in the time or frequency domains. All operational Doppler radars apply this kind of filtering before the radial velocity is determined. For a complete discussion on the problem of the bias introduced in the radar wind spectrum due to the clutter and clutter-suppression algorithms, the reader is referred to Seltmann (2000).

To assess the a-priori quality of wind profiles, the application of Doppler clutter filtering and the rejection of radial wind close to zero should be indicated.

7.1.3 Birds and actively-flying insects

Non-hydrometeor targets such as insects and birds are detected by (Doppler) radar as well. While some insects can provide a help in defining the boundary layer wind, birds and actively-flying insects are a serious problem for velocity retrieving algorithms (Koistinen, 2000). Erroneous wind data due to birds can often be recognized by inconsistency of the velocity data. The application of a bird-wind rejection algorithm should be indicated and otherwise the likeliness of bird contamination and/or preferred azimuths of migrating birds should be listed. Examples of contamination by birds and insects are shown in Section 5.10.

7.2 Weather Radar Wind Profiles

7.2.1 Profile retrieval

Wind profiles can be obtained from single-site radar data under the assumption of a linear wind model. In this model the wind in the vicinity of the radar (at the origin) is expressed as:

$$U(x, y, z) = u_0 + x\frac{\partial u}{\partial x} + y\frac{\partial u}{\partial y} + (z - z_0)\frac{\partial u}{\partial z} \tag{7.3}$$

and likewise for $V(x, y, z)$ and $W(x, y, z)$. Using this linear wind field, the radial wind can be calculated as a function of range, azimuth, and elevation.

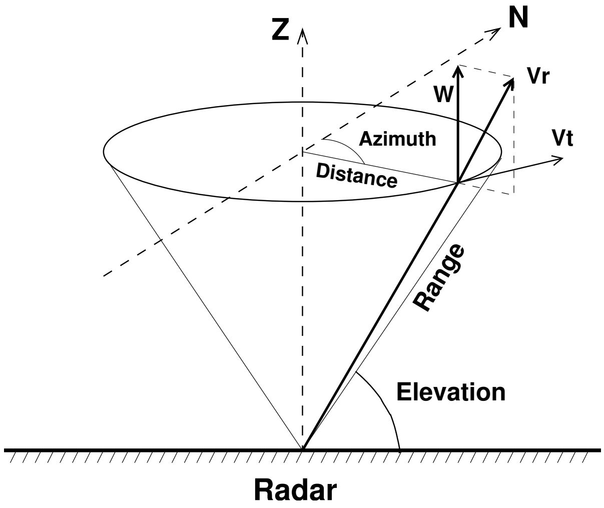

Figure 7.1: Radar geometry for measuring wind profiles.

For a uniform wind field this results in:

$$V_{radial} = u_0 \cos\theta \sin\phi + v_0 \cos\theta \cos\phi + w_0 \sin\theta \tag{7.4}$$

When Doppler radar data is displayed at constant range and elevation (θ), the radial wind as a function of azimuth (ϕ) will have the form of a sine. The wind speed and direction can be determined from the amplitude and the phase of the sine, respectively. This technique is called Velocity-Azimuth Display (VAD), and it was introduced by Lhermitte and Atlas (1961) and Browning and Wexler (1968). The radar geometry used to measure these volume scans is shown schematically in Figure 7.1.

Instead of processing, for each height, a single VAD or a series of VADs, one can also process all available volume data in a certain height layer at once. This so-called Volume Velocity Processing technique (VVP) has been introduced by Waldteufel and Corbin (1979). Using equation 7.3 of the linear wind model, the radial wind can be calculated for all points within a layer centered at height z_0. Via a multi-dimensional and multi-parameter linear fit, the parameters of the linear wind field can be extracted. The VVP technique is typically applied to thin layers of data at successive heights to obtain a wind profile.

The standard deviation of the radial velocity σ is calculated from the SVD solution using the chi-square merit function (Press et al., 1992):

$$\sigma^2 = \sum_{i=1}^{N} (V_{r,i} - V_r(\vec{r}_i))^2 / (N - M) \tag{7.5}$$

where $V_{r,i}$ are the observed radial velocities, N is the number of radial velocity data, and M is the number of parameters in the radial velocity model. The retrieved wind vectors are quality controlled by rejection of the vectors with a standard deviation larger than a certain threshold. The quality and availability of wind vectors are coupled, and the optimum setting of standard deviation threshold depends on the application of the profiles

For wind profile products, the retrieval technique used to extract the wind profiles from the volume data, e.g., VAD, EVAD, or VVP, and the maximum range used for profile retrieval should be indicated in the BUFR message. Furthermore, quality indicators resulting from the retrieval of the wind at each height, like the number of valid points, the chi-square of the fit, standard deviations of wind speed and direction, are useful. Finally, the quality of the wind profiles is different for clear air, stratiform precipitation, or convective situations. The median reflectivity at each height could be used to indicate the meteorological situation.

For the definition of the quality indicators for Weather Radar Wind Profiles, the specification for WRWP products by Galli et al. (1999) is taken into account. Most of the quality descriptors defined for the base data can also be used for the wind profile product. Especially the type of clutter treatment is of importance for the wind profile product.

7.2.2 Profile quality

The intercomparison of different implementations of the VAD and VVP wind profile retrieval methods using radiosonde profiles as a reference revealed that the VVP method performs slightly better than the VAD method (Holleman, 2005). Furthermore it was found that the most simple implementation of the VVP retrieval method, i.e., using a uniform wind field, provides the best horizontal wind data. Figure 7.2 shows a timeseries of weather radar (VVP) and Hirlam NWP wind profiles for 8 January 2005 between 06 and 12 UTC in black and blue, respectively. On this day a low pressure area with strong winds moved over the Netherlands. In figure 7.2 wind speeds up to 50 m/s are observed between 4 and 6 km altitude. Evidently the agreement between the radar and model wind vectors is good, but the update frequency and availability are different.

Histograms of the wind speeds observed by Doppler radar have been constructed for three different height ranges. The constructed histograms for the 0-2 km, 2-4 km, and 4-6 km height ranges are shown in figure 7.3. The vertical axis represents the wind vector count per 1 m/s-wide bin using all available radar wind profiles between 1 October 2001 and 30 June 2002. Comparing the histograms for the three height ranges, it is evident that

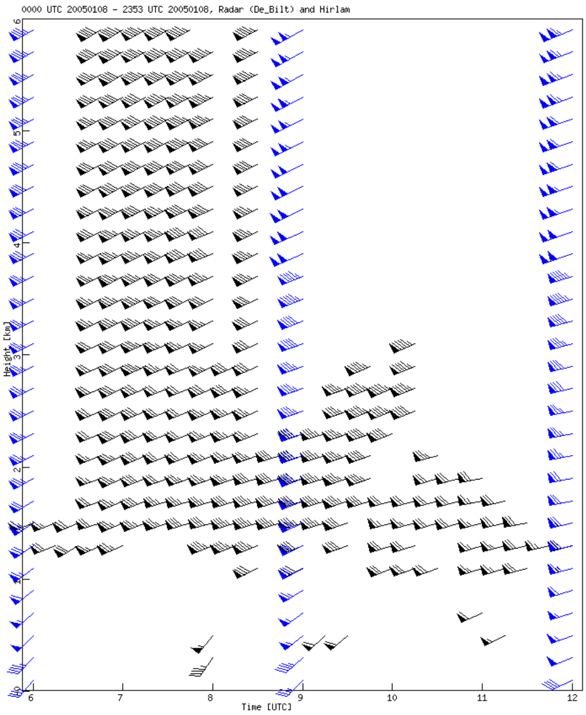

Figure 7.2: A time-height plot with the weather radar wind vectors (VVP) for 8 January 2005 between 06 and 12 UTC. The wind profiles from the Hirlam NWP model are overlayed in blue. Wind speed and direction are indicated by wind vanes. Each full barb represents a wind speed of 5 m/s and each triangle a wind speed of 25 m/s.

the total number of available wind vectors and the mean wind speed are decreasing and increasing, respectively, with increasing height. The fraction of the number of available wind vectors to the maximum number of vectors decreases from 0.39 at ground level to 0.16 at 6 km altitude.

The observation minus background statistics for the weather radar (upper frames) and radiosonde (lower frames) wind profiles against the Hirlam NWP model are shown in figure 7.4. The figure shows the bias and standard deviation of the Cartesian u- and v-components of the wind vectors calculated for the 9 months verification period (1 October 2001 and 30 June 2002). In this comparison the radiosonde has a clear advantage over the weather radar because the radiosonde profiles are assimilated by the Hirlam model. It is therefore not a surprise that the observed biases of the wind vector components from the radiosonde are only a few tenths m s^{-1} and thus negligible. The standard deviation of the radiosonde wind vector components

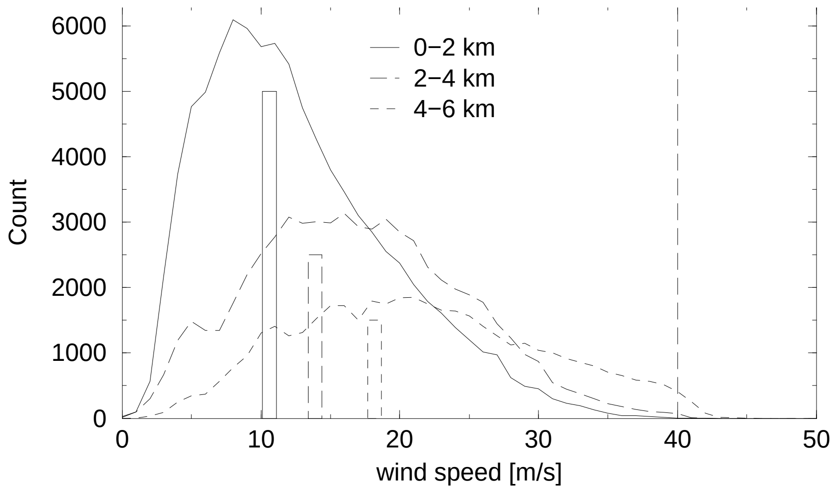

Figure 7.3: This figure shows histograms of the observed wind speeds for three different height layers and using wind speed bins of 1 m/s. The wind speeds are obtained from the radar using the VVP retrieval method. The vertical bars represent the mean wind speeds as obtained from the radiosonde observations over the same period.

against the Hirlam background is between 1.5 and 2.0 m s^{-1} at ground level and gradually increases to almost 3.0 m s^{-1} aloft. This increase is probably due to the increase of the wind speeds with height and to the drifting of the radiosonde. For the radar wind data, a small positive bias for both Cartesian components is found. The standard deviation of the VVP wind vector components against the Hirlam background is around 2.0 m s^{-1} at ground level and about 2.5 m s^{-1} aloft. Figure 7.4 shows that observation minus background statistics of the weather radar wind profiles are at least as good as those of the radiosonde profiles. This result evidently demonstrates the high quality of the weather radar wind profiles.

7.3 Radial Velocity Super-Observations

The so-called "Super-Observations", i.e., proximate observations combined into a single observation representative at a larger spatial scale compatible with a NWP model, have been introduced by Lorenc (1981). The derivation and assimilation of radar super-observations of radial velocity is described extensively by Michelson (2003). For the generation of super-observations the radial velocity data are averaged into polar bins “voxels” with a typical size of 10 km in range and 3.5 deg in azimuth. For each super-observation

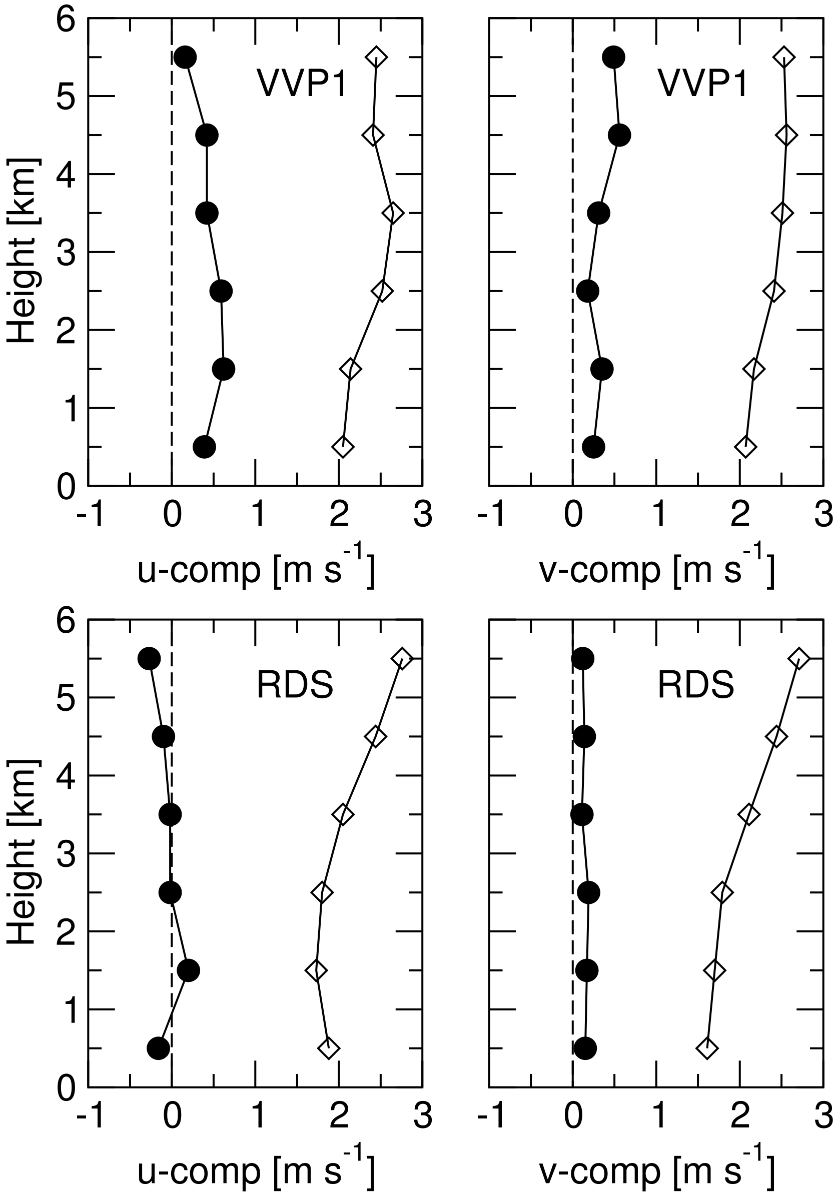

Figure 7.4: Profiles of the bias (•) and standard deviation (⋄) of the Cartesian u- and v-components from the verification of the radar (upper) and radiosonde (lower) wind data against the Hirlam model.

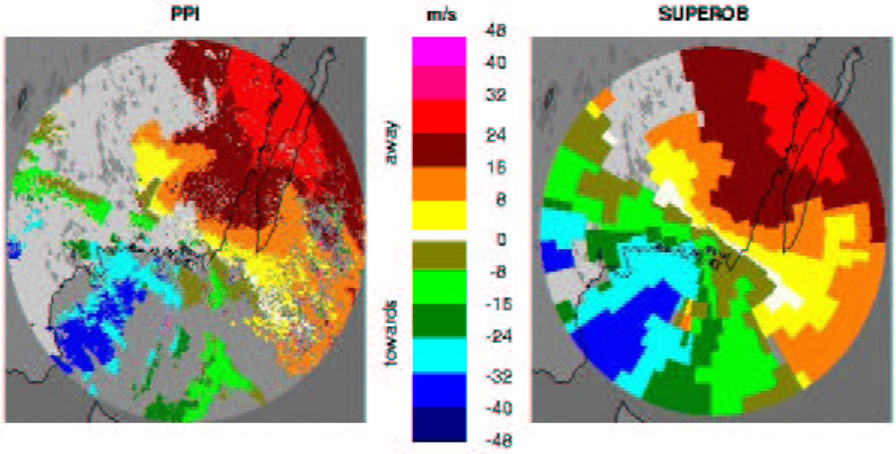

Figure 7.5: Raw radial wind data (left) and radial wind super-observation (right) for a winter storm captured by Radar Karlskrona on 3 December 1999 at 1830 UTC (figure taken from Michelson (2003)).

an extensive set of metadata and statistic properties are generated:

Longitude/Latitude of the super-observation

Elevation angle of the super-observation

Range of the super-observation from radar

Azimuth of the super-observation with respect to radar

Averaging lengths in horizontal and vertical directions

Average radial wind velocity from all raw bins in super-observations

Radial wind variance square of radial velocity standard deviation

Sample size of radial velocity bins in super-observation

Average reflectivity over super-observation volume

and much more. An example of a radial wind super-observation is shown in Figure 7.5.

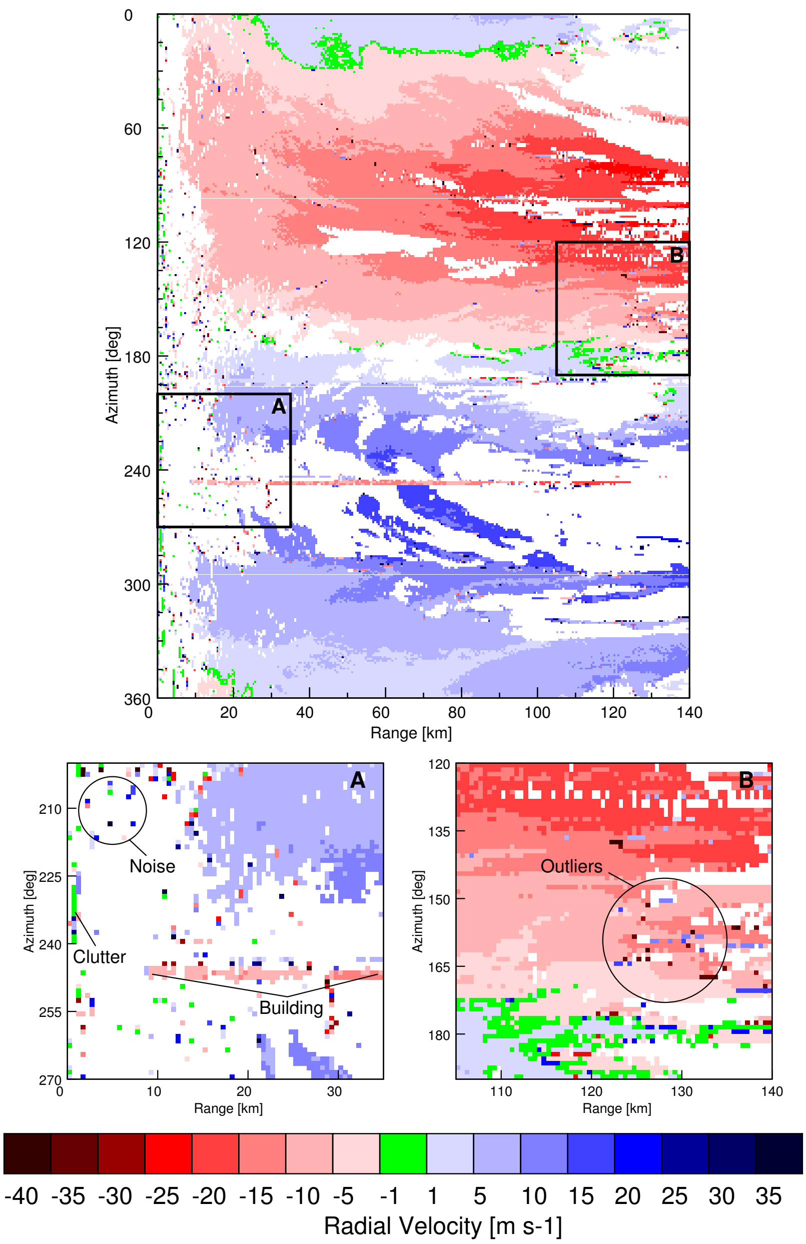

Figure 7.6: B-scope display of raw dual-PRF velocity data from 1454 UTC 6 November 2001. The azimuthal scan was recorded at an elevation of 0.5 degrees using PRFs of 750 and 1000 Hz. Areas A and B of the main figure have been enlarged in the two frames on the right. Several sources of contamination have been marked in the figure. White indicates areas with "missing data".

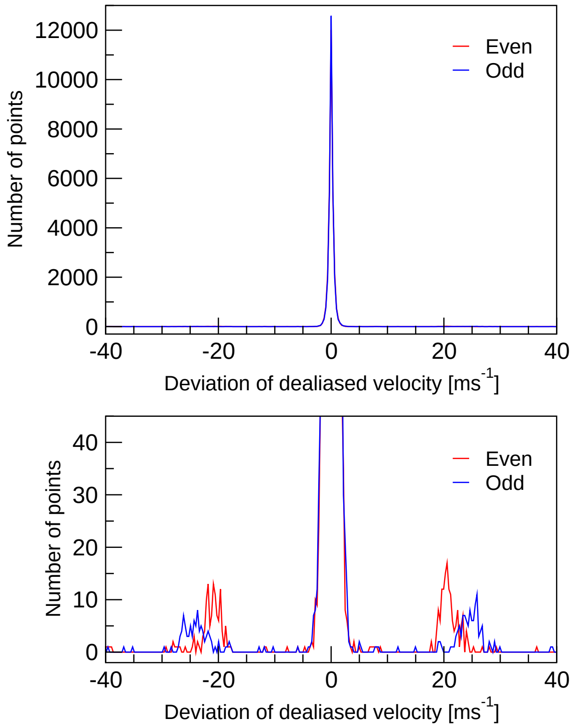

Figure 7.7: Histogram of the deviations of each dealiased velocity from the local median velocity. This histogram has been compiled using the data of the azimuthal scan of Fig. 7.6. Separate histograms are shown for even and odd azimuths. The central peaks go up to a number of about 12,500 (off-scale).

7.4 Raw Radial Velocity Data

To elucidate the error characteristics of dual-PRF radial velocity data, an analysis of measured velocity data has been performed (Holleman and Beekhuis, 2003). Figure 7.6 shows a typical example of raw dual-PRF velocity data. The velocity data are presented in a so-called "B-scope display" or range-azimuth indicator, and two regions of interest have been enlarged in the right frames. From a close examination of Fig. 7.6 and other data, it appears that (dual-PRF) velocity data are typically contaminated by clutter, noise, and outliers (see also Chapter 5). These sources of contamination have been indicated in the side frames of Fig. 7.6. There is some sidelobe clutter present at ranges shorter than 10 km in Fig. 7.6, but the most distinct clutter is caused by specular reflection of the radar beam from a building located at 246 degrees azimuth (see upper-right frame of Fig. 7.6). Noise from incidental scatterers is predominantly visible at short range ($<$ 35 km) because the echoes from nearby targets are very strong. The presence of velocity outliers in large areas of high-quality data is characteristic for data obtained using the dual-PRF technique. Large areas with falsely dealiased velocities, which are characteristic for single-PRF data, are not present in dual-PRF data provided that the maximum velocity is below the dual-PRF unambiguous velocity.

A quantitative analysis has been performed to obtain detailed information on the quality and outliers of dual-PRF velocity data. For this, each velocity datapoint in an azimuthal scan is compared with the local median velocity. The local median velocity is calculated from the datapoint itself and the surrounding datapoints. An area measuring five range times three azimuth points is taken, and it is required that at least nine out of the fifteen datapoints contain valid data. The deviation of the datapoints from the local median values has been analyzed. In Fig. 7.7 histograms of the velocity deviations observed in the azimuthal scan of Fig. 7.6 are shown. For a reason that will become clear, velocity data from even and odd azimuths have been collected into different histograms. The histograms have been constructed using a velocity bin size of 0.3 m s^{-1} matching that of the dual-PRF velocity data.

The central peaks of Fig. 7.7, containing the points with hardly any deviation from the local median velocity, go up to a number of about 12,500. The vast majority of the analyzed points obeys local continuity. The width of the central peaks is determined by the variance of the velocity data. A standard deviation of 0.50 m s^{-1} is obtained. Apart from the central peak, two distinct sideband peaks are evident in both histograms of Fig. 7.7. The sideband peaks correspond to the velocity outliers which are characteristic for the dual-PRF technique. The number of points within the sidebands can be used to calculate the fraction of velocity outliers. The fraction of outliers is 9.1×10^{-3} and 7.3×10^{-3} for the even and odd azimuths, respectively. It is evident from Fig. 7.7 that the sidebands for even and odd azimuths are centered at different velocity deviations. The median deviation of the even azimuth sidebands is 20.9 m s^{-1} and that of the odd azimuth sidebands is 24.6 m s^{-1}. These velocity deviations roughly match the unambiguous intervals of the low PRF (20.0 m s^{-1}) and high PRF (26.6 m s^{-1}) measurements.

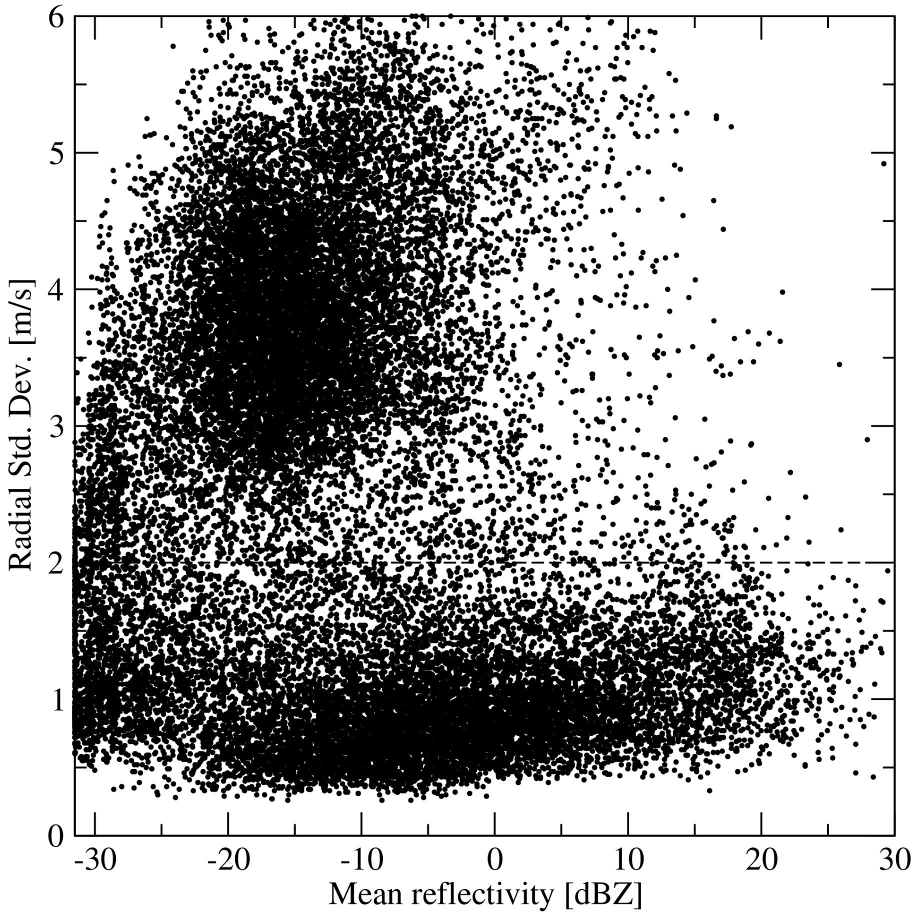

Figure 7.8: Scatterplot of observed standard deviation and reflectivities for wind profiles of the radar in De Bilt in March 2003.

7.5 Recognition of bird migration contamination

The radial standard deviation obtained from a VAD or VVP wind profile retrieval can be used to recognize bird migration contamination in Doppler velocity data. In the Netherlands a quantitative comparison of “wind data” from the Doppler weather radar with data from the dedicated bird radar over the period March to May 2003 has been performed (van Gasteren et al., 2006). The Royal Netherlands Airforce (RNLAF) employs a Flycatcher tracking radar which is modified to operate as a dedicated bird radar. The radar is performing both PPI scans and RHI scans perpendicular to the main direction of the bird migration. The PPI scans provide speed and flight-direction data, while the RHI scans provide the bird densities at various altitudes. The distance between the KNMI and RNLAF radars was approximately 80 km.

Figure 7.8 shows a scatterplot of observed standard deviation and reflectivities for wind profiles of the radar in De Bilt in March 2003. It is found that the standard deviation of the radial velocity can be used to separate the profile data from the Doppler weather radar into “true” wind vectors and bird movement vectors. Standard deviations larger than 2 m/s indicate bird migration and smaller ones point to good wind data. In addition, thresholds on reflectivity (roughly 0 dBZ) and wind speed can be used to filter bird migration contamination. This implies that high quality wind vector data, i.e., without bird signatures, can be obtained. Moreover, these results show that the “wind” profiles from Doppler weather radars contain quantitative information on the temporal and vertical distribution of migrating birds.

7.6 Proposed quality indicators for wind data

In OPERA working document (Holleman et al., 2002) a list of static quality descriptors has been proposed which is still useful:

Quality factor	Quality indicator	Notation	Typical value	Affects
Scanning:	Antenna azimuthal speed	V_{ant} [deg/s]	6 - 36	Noise, resolution
	Pulse Repetition Frequency	PRF [Hz]	250 - 1200	
	Pulse width	Δ [μs]	0.5 - 2	Noise, resolution
Velocity range	Lowest estimable radial wind	V_n [m/s]	0-5	
	Highest estimable radial wind	V_x [m/s]	10-50	Speed
Volume:	Inner radius of measured vol.	R_x [km]	0 - 10	
	Outer radius of measured vol.	R_n [km]	20 - 50	
Retrieval:	Doppler wind methods	Table		
	Re-run without outliers	Flag		Clutter
Birds:	Bird removal methods	Table		Speed and dir.
	Bird contamination likely	Flag		
	Preferred azimuths	ϕ [deg]	0-360	

From the review of quality factors for weather radar wind data, the review of VAD/VVP wind profiles and super-observation algorithms, and the analysis of raw velocity data it appears that the radial velocity standard deviation is a useful and commonly available quality indicator. The usefulness of this quality indicator is corroborated by the example on bird migration contamination in wind profiles. All in all, the proposed quality indicators for weather radar wind data are:

Quality factor	Quality indicator	Notation	Typical value	Affects
Echoes	Number of valid points	N	50 - 5000	Retrieval
	Reflectivity in retrieval volume	$\bar{Z}$ [dBZ]	-30 - 50	
Variability	Spectral width in retrieval volume	$\bar{W}$ [m/s]	0.1 - 10	Speed and dir.
	Radial velocity standard deviation	σ_{rad} [m/s]	0.1 - 10	

Chapter 8

Examples of using of quality information

8.1 Assimilation of reflectivity data

A first example of how the framework proposed in chapter 3 can be implemented in a real world case is given in Section 3.5. Here, we provide a second example by adding references to other chapters. Say, an Alpine weather service plans to use radar reflectivity in order to get a better estimate of the initial conditions of the operational numerical weather prediction model. Radar reflectivity measurements are assimilated by means of a latent heat nudging scheme using the radar product with the best estimate of the surface precipitation rate (chapter 6). If the radar hardware is stable (chapter 4) and ground clutter is effectively eliminated (section 5.5) the main factor for the quality of radar measurements in a mountainous region is beam blocking, see section 5.4 and Pellarin et al. (2002). Note that VPR errors (section 6.1) are mainly a consequence of beam blocking. If beam blocking is the most relevant quality factor, a simple approach to incorporate radar quality into the assimilation scheme is to convert beam blocking above a given location into a weight in the latent heat nudging scheme. In the terminology of chapter 3 the beam blocking map corresponds to the *quality indicator*, the weight to the *quality index*, and the applied conversion to the *quality output method* (see also Fig. 3.1). A similar approach was implemented for first attempts of radar assimilation into the aLMo model of MeteoSwiss (Leuenberger, 2005). Figure 8.1 shows the observation weights used in the LHN scheme as derived from radar quality. The weights are interpolated onto the 7km model grid. Dark shading denotes high quality, bright values low quality. The bold solid line outlines the 1000m contour of the model topography. The white trian-

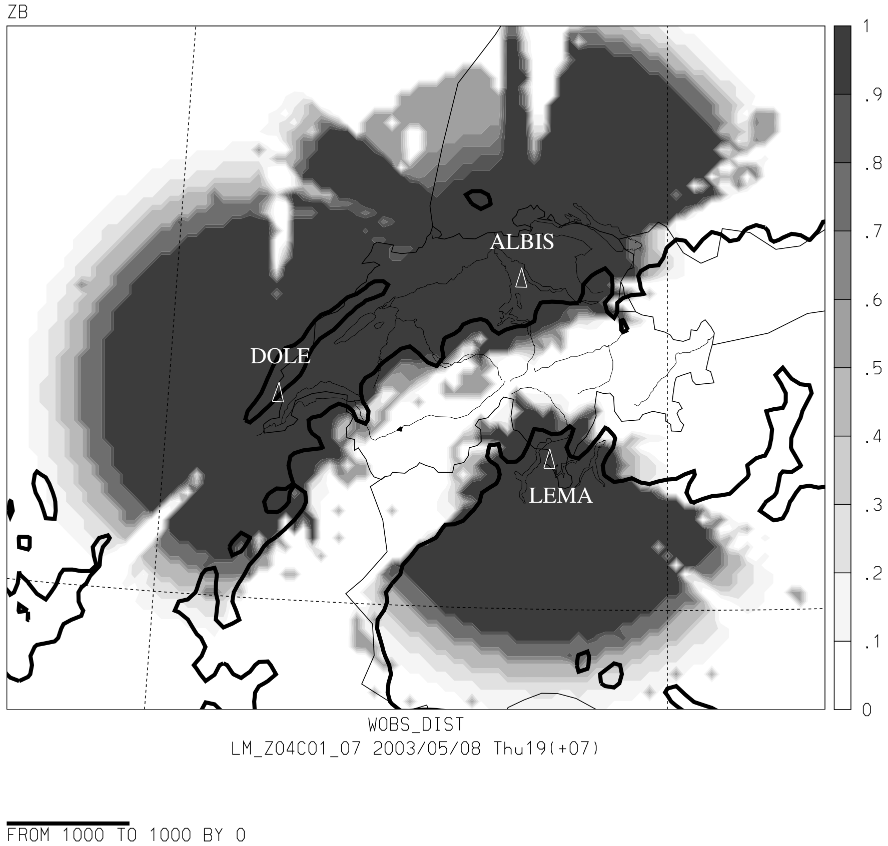

Figure 8.1: LHN observation weights as derived from radar quality (Figure taken from Leuenberger (2005).)

gles mark the locations of the 3 Swiss radars. For more details the reader is referred to Leuenberger (2005), section 4.2.3.

8.2 Visualization

Once quality information is available in a system, a straightforward application to consider is to somehow visualize it. Often, the geometry of quality data is similar to that of measurement data hence one may treat quality data as an additional "channel", perhaps clickable over, or in parallel. An example of introducing visual quality information in intersection products is shown in Fig. 8.2.

In practical meteorological applications, there is often many data sources competing from the visual attention of the user. Hence, visualizations of

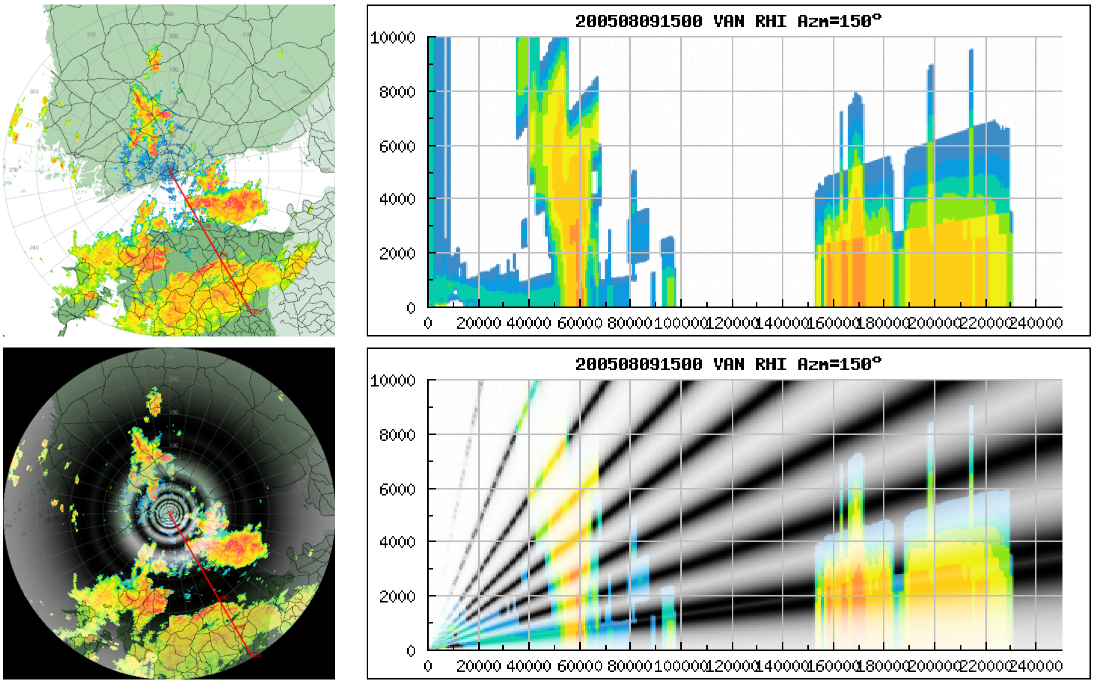

Figure 8.2: Traditional (top) and quality-visualized (bottom) intersection products. In this illustration, distance to actual measurement points (only) has been applied as quality information.

quality information can be viewed only on demand, if the main data looks suspicious or clearly erroneous. In addition, quality data visualizations should be important in training the end-users of the applications – reminding about the uncertainties more or less frequently appearing in data.

8.3 Compositing

In operational automated processes, quality information can and should be used for altering the main data as to increase the quality of the final products. A straightforward principle is to discard measurements having quality (index) lower than some threshold. What this "discarding" practically means can be ambiguous. For example, if suspicious measurements must be replaced by some kind of default values, what would be a neutral choice? In principle, data points with quality index close to zero should be treated as "no-data", like locations outside the radar scope. Sometimes a good policy is to replace an unreliable measurement with spatially neighboring values or previous reliable values at the same location.

Sometimes several measurements from the same location are available - as within overlapping ranges of neighboring radars. In radar image composites, MAXIMUM measurement value has been a conventional choice for a compositing principle (Fig. 8.3). However, also contaminated data is easily passed through. Another conventional principle AVERAGE, has the advantage of compromising data discrepancy; one can reason that "all" the information is taken into account. However, this principle fails for example in the case of attenuation, as shown in Fig. 8.3, right (bottom of the image). It must be pointed out that in their basic forms, neither of these principles applies quality information.

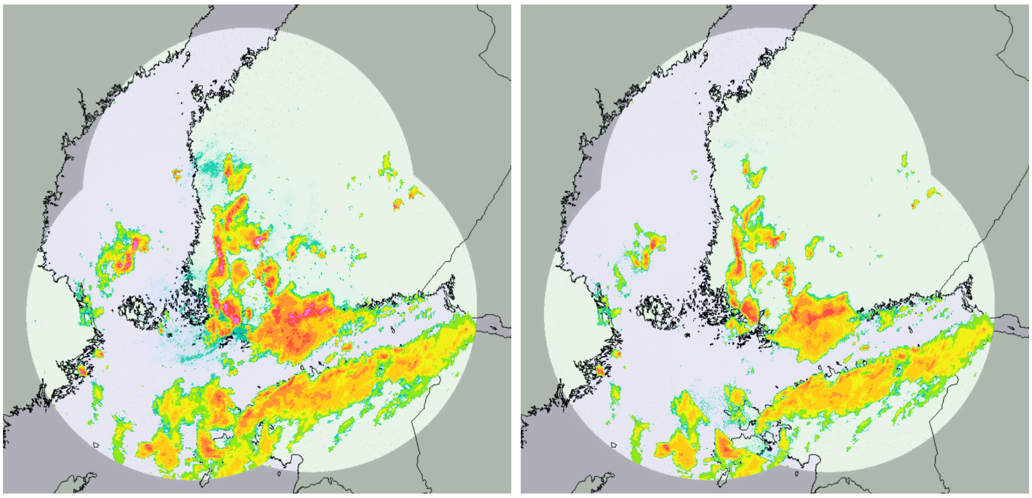

Figure 8.3: Composites using MAXIMUM (left) and AVERAGE (right) algorithms.

In applying MAXIMUM-QUALITY principle, the measurement having the highest quality is applied. A conventional NEAREST-RADAR composite can actually be seen as such a composite, using distance to a radar as a indication of quality. Moreover, one can mix measurement values of varying reliability in a multitude of ways. For example, one can apply WEIGHTED AVERAGE principle, using a global quality index for each radar, or down at single measurements (bins), indices varying from pixel to pixel (Fig. 8.5). Finally, using suitable "quality algebra" (Peura et al., 2006) it is possible to smoothly alternate between the aforementioned principles.

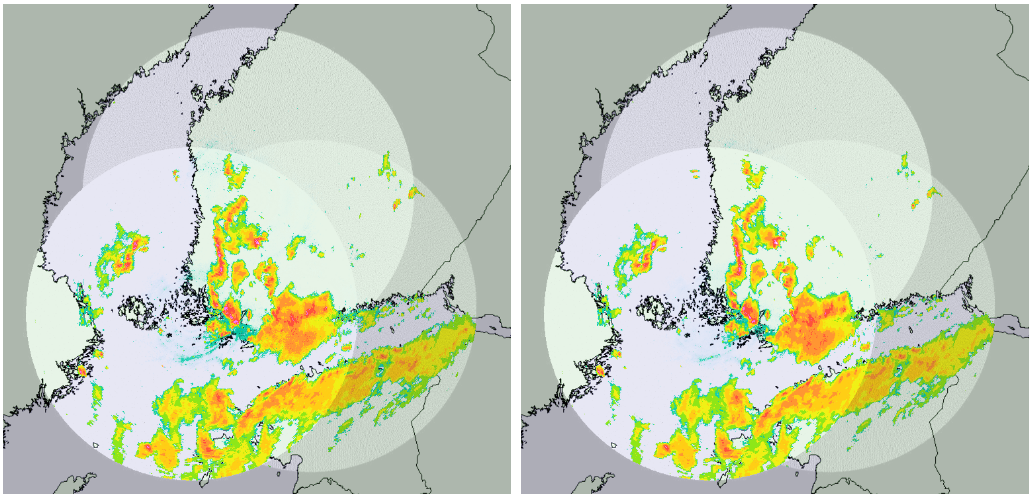

Figure 8.4: Composites using Maximum-Quality (left) and Quality-Weighted-Average (right) algorithms.

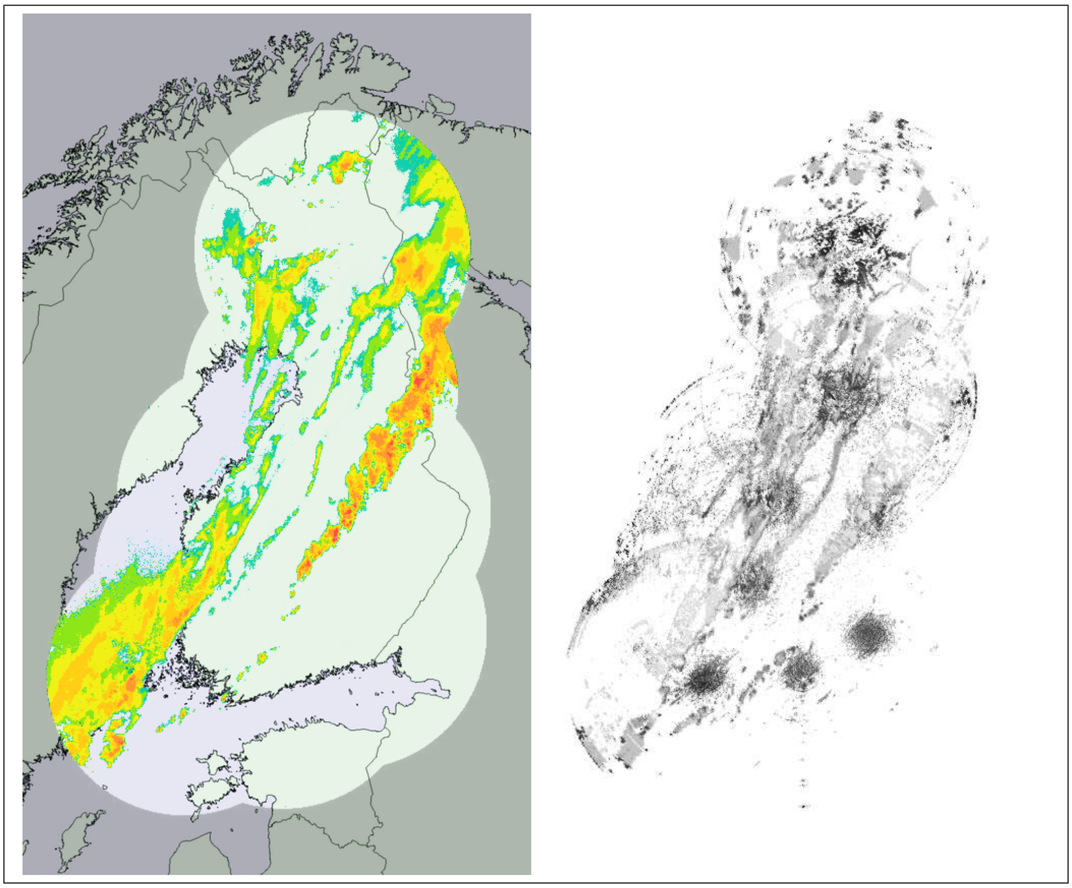

Figure 8.5: A composite (left) using Quality-Weighted-Average algorithm and its quality field (right) obtained as Average composite of the original single-radar quality data.

Chapter 9

Conclusions and recommendations

The increasing interest from the hydrological and NWP modeling communities in weather radar has initiated a change from mainly a qualitative use to a more quantitative use of radar data. For the traditional use in nowcasting mainly qualitative requirements have to be fulfilled, but for radar compositing, quantitative precipitation estimation (QPE), or assimilation in an NWP model stringent quantitative requirements are usually in force.

In this working document a generalized framework is presented to facilitate the propagation of uncertainty information at the interface between weather radar and meteorological and hydrological applications. Furthermore the quality factors for radar systems, volume data, surface rainfall estimates, and radar wind data have been reviewed in several chapters. Based on the quality factors proposals for quality indicators have been made. Finally examples of the use of quality information in NWP assimilation, visualization, and compositing have been presented.

Naturally not all (fundamental) issues could be solved during this project and the discussions in the working group of OPERA. A remaining question is the amount and type of quality information the data providers should provide to the users. Should we provide all quality indicators or quality indices? In the former case the users should run the quality output methods themselves and the data provider only offers help. In the latter case the data providers run the quality output methods, which have been developed in collaboration with user groups, for different users. It should be noted that in some cases the data provider is also the user, e.g. with quality-weighted compositing of single-site products. Another frequently discussed topic is the use of scaled quality indicators or unscaled indicators, i.e., in original physical units. A related issue is the combination of quality indicators during the treatment of radar data in a processing chain. Because of the great interest in the work on quality information, this work definitely needs continuation and more discussion in the next phase of OPERA.

The vehicle to transport the quality information, either quality indicators or indices, to the users is the data format. The data format which is currently used for operational exchange of radar data is BUFR. BUFR offers (limited) possibilities for additional of associated quality information. For this BUFR templates together with all required additional BUFR descriptors to represent the quality information have to be defined. In the OPERA work package 2.1 on "New data representation formats", the HDF5 format is recommended for consideration as an official European standard format for weather radar data and products. Therefore it is recommended to consider the HDF5 format also for the exchange of quality information. Furthermore, it is recommended to develop documentation illustrating the set of relevant and important quality indicators including a detailed and physical meaningful description. Finally, it is important to make the conceptual model for representation of quality information as presented in this document more concrete by producing a set of example files containing radar products and the corresponding quality information. These examples can then be used to initiate an (operational) exchange of quality information in the next phase of OPERA.

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