High-Repetition Millimeter-Wave Passive Remote Sensing of Humidity and Hydrometeor Profiles from Elliptical Orbit Constellations

FRANK S. MARZANO
Department of Electronic Engineering, Sapienza University of Rome, Rome, and Center of Excellence CETEMPS, University of L’Aquila, L’Aquila, Italy

DOMENICO CIMINI
Center of Excellence CETEMPS, University of L’Aquila, L’Aquila, Italy

TOMMASO ROSSI
Department of Electronic Engineering, University of Rome, Rome, Italy

DANIELE MORTARI
Department of Aerospace Engineering, Texas A&M University, College Station, Texas

SABATINO DI MICHELE AND PETER BAUER
European Centre for Medium-Range Weather Forecasts, Reading, United Kingdom

(Manuscript received 19 June 2009, in final form 28 November 2009)

ABSTRACT

The potential of an elliptical-orbit Flower Constellation of Millimeter-Wave Radiometers (FLORAD) for humidity profile and precipitating cloud observations is analyzed and discussed. The FLORAD mission scientific requirements are aimed at the retrieval of hydrological properties of the troposphere, specifically water vapor, cloud liquid content, rainfall, and snowfall profiles. This analysis is built on the results already obtained in previous works and is specifically devoted to evaluate the possibility of (i) deploying an incremental configuration of a Flower constellation of six minisatellites, optimized to provide the maximum revisit time over the Mediterranean area or, more generally, midlatitudes (between $6^\circ$S and $6^\circ$N); and (ii) evaluating in a quantitative way the accuracy of a one-dimensional variational data assimilation (1D-Var) Bayesian retrieval scheme to derive hydrometeor profiles at quasi-global scale using an optimized set of millimeter-wave frequencies. The obtained results show that a revisit time over the Mediterranean area (latitude $25^\circ$S–$45^\circ$S, longitude $10^\circ$W–$35^\circ$E) of less than about 1 and 0.5 h can be obtained with four satellites and six satellites in Flower elliptical orbits, respectively. The accuracy of the retrieved hydrometeor profiles over land and sea for a winter and summer season at several latitudes shows the beneficial performance from using a combination of channels at 89, 118, 183, and 229 GHz. A lack of lower frequencies, such as those below 50 GHz, reduces the sounding capability for cloud lower layers, but the temperature and humidity retrievals provide a useful hydrometeor profile constraint. The FLORAD mission is fully consistent with the Global Precipitation Mission (GPM) scope and may significantly increase its space–time coverage. The concept of an incremental Flower constellation can ensure the flexibility to deploy a spaceborne system that achieves increasing coverage through separate launches of member spacecrafts. The choice of millimeter-wave frequencies provides the advantage of designing compact radiometers that comply well with the current technology of minisatellites (overall weight less than 500 kg). The overall budget of the FLORAD small mission might become appealing as an optimal compromise between retrieval performances and system complexity.

Corresponding author address: Frank S. Marzano, Dept. of Electronic Engineering, Sapienza University of Rome, Via Eudossiana 18, 00184 Rome, Italy.
E-mail: marzano@die.uniroma1.it

DOI: 10.1175/2010JAMC2329.1

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Introduction

The concept of the Global Precipitation Measurement (GPM) mission is basically founded on the constellation of spaceborne sensors able to provide microwave (MW) and millimeter-wave (MMW) passive observations of precipitating clouds (Hou et al. 2008; Smith et al. 2007). The key role of the GPM mission program is based on the consideration that both natural and human-induced climate variations affect the global water cycle (e.g., Chahine 1992). Higher evaporation and precipitation rates might occur if global temperature will increase, as is commonly accepted, thus causing a positive feedback loop with a possible increase of weather extremes and durations of flood and drought episodes (Levitus et al. 2001; Ziegler et al. 2003). This scenario clearly raises the need for accurate, stable, and continuous space–time sampling of atmospheric precipitation over land and ocean toward a precise estimate of accumulated water (and related phenomena such as moisture transport, cloud formation, evapotranspiration, latent heating, and runoff) at both regional and global scales (Prabhakara et al. 2000; Mariotti et al. 2002). These scientific requirements, characterized by a high social impact, are well addressed by the GPM mission program, which is an essential element of the space-based component of the Global Observing System (Hinsman and Purdom 2007).

GPM can be thought of as a system of systems or, more specifically, an ensemble of current and planned passive microwave missions around the design of the GPM mission core platform itself, where a scanning microwave radiometer (GMI) with channels at 10.7, 19.0, 21.3, 37.0, and 89.0 GHz (plus possible channels near the 165- and 183-GHz bands) and a dual-frequency precipitation radar (DPR) with two channels at 13.6 and 35.5 GHz are foreseen (Hou et al. 2008). The main current components of the GPM microwave observing system are well known: the Special Sensor Microwave Imager (SSMI/I) and the Special Sensor Microwave Imager/Sounder (SSMI/S) aboard the Defense Meteorological Satellite Program (DMSP) satellite, the Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E) aboard the Aqua satellite, the Advanced Microwave Sounding Unit A (AMSU-A) aboard the NOAA-18, -19, Aqua, and MetOp satellites, the Microwave Humidity Sounder (MHS), which replaced AMSU B (AMSU-B), aboard the NOAA-18, -19, and MetOp satellites, the Humidity Sounder Brazil (HSB) aboard the Aqua satellite, and the Cloud Profiling Radar (CPR) aboard the CloudSat satellite. Planned major programs to extend this capability are linked to the American National Polar-orbiting Operational Environmental Satellite System (NPOESS), whose first satellite is to be launched in 2013 and that carries the Advanced Technology Microwave Sounder (ATMS) and as of 2016 the Microwave Imager Sounder (MIS), and the Post European Polar System (PostEPS), to be launched in 2020 and carrying a microwave imager and sounder that are still to be defined (e.g., Menzel 2007; Schmetz et al. 2007).

Within this international context, the potential of enlarging as much as possible the rainfall observing system constellation is very appealing, mainly to increase the revisit time of a certain geographical area and, consequently, the space–time sampling of cloud and precipitation systems (Hinsman and Purdom 2007). Moreover, a rich satellite constellation would reinforce the concepts of statistical blending of infrared data derived from geostationary satellites and MW estimates measured from low Earth orbit (LEO) platforms (e.g., Tapiador et al. 2004; Marzano et al. 2004). Small space missions, focused on minisatellites with radiometers having low weight, small size, and low power consumption compatible with high-level characteristics in terms of system specifications and atmospheric product accuracy, may represent a suitable compromise between cost and benefit (Marzano et al. 2008). The small–space mission concept will also be compliant with the need for long-term planning of atmospheric satellite missions aiming at climate change monitoring and trend detection (Wertz and Larson 1999).

A small–space mission concept would tend to favor millimeter-wave sensors because of the reduced size of the overall system compared to a microwave sensor with lower-frequency channels. On the other hand, MMW sounding can exploit window frequencies and various gaseous absorption bands at 50/60, 118, and 183 GHz (e.g., Gasiewski and Staelin 1990; Kidder et al. 2000; Rosenkranz 2001; Bauer and Mugnai 2003; Boukabara et al. 2007; Mgnai et al. 2007; Surussavadee and Staelin 2008a). These bands can be used to estimate tropospheric temperature profiles, water vapor and cloud liquid water contents, and to some extent, rainfall and snowfall, at the same time reducing the degree of ambiguity of signal contributions from the individual geophysical variables. While precipitation retrieval errors may be larger compared to using lower microwave frequencies, spatial resolution will be better and overall system size will be smaller (Staelin and Surussavadee 2007; Surussavadee and Staelin 2008a,b). Indeed, simulation results clearly show the potential of MMW radiometers to estimate liquid and ice precipitation even with a reduced number of channels (Bauer and Mugnai 2003; Leslie and Staelin 2004). Existing channel selection and mission specifications could be further optimized to meet the observation requirements.

Microwave imagery data are widely used for numerical weather prediction (NWP) as well as nowcasting (NWC)
and climate applications. Observations from the SSM/I series of instruments, beginning in 1987, have been widely used in the analysis of ocean surface wind speed and moisture fields under clear-sky conditions (e.g., Gerard and Saunders 1999). More recently SSM/I radiances have been used to constrain moisture analyses in cloudy and precipitating situations (Bauer et al. 2006a,b). The explicit analysis of cloud variables in variational assimilation systems is not yet mature, but significant developments are expected in this area in the near future (English et al. 2006).

For sounding applications, frequencies below 200 GHz have been widely exploited for meteorology, most notably from the AMSU radiometer, which exploits the oxygen band between 50 and 60 GHz for temperature and the water vapor lines at 22.235 and 183.31 GHz for moisture observation. The impact of AMSU data on the skill of numerical weather prediction exceeds that of the High Resolution Infrared Radiation Sounder (HIRS) since infrared data are more strongly affected by the presence of clouds. Until the recent launch of a new generation of advanced infrared sounders, AMSU-A represented the single most important instrument in NWP.

In a satellite constellation framework, some components of the space network could be devoted to the observation of specific regions. Regionalized analyses are becoming of increasing interest for meteorological and climate change studies (Pelino et al. 2006; Giorgi and Lionello 2008). Polar and near-polar regions are usually well covered by sun-synchronous LEO platforms, whereas midlatitude and equatorial regions are those most penalized in terms of revisit time (Kidder and Vonder Haar 1995). In this respect the TRMM mission has been one of the first examples of a meteorological mission with a low-inclination orbit that favors the observation of lower latitudes. A minisatellite constellation, exploiting circular LEO in a sun-synchronous configuration, has very few degrees of freedom if the need is to enhance the revisit time in a specific region (Abdelkhalik et al. 2005). Therefore elliptical orbits can represent a viable alternative using the variable satellite velocity along the orbit itself (slower at the apogee and faster at the perigee) to augment the revisit time (Kidder and Vonder Haar 1990). If sun-synchronicity is not required, the design of the elliptical orbit constellation has to tackle the shift of the perigee argument.

In this work we will discuss the potential of a constellation of MMW radiometers in a particular set of elliptical orbits, called Flower orbits, that can provide the theoretical framework to design a high revisit time–spacemission over a given region. The latter has been chosen to be the Mediterranean region or, more generally, all midlatitudes between ±35° and ±75°. The metrics of the revisit time have been expressed in terms of the cumulative probability function of gap time between two successive overpasses over the target area. A satellite constellation that features a relatively short revisit time (on the order of a few hours or even less than 1 h, depending on the configuration) on a portion of the globe as available from geostationary observations, and that also provides a relatively high spatial resolution (on the order of 10 km or less) over the entire globe as typical of LEO microwave observations, has led us to the concept of the pseudo-geostationary scale. This is different from the geostationary scale, that is, the spatial resolution obtainable from an MMW aboard a geostationary platform, because the geostationary scale is at best several tens of kilometers at frequencies around 100 GHz (Bizzarri et al. 2007; Lambbrigtsen et al. 2007; Surussavadee and Staelin 2008b). In a way, the concept of an elliptical-orbit constellation of MMW radiometers leads to an appealing compromise between revisit time and spatial resolution requirements of precipitation observation. In other words, it is a compromise between an MMW payload on a sun-synchronous LEO mission (e.g., MetOp with AMSU and MHS) and an MMW payload on a geostationary mission (e.g., see Lambbrigtsen et al. 2007).

In previous works, we explored the design of the Flower constellation (FC), exploiting three or four minisatellites in slightly and moderately elliptical orbits (Marzano et al. 2008, 2009). The small-mission concept was named Flower Constellation of Millimeter-Wave Radiometers (FLORAD). Its optimal configuration was demonstrated to be an FC of three minisatellites at an orbital height between 600 and 1200 km to fulfill the scientific requirements (Marzano et al. 2009). The launch strategy of the FLORAD was also discussed, pointing out the need for a multiple-satellite launch; a further analysis is needed to deal with possible problems in terms of deployment time, orbit maneuvers, and launcher accommodation (e.g., Wertz and Larson 1999). Moreover, the design of the FLORAD multifrequency compact radiometer was supported by a reduced-entropy analysis of the MMW information content obtaining an overall set of 10 channels between 89 and 229 GHz. The comparison among the various FLORAD radiometer configurations was carried out by using two statistical inversion schemes, namely a multiple regression (MR) and a maximum-likelihood (ML) algorithm, for retrieving temperature, humidity, and hydrometeor profiles (Marzano et al. 2009). These simplified inversion algorithms were developed for an algorithm intercomparison analysis over a specific target area using a case study. A systematic feasibility study of the FLORAD potential capabilities should generalize and verify these results through more sophisticated retrieval techniques, such as the variational ones, over
different regions at the global scale and with a bigger data sample (Deblonde and English 2003; Bauer and Di Michele 2007).

In view of the open issues mentioned above, the specific goals of the present work are to extend the previously obtained results by (i) investigating other FC constellation architectures to provide a wide set of strategies for the launch of the minisatellite constellation, even in a long-term climatological perspective; (ii) evaluating the best combination of MMW channels in terms of information content, measured by entropy reduction, using a global-scale atmospheric dataset; and (iii) adapting and applying a self-consistent Bayesian variational algorithm to evaluate the theoretical error budget for the retrieval of humidity and hydrometeor profiles using a reduced number of MMW frequency channels on global scale.

The paper is organized as follows: in section 2 we will provide a brief background on the FC theory and then illustrate the design of an incremental set of FCs to ensure a high revisit time over a single target region. In section 3 the analysis of the best set of MMW frequencies, above 89 GHz, will be discussed and a one-dimensional (1D) variational inversion algorithm will be described. The latter will then be used to evaluate the expected retrieval errors associated with liquid and ice hydrometeor profile retrievals over ocean and land for various climatological regions. Conclusions will be drawn in section 4.

2. Flower constellations at pseudo-geostationary scale

The FLORAD small-mission concept is based on the combined use of atmospheric MMW radiometry and the Flower constellation concept within a pseudo-geostationary-scale framework. In a previous study we analyzed the feasibility of designing an FC with three minisatellites at relatively high apogee around 1200 km (Marzano et al. 2009). This solution envisaged three minisatellites, but turned out to be problematic in terms of launch strategy. A better option would be a single launch deploying all three platforms by exploiting a Hohmann maneuver (Wertz and Larson 1999). This launch with a transfer of the payload to about 2000 km would require about 125 days for a relative drift of 120° and about 220 days for a relative drift of 240°. If the first satellite can be deployed into its elliptical orbit during the launcher’s descent, the deployment of a three-satellite constellation should take about 7 months.

Indeed, the capability of current launchers is a critical item, especially when dealing with three minisatellites. A critical factor is the deployment time and the propellant needed to perform all maneuvers. If small launchers are considered, then the accommodation of three satellites becomes a delicate issue as well. A more conservative strategy would be to deploy two minisatellites with one launch in a single orbital plane without needing orbital maneuvers. The full FC might be completed following an incremental concept by performing successive launches of another two minisatellites into FC predefined orbital planes. The latter concept, named incremental Flower constellation (IFC), will be described in section 2b.

a. Background on Flower constellation theory

The theory of FCs is a new methodology to design satellite constellations (Mortari et al. 2004; Mortari and Wilkins 2008). They are a natural consequence, and an extension to $n$ satellites, following the theory of compatible orbits (also called resonant or repeating ground track). Compatible orbits constitute a set of special orbits whose orbital period $T_r$ is synchronized with the period $T_p = 2\pi/\omega_r$ of a rotating frame (Mortari and Wilkins 2008),

$$N_p T_r = N_d 2\pi/\omega_r,$$

where $N_p$ and $N_d$ are two arbitrary integers, $T_r$ is the orbital period, $a$ is the orbit semimajor axis, and $\omega_r$ is the angular frequency of a rotating frame with $\mu$ as Earth’s gravitational parameter (i.e., the product of gravitational constant and Earth mass). For different values of $N_p$ and $N_d$, there is a value of $\omega_r$ providing the same orbital period. This means that a compatible orbit is also compatible with an infinite set of rotating reference frames. Once $N_p$ and $N_d$ are chosen, the orbital period of the satellite can be computed from (1), whereas the semimajor axis $a$ is derived from the inversion of the third Keplerian law as in the second term of (1).

The Earth-fixed Earth-centered (ECEF) rotating frame is particularly (or the most) important. However, the “compatibility” concept is a relative concept (relative to a rotating frame); hence any orbit can be seen as compatible. An important aspect of a satellite on a compatible orbit is that its trajectory in the rotating reference frame constitutes a closed loop with assigned repetition time. The FC theory explains how to place satellites on the same relative trajectory so that the whole constellation is made of satellites that fly along relative trajectories, one after another. Repeating ground track is not a unique property of Flower constellations, but the innovative concept of the Flower constellations is based on two main properties: compatibility and phasing (Mortari and Wilkins 2008). As previously introduced, compatibility property rules satellite dynamics synchronization...
with respect to a set of rotating reference frames, while the phasing determines satellite distribution along 3D “space track” (with respect to the rotating reference frames).

To meet the constraint of commonly repeating space tracks, all the satellites of an FC have common values of the semimajor axis $a$, ellipticity $e$, inclination $i$, and argument $\omega$ of the perigee, while the argument $\Omega_k$ of right ascension of the ascending node (RAAN) and mean anomaly $M_k$ of the $k$th satellites must satisfy proper phasing rules. This means that FCs are characterized by six integers and five Keplerian orbit parameters. The first two integers ($N_p, N_d$) of the previous list define the semimajor axis (or the period), whereas the other three integers ($N_s, F_m, F_a$) define the satellite distribution along the relative path. The Keplerian parameters define the orbit shape, orientation, and synchronization with Earth (note that $h_p$ is equivalent to ellipticity $e$). The number of orbits is determined by the $N_p$ parameter and all the orbits have identical shape, inclination, and argument of perigee. They are only rotated in RAAN to obtain an even distribution about the central body. Flower constellations are a very ductile and useful tool, allowing an “optimized design” of satellite constellations; genetic algorithms can be exploited to optimize FCs with respect to given mission requirements (e.g., Marzano et al. 2009).

b. Analysis of incremental Flower constellations

The optimal design of an FC is a complex task. Further constraints on FC design come from the sensor specifications, in particular the orbit height range and sensor swath (that affect the spatial resolution and observation repeat time). The orbit height has been set within the range 650–1270 km and sensor swath to about 2500 km (depending on the scanning system here fixed to ±50° around the antenna boresight), in agreement with the previous study (Marzano et al. 2009). Another major concern is the choice of the inclination angle $i$, which might be chosen either to be a generic freedom parameter or to satisfy sun-synchronicity or to keep a constant perigee argument by imposing the orbit inclination angle $i = 63.4°$. Indeed, a safety constraint might be also considered: when launching from specific sites (i.e., Korou in New Guinea), the inclination must be larger than 70° to avoid risks of overpassing highly populated areas.

To extend previous analyses, the design of the FC has been focused on the incremental feature concept by analyzing the following configurations:

1) incremental FCs at $i = 63.4°$, having moderately elliptical orbits with perigee/apogee ratio equal to about 650/1270 km, with either two satellites (IFC-ME2) or four satellites equally distributed in two different orbit planes (IFC-ME4) or six satellites equally distributed in three different orbit planes (IFC-ME6),

2) Walker Constellation of Circular Orbits (WK-CO6) with six minisatellites in different orbital planes with $i = 63.4°$, following the design concept of Walker (having the same “average distance” from Earth as the FC, 1060 km), and

3) Sun-Synchronous Circular Orbit (SS-CO6) constellation with six minisatellites equally distributed along the same orbit plane at an altitude of about 1000 km.

Two target regions of interest have been identified: (i) the Mediterranean Scale Basin (MSB) windows, defined between 25°–45° latitude and −10°–35° longitude [this area is larger than the corresponding one used by Marzano et al. (2009)]; (ii) the Regional Scale European (RSE) window, delimited by the following latitude–longitude corners, respectively: 23° to −10°, 64° to −40°, 64° to 66°, and 23° to 36° [this area is identical to that used by Marzano et al. (2009)]. As a metric of space–time coverage we have again adopted the target area revisit time interval or gap time $\Delta T_{rev}$ as the time interval between two satellite overpasses over the target area, counted when the sensor swath of any constellation satellite partially intersects the target area (to have a useful observation, a connection time threshold of 5 min has been considered). To compare the various satellite constellations, we have compared them in terms of the cumulative distribution function (CDF).

Figure 1 shows the gap time CDF for IFC-ME6 and WK-CO6 and SS-CO6 constellations over the MSB area. Figure 2 shows the same as in Fig. 1, but for the RSE area. The deployment of six minisatellites with a large swath sensor allows revisit time gaps less than 1 h, almost comparable to a geostationary platform. It can be noticed how FC provides better revisit time performance for every time percentage with respect to WK performance.

The incremental features of FCs can be appreciated in Fig. 3, which shows the comparison among the gap time CDFs for IFC-ME2, IFC-ME4, and IFC-ME6 constellations for the MSB area. Figure 4 shows the same as in Fig. 3, but for the RSE area. As shown in the figures, IFC becomes very efficient since the second batch of satellites is operative (IFC-ME4); as a matter of fact, revisit time interval performance reaches a very high level, being lower than 1 h for 70% of the total time for the MSB window.

Table 1 shows the orbit elements for the incremental Flower constellation with six satellites distributed within three different orbit planes.
A further analysis has been performed for the evaluation of constellation performance over single sites located within the Mediterranean basin; in this frame the gap time is the time interval between two satellite overpasses over a single point on Earth. It is worthwhile to underline that single sites’ gap time performance is clearly lower than the one obtained for regional coverage (being the regional access calculated considering a large number of sites). Table 2 provides the median value of the gap time $\Delta T_{\text{rev}}$ of IFC-ME6 and WK-CO6 constellations for specific sites within the Mediterranean basin such as Rome (Italy), Madrid (Spain), Athens (Greece), Ankara (Turkey), Belgrade (Serbia), Cairo (Egypt), Algiers (Algeria), and Rabat (Morocco). For SS-CO6 the median value gap is about 11 h for every site. It is worth noting that IFC performances are better with respect to WK one for every site; the performance increase ranges from a few minutes to 1 h (the median value gap is 5.5 h for WK-CO6 while it is 5 h for IFC-ME6).

3. Millimeter-wave retrieval of humidity and hydrometeor profiles

The FLORAD mission is devoted to the deployment of minisatellites equipped with compact MMW radiometers. The mass and dimension constraint naturally leads to a restriction of channels to the range above 50 GHz where microwave front end and antennas are usually smaller and lighter. The channel selection aims at trading off the information content provided by a radiance measurement at a specific frequency and the number of available channels in protected frequency bands.

In the following we will provide a short background on the Bayesian theory and variational methodology, its application to the channel information content analysis, and the numerical results obtained by adopting a variational inversion algorithm for humidity and hydrometeor profile retrieval. It should be noted that the FLORAD mission is not designed for European regions only, but for global coverage between about $\pm 70^\circ$ latitude (including a swath of about 2000 km). The observation differences within this quasi-global region are due to the satellite orbit height, which is about 1200 km at the apogee in the Northern Hemisphere and 600 km at the perigee in the Southern Hemisphere. This means that the sensor spatial resolution will change along the elliptical orbit, being larger at the apogee and smaller at the perigee. In this paper we did not consider this field-of-view variability that is inherent when exploiting elliptical orbits and might be used to regionalize the mission products. On the other hand, we have also disregarded the possible impact of the increasing FLORAD revisit time on the variational inversion algorithm, as this aspect should be evaluated by performing data assimilation.
sensitivity experiments that are beyond the scope of this work.

a. Background on linearized Bayesian analysis and inversion

The problem of the inversion of observations from space is not fully constrained, in particular in the presence of clouds and precipitation. The application of statistical principles is therefore fundamental for solving the inverse problem (Rodgers 1976, 2000), and to estimate the strongly state-dependent uncertainty associated with a given retrieval. In the following, the state of the atmosphere (i.e., temperature, humidity, and hydrometeor profiles) is denoted as a vector \( \mathbf{x} \) and the multiple-channel observations from a hypothetical microwave radiometer are indicated by a vector \( \mathbf{y} \). The statistical link between \( \mathbf{y} \) and \( \mathbf{x} \) is expressed by means of Bayes’ theorem, which denotes \( p(\mathbf{x}|\mathbf{y}) \), the a posteriori probability density function (pdf) of \( \mathbf{x} \) when \( \mathbf{y} \) is observed, in terms of the likelihood pdf \( p(\mathbf{y}|\mathbf{x}) \) and a priori pdf \( p(\mathbf{x}) \). In our context the link between \( \mathbf{x} \) and \( \mathbf{y} \) is described by the radiative transfer observation operator, \( \mathbf{H} \), which may be strongly nonlinear and characterized by an error distribution \( \mathbf{e} \), summarizing both observation errors and forward modeling errors with an overall error covariance matrix \( \mathbf{C}_e \).

For linear problems the Bayesian theory reduces to the optimal estimation theory (Rodgers 2000). The latter requires a priori information on the state vector \( \mathbf{x}_b \) (and its error covariance matrix \( \mathbf{B}_e \)) that is close enough to the true state so that the forward model behaves linearly. While this is realistic for clear-sky applications, it may be generally questionable for applications to clouds and precipitation. If we suppose the problem to be only weakly nonlinear around \( \mathbf{x}_b \), the forward model simulation can be written as

\[
\mathbf{y} = \mathbf{H}(\mathbf{x}_b) + \mathbf{H}(\mathbf{x} - \mathbf{x}_b) + \mathbf{e},
\]

which corresponds to the first-order Taylor development with the tangent-linear approximation \( \mathbf{H} \) of the forward model \( \mathbf{H} \). By definition in a Bayesian context, a solution is optimal when the posterior pdf \( p(\mathbf{x}|\mathbf{y}) \) is maximized. It can be shown that in the linear case, the optimal analysis state \( \hat{\mathbf{x}} \) has the following expression:

\[
\hat{\mathbf{x}} = \mathbf{x}_b + \mathbf{A}_e \mathbf{H}^\top \mathbf{C}_e^{-1} (\mathbf{y} - \mathbf{Hx}_b)
= \mathbf{x}_b + \left( \left( \mathbf{B}_e^{-1} - \mathbf{H}^\top \mathbf{C}_e^{-1} \mathbf{H} \right)^{-1} \right) \mathbf{H}^\top \mathbf{C}_e^{-1} (\mathbf{y} - \mathbf{Hx}_b),
\]

with \( \mathbf{H}^\top \) (T is the matrix transpose) being the adjoint of the observation operator, the angular superscript (\(^\top\)) denotes an estimated state, and \( \mathbf{A}_e \) is the so-called analysis error covariance matrix. The improvement of estimation error depends on the sensitivity of the observation \( \mathbf{y} \) to the state \( \mathbf{x} \) and on the accuracy of the measurement and
modeling [i.e., on H and Ce, their respective magnitudes, and finally on the accuracy of the a priori information (through Be)]. The optimal estimation formulation of the inversion problem furnishes a number of useful diagnostics to measure the quality of the results. The most important of these is the A_e, which provides a direct estimate of the uncertainty in the retrieved rain-rate profile due to uncertainties associated with the a priori profile, forward model, and measurements themselves.

The optimal estimation theory, previously described, can be adopted to perform information content analysis (Rodgers 2000). One figure of merit for the information content is the entropy reduction (ER), reflecting the improvement given by each channel to the retrieval error and measuring the reduction of entropy in a posteriori pdf. The entropy reduction is defined as the difference between the entropy of the a priori PDF p(x) and that of the a posteriori probability p(x|y). The log with basis 2 is usually chosen for expressing ER in units of bits. The channel selection is an iterative procedure proposed by Rodgers (1996) in which the contribution of each channel is sequentially quantified based on the hypothesis of error non correlation among channels (i.e., that C_e is diagonal). Iterative methods loop over channels and sort them by decreasing information content given a priori information (from the model background Be) and information from the ones previously selected.

Given a set of candidate channels, the iterative selection method starts with no channels selected and sequentially chooses the channel with the highest information content, taking into account the information provided by previously selected channels (Bauer and Di Michele 2007). Therefore at each iteration (3) requires an update to A_e (initially, A_e,0 = Be). The difference of A_e between two iteration steps k and k + 1 determines the information gain or reduction of ER (ΔER):

\[ \Delta ER = \Delta(E[p(x)] - E[p(x|y)]) = \frac{1}{2} \log_2 \left[ \frac{A_e(k) - 1}{A_e(k)} \right]. \]

The iteration procedure may be terminated when all channels have been selected or the information content of additional channels reaches a certain threshold. Details on this procedure are given by Di Michele and Bauer (2006). Depending on the application the radiometer is designed for, the different geophysical variables contributing to the measured radiation can be considered either sources of information or sources of uncertainty (see Di Michele and Bauer 2006).

The previous theoretical framework can be also used to introduce the one-dimensional variational data assimilation (1D-Var) inversion technique (Rodgers 2000;
Employing a 1D-Var technique for the solution of a retrieval problem has several advantages: (i) handling of nonlinear problems (i.e., state dependent Jacobians are dealt with through the multiple iterations of the linear 1D-Var); (ii) more flexibility in handling non-Gaussian errors; and (iii) the ability to target specific problems through carefully designed simulation studies. As already mentioned, given an observation y, the best (optimal) estimate of x is the value maximizing $p(y|x)$. It can be shown that, under the hypothesis of Gaussian error distributions, this corresponds to minimizing the following cost function $J$:

$$J(x) = \frac{1}{2}(x - x_b)^T B^{-1}_e (x - x_b) + \frac{1}{2} [y - H(x)]^T C^{-1}_e [y - H(x)].$$

(5)

In (5), $J(x)$ quantifies the penalty arising from the difference between the estimated state ($x$) and the background state ($x_b$) as well as the observations ($y$), each weighted by their error covariance matrices. Equation (4) can be solved numerically by iterative procedures. We refer to this as a variational retrieval. In general, the minimization of Eq. (4) requires the evaluation of the gradient of $J(x)$, given by

$$\nabla J(x) = B^{-1}_e (x - x_b) + H^T C^{-1}_e [y - H(x)].$$

(6)

From (3), we deduce that the optimal estimate, derived from a Newtonian iteration, at the $(n+1)$th step can be expressed as

$$\hat{x}_{n+1} = \hat{x}_n + A_e [H^T C^{-1}_e [y - H(x_n)] + B^{-1}_e (x_b - x_n)],$$

(7)

TABLE 1. Orbit elements (semimajor axis, ellipticity $\epsilon$, inclination $i$, argument of the perigee $\omega$, argument of right ascension of the ascending node RAAN, and mean anomaly $M_0$) for the incremental FC with six satellites distributed within three different orbit planes.

<table>
<thead>
<tr>
<th>Satellite No.</th>
<th>Semimajor axis (km)</th>
<th>$\epsilon$</th>
<th>$i$ (°)</th>
<th>$\omega$ (°)</th>
<th>RAAN (°)</th>
<th>$M_0$ (°)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7436.8226</td>
<td>0.0273</td>
<td>63.42</td>
<td>266.93</td>
<td>0</td>
<td>87.1</td>
</tr>
<tr>
<td>2</td>
<td>7436.8226</td>
<td>0.0273</td>
<td>63.42</td>
<td>266.93</td>
<td>120</td>
<td>267.1</td>
</tr>
<tr>
<td>3</td>
<td>7436.8226</td>
<td>0.0273</td>
<td>63.42</td>
<td>266.93</td>
<td>240</td>
<td>87.1</td>
</tr>
<tr>
<td>4</td>
<td>7436.8226</td>
<td>0.0273</td>
<td>63.42</td>
<td>266.93</td>
<td>0</td>
<td>267.1</td>
</tr>
<tr>
<td>5</td>
<td>7436.8226</td>
<td>0.0273</td>
<td>63.42</td>
<td>266.93</td>
<td>120</td>
<td>87.1</td>
</tr>
<tr>
<td>6</td>
<td>7436.8226</td>
<td>0.0273</td>
<td>63.42</td>
<td>266.93</td>
<td>240</td>
<td>267.1</td>
</tr>
</tbody>
</table>
where $A_k$ is given by (3), $y_n = H(x_n)$ is the simulated measurement vector at the $n$th step, and $H^T_n$ is the observation-operator adjoint or kernel (weighting) function computed at the $n$th step, representing the sensitivity of the model to the parameter being retrieved. It is clear from (7) that a forward model $H$ that is very sensitive to $x$ is desirable since the Kernel functions weight the measurement portion of the retrieval as a strong function of state. Details on the implementation of the 1D-Var retrieval algorithm will be given in section 3c.

b. Millimeter-wave information content analysis

Atmospheric profiles were extracted from Cycle31R2 of the European Centre for Medium-Range Weather Forecasts (ECMWF) forecasting system (e.g., Bauer et al. 2006a,b). The spectral model was truncated at wave-number 799, which corresponds to a horizontal resolution of 25 km. Vertical resolution is achieved using 91 pressure levels between 0.01 hPa and the surface. Forecasts for the to 36-, 42-, 48- and 54-h range of days 1, 10, and 20 of every month between July 2006 and June 2007 were chosen to give a total of 144 global snapshots of the atmosphere, each composed of 843 490 profiles (i.e., dimension of the global grid), altogether providing 121 462 560 profiles. To avoid excessive computation, the original samples were reduced by a random resampling into uniform distributions to prevent biasing the results of channel selection toward profiles with less intense clouds and precipitation. To ensure global coverage this sampling was separately performed over profiles located in $15^\circ \times 10^\circ$ latitude–longitude grid boxes. The sampling was repeated for profiles with different times of day and months to maintain the meteorological representativeness. Figure 5 shows the geographical distribution of the selected profiles.

The observation operator consists of a radiative transfer model that accounts for multiple scattering at microwave frequencies in clouds and precipitation (Matricardi et al. 2004; Bauer et al. 2006b). The model is part of the Radiative Transfer Model for the Television and Infrared Observation Satellite (TIROS) Operational Vertical Sounder

![Fig. 5. Geographical location of profiles dataset. Gray shades denotes number of occurrence at ECMWF model grid points.](image-url)
modeling errors. These are difficult to estimate because of the complex interaction of electromagnetic radiation with soil, vegetation, and snow cover as well as the partial derivatives of brightness temperatures due to perturbations in input parameters. While the relative contribution of temperature and water vapor profiles to the total signal in clouds and precipitations is small, surface emissivity largely affects the observations in thin and semitransparent clouds. For an ocean surface, emissivity is modeled according to the fast emissivity model FASTEM-2 (Ellison et al. 2003) that is part of RTTOV. Land surface emissivity is particularly difficult to simulate because of the complex interaction of electromagnetic radiation with soil, vegetation, and snow cover as a function of a large number of unknown state variables. Therefore, land emissivity was modeled based on climatologies derived from SSM/I observations and integrated NWP and satellite products (Prigent et al. 1997). Surface emissivity maps retrieved from all seven SSM/I channels were employed to interpolate SSM/I emissivities to the frequencies of the channels under investigation. The parametric fit developed by Grody (1988) was used for this purpose, as described in O’Dell and Bauer (2007). This procedure, which only provides values of land emissivity at 53°, was complemented by the approach proposed by Karbou (2005) to model the emissivity scan dependence. The classification defined in the Biosphere–Atmosphere Transfer Scheme land cover classification was used for this purpose, obtained using AMSU data for the period from 15 August to 15 September 2005.

The formulation of the methodology for channel selection in section 3a clearly showed that the results not only depend on the background error covariance statistics, but also on the definition of observation plus modeling errors. These are difficult to estimate because they contain uncertainties in microphysical and radiative transfer modeling that are impossible to measure directly. The errors are therefore expected to be larger than common radiometric noise contributions in those channels that are most sensitive to clouds, precipitation, and surface emission. In this study, the values estimated in Bauer and Di Michele (2007) were used that were derived from real SSM/I observations and model simulations. The definition of the background error covariance matrix of temperature, water vapor, and for hydrometeor contents is also required and an uncertainty needs to be assigned to surface temperature and surface emissivity. For this purpose the operational analysis error fields (Andersson et al. 2005) that correspond to each sampled profile were extracted to serve as background errors for temperature and specific humidity.

If $z_i$ are the altitude discrete levels with $i = 1 - N_z$, the atmospheric state vector $x$ is then represented by a water vapor vertical profile $V(z_i)$, a nonprecipitating (cloud) water content vertical profile $W_c(z_i)$, a precipitating (rain) water content vertical profile $W_r(z_i)$, a nonprecipitating (ice crystals and aggregates) water content vertical profile $W_i(z_i)$, and a precipitating (snow and graupel) solid water content vertical profile $W_s(z_i)$. The measurement vector $y$ is, in general, represented by the set of $T_{Bp}(v_i, \theta)$ at prescribed frequencies $v_i$, polarization $p$, and incidence angle $\theta$.

The ER-based channel selection methodology has been applied choosing a starting set of frequency channels between 23.8 and 230 GHz at vertical and horizontal polarization based on a channel set that has been optimized for future microwave sounders and imagers as part of the post–European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Polar System (post–EPS) program (Schlüssel et al. 2008). The final ranking of the considered frequency set is done by evaluating an average $\Delta ER$ over all the profiles of the dataset. Table 3 summarizes the results for each tropospheric

<table>
<thead>
<tr>
<th>Priority</th>
<th>Water vapor over ocean</th>
<th>Water vapor over land</th>
<th>Clouds</th>
<th>Clouds and precipitation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Clear sky</td>
<td>Cloudy</td>
<td>Ocean</td>
<td>Land</td>
</tr>
<tr>
<td>1</td>
<td>183.31 ± 1.8</td>
<td>183.31 ± 1.8</td>
<td>50.3</td>
<td>118.75 ± 2.1</td>
</tr>
<tr>
<td>2</td>
<td>23.8 ± 183.31 ± 1.0</td>
<td>183.31 ± 1.0</td>
<td>33.4</td>
<td>31.4</td>
</tr>
<tr>
<td>3</td>
<td>183.31 ± 3.0</td>
<td>23.8 ± 183.31 ± 1.0</td>
<td>39.0</td>
<td>50.3</td>
</tr>
<tr>
<td>4</td>
<td>183.31 ± 4.5</td>
<td>183.31 ± 3.0</td>
<td>52.8</td>
<td>89.0</td>
</tr>
<tr>
<td>5</td>
<td>183.31 ± 1.0</td>
<td>183.31 ± 4.5</td>
<td>118.75 ± 3.0</td>
<td>118.75 ± 3.0</td>
</tr>
<tr>
<td>6</td>
<td>183.31 ± 7.0</td>
<td>183.31 ± 7.0</td>
<td>118.75 ± 5.0</td>
<td>118.75 ± 5.0</td>
</tr>
<tr>
<td>7</td>
<td>50.3 ± 183.31 ± 7.0</td>
<td>166.0</td>
<td>118.75 ± 2.1</td>
<td>118.75 ± 2.1</td>
</tr>
<tr>
<td>8</td>
<td>118.75 ± 1.5</td>
<td>118.75 ± 1.5</td>
<td>118.75 ± 2.1</td>
<td>118.75 ± 2.1</td>
</tr>
<tr>
<td>9</td>
<td>118.75 ± 1.5</td>
<td>118.75 ± 1.5</td>
<td>118.75 ± 2.1</td>
<td>118.75 ± 2.1</td>
</tr>
<tr>
<td>10</td>
<td>229.0</td>
<td>229.0</td>
<td>118.75 ± 1.1</td>
<td>166.0</td>
</tr>
</tbody>
</table>
parameter of interest (i.e., humidity, clouds, and precipitation). Moreover, both land and ocean surfaces are distinguished, whereas humidity results are also separated for cloudy and clear sky. Only results for the conically scanning radiometer at 53° off-nadir angle are also considered, as those for the cross-track linear scanning are similar. Dual-side band channels are also considered in Table 3, even though the bandwidth effect has been neglected.

Frequencies below 52.8 GHz are valuable for clouds and precipitation together with channels located in the far wings of the 118-GHz absorption line, as expected, while 23.8 GHz contributes strongly to the water vapor profiling over ocean. Over both land and ocean the role of the 118-GHz frequency band for cloud and precipitation observation is more obvious than 89 GHz, whereas the 183-GHz frequency band is essential for humidity profiling over both land and ocean.

Restricting the frequency range to 89–229 GHz (to reduce antenna size; see section 3a), Fig. 6 shows the channel ranking for humidity profiling at each iteration $k$ (see equation within the optimization procedures over entire globe using average results over boxes of $3° \times 3°$). Figure 7 shows the same as Fig. 6, but for hydrometeor profiling. Each channel is color coded and its ranking is shown for each successive iteration of the ER procedure over the entire globe (see Fig. 5). This means that for each grid box, Figs. 6 and 7 show the geographically distributed information content priority of each channel.

It is worth noting that colors are not uniform over each panel meaning that the priority ranking will vary with latitude and longitude. This indicates that different channels dominate in different cloud conditions and underlines the fact that a large number of channels is required to optimize the observation of clouds and precipitation under all weather conditions. However, since only the channels above 89 GHz were included in this study, less spatial and spectral variability is found than expected if channels between 10 and 89 GHz were also included. The variability is generally more pronounced over the poles and around the intertropical convergence zone, especially for humidity after iteration 4.
c. Retrieval numerical results

From Table 3 we have derived a large set of channels in the millimeter-wave range that is able to provide humidity and hydrometeor profile information. If our aim is to keep the overall size of the radiometric payload small, we will restrict our analysis to frequencies above 89 GHz as shown in Figs. 6 and 7. Moreover, if more than 10 channels are considered, size and weight of the passive sensor will exceed what is compatible with a minisatellite bus (Marzano et al. 2009). Our choice for the radiometer configuration was based on an analysis comparing retrieval performances of a variety of subsets of the channels ranked in Table 3 (Marzano et al. 2009). The channel combination that provided the best performances is used in this paper, which is given by the following set: (89H GHz, 89V GHz, 166.0V GHz, 118.75V GHz, 118.75V 6.0 GHz, 118.75V 6.2 GHz, 118.75V 6.3 GHz, 183.31V 6.1 GHz, 183.31V 6.3 GHz, 190.3V GHz, 229.0H GHz), where V and H stand for vertical and horizontal linear polarization, respectively. This means that $T_{BP}(\nu, \theta)$ is a vector of 10 elements assuming a conically scanning radiometer with a 53° incidence angle at the surface. This configuration is called the Florad Millimeter-Wave Imaging Sounder (FLOMIS) and is the same one used by Marzano et al. (2009).

The 1D-Var methodology has been implemented using the 1D-Var perturbation approach (1D-VarP) described in Bauer and Di Michele (2007). 1D-VarP represents a self-consistent testing environment to evaluate the performance of a given instrument configuration. This is because all ingredients are defined, that is, state variables, observables, as well as their error characteristics, and based on realistic estimates of errors and meteorological representativeness. Retrieval accuracy can be determined, for instance, as a function of instrument noise, biases, channel cross correlation, and other parameters. It is based on a similar approach as already applied to clear-sky retrieval studies (e.g., Deblonde and English 2003).

The procedure for evaluating the retrieval accuracy is briefly described by the following points:

1) The control vector $x$ (state) contains vertical profiles of temperature and humidity, surface skin temperature, and 10-m wind speed ($u$ and $v$ components) relative to a single atmospheric state. In the case of profiles over
land, wind speed is replaced by emissivity parameters. Profiles of temperature, humidity, surface temperature, and additional variables, obtained from the short-range ECMWF model forecasts, are extracted from the global database described in section 3b.

2) The covariance $B_x$ represents the uncertainty associated with each of the components of $x$. In 1D-VarP, the first guess covariance statistics from the operational forecasts are used as the background error covariance matrix for temperature and humidity. Values relative to the corresponding time and location are associated with each profile of the database. For surface skin temperature and ocean wind speed, average values of background errors are used. In the case of profiles over land, the errors of surface emissivity are assumed to be equivalent to the spatial/temporal variability of emissivity that is included in the emissivity climatology at the location of interest.

3) The forecast ("true") profiles and background error covariances are used to generate the first guess needed for the 1D-VarP. The first guess is obtained from adding random perturbations to the forecast profiles. The random perturbation $\delta x_i$ of the $i$th element of $x$ is determined through an eigenvalue analysis and a Gaussian random number generator whose distribution has zero mean and unity variance.

4) Hydrometeors associated with the true profiles can be created by applying cloud and convection models to temperature and humidity and additional input variables (e.g., tendencies and surface fluxes). Observations, $y_{true}$, are simulated by processing the true profiles with the RTTOV model as described above. To produce realistic observations ($y_o$), noise is added to $y_{true}$. The noise corresponds to the radiometric noise that has been specified by Schlüssel et al. (2008). The observation error covariance matrix $C_e$ is assumed to be diagonal and derived from the observation statistics in Bauer and Di Michele (2007).

5) The (perturbed) first guess profiles and the simulated observations (from the unperturbed profiles) are then fed into the 1D-VarP retrieval block. The minimization module that is employed in 1D-VarP to compute (5) is the limited-memory quasi-Newton software developed by Gilbert and Lemarechal (1989). The retrieval error estimates are derived from the comparison of retrieved and unperturbed (true) profiles in terms of biases and error standard deviations. In our current configuration, 350 perturbations are performed per profile. This ensures a good compromise between accuracy of the results and computational efficiency.

The 1D-VarP method was applied to the global dataset described in the previous paragraph, but results are shown here just for the midlatitude region (latitude ranging from $-70^\circ$ to $-35^\circ$ and from $35^\circ$ to $70^\circ$). This region denotes the target area of the designed FLORAD mission.

The retrieval performance is quantified in terms of statistics of the residual error between the true profiles and the profiles retrieved from the simulated observations using 1D-Var (analysis). The retrieval performance is also compared to the variability of the respective geophysical variable in the true dataset. This demonstrates the improvement of the retrieval over an estimate based on the mean climatological profile and its variability. In addition, the statistics of the residual error between the true profiles and the first guess profiles used for initializing the 1D-Var are computed corresponding to the a priori knowledge. It is worth a reminder that the first guess profiles were generated by random perturbation of the true temperature and humidity profiles using the background error covariance from the operational forecast model. Therefore, any improvement of the analysis with respect to the first guess residual error demonstrates the FLOMIS observational contribution. Of course, it is expected that the improvement with respect to the operational forecast is substantially smaller than the improvement with respect to an estimate based on the mean climatological profile only. This is because the operational forecast has much higher skill than climatology.

Statistics were computed separately for cases over ocean and over land. Moreover, the dataset was further fractioned into clear-only, cloudy, and precipitating cases. Results for all of these combinations are presented in Figs. 8–13. In Fig. 8 the vertical profiles of bias and error standard deviation (std) for temperature and humidity estimates in clear-sky conditions over ocean are shown. Our analysis shows that the bias of the analysis resembles the bias of the first guess, and is negligible for both temperature and humidity. The error std statistics demonstrate that the FLOMIS contribution to the forecast is rather small but consistently positive in the troposphere for temperature and substantial for humidity with up to 30% near the surface. Note also that, as expected, the std error for the forecast is already substantially less than the variability of the atmospheric profiles (expressed here in terms of the std of the midlatitude subset). Similar results are shown for clear-sky conditions over land in Fig. 9, although in this case the FLOMIS contribution for the humidity profile is limited to 10% while for temperature it is slightly greater than over ocean. The reduction in humidity retrieval accuracy over land is explained by the much reduced radiometric sensitivity to moisture over surfaces with high emissivity.

Figures 10–11 show the results for the cloudy cases (ocean and land, respectively) including the retrieval errors for cloud liquid and ice water. The vertical profiles of
error bias and std for temperature, humidity, rain, and snow retrievals over ocean are shown in Fig. 12. With respect to the clear-sky cases, we note an increase in error reduction for temperature profiles throughout the troposphere, reaching 20%. This may be explained by the strong cloud contribution to emission that enhances the radiometric sensitivity to the temperature of liquid water. The fact that both temperature and liquid water error statistics are improved suggests that there is little aliasing and that the chosen channels are able to distinguish between the signal contribution from temperature and hydrometeors, respectively. However, the increased biases show that some aliasing is present because of the ambiguity of signal contributions. The reduction of the humidity profile retrieval error is largely reduced in the presence of liquid water. This may be explained by the strong sensitivity of the 183-GHz channels to liquid water, which causes these channels to become sensitive to temperature rather than humidity in the presence of liquid water.

Over land (Fig. 11) the observations add a little skill to the a priori knowledge for moisture and cloud liquid water and similar skill for temperature. The main observational impact is seen for temperature, which matches the impact over ocean, and cloud ice. The latter is expected to be mainly contributed by the 183-GHz channels. The comparison of a priori and climatology standard deviations shows that for cloud variables the short-range forecast has less skill over land than over ocean and that the substantial skill of moisture prediction over both land and ocean is not fully propagated into cloud variables.

If precipitation is included (Fig. 12) the FLOMIS contribution to the estimation accuracy reaches 10% for rain profiles while it increases to up to 50% for snow profiles. Figure 13 shows the results for the precipitation dataset over land. Here, the broad picture is unchanged, although we note a small increase of the FLOMIS contribution to both rain and snow profiling accuracy. Again, a small aliasing effect is visible expressed as increased
biases in lower-level temperatures and humidity. This is a common problem of underconstrained retrievals, here amplified because of the limited sensitivity of microwave radiances over high emission surfaces and the ambiguity of signal contributions by temperature, moisture, liquid water (cloud and rain), and surface emission. The largely different spectral signature of frozen particle scattering reduces the ambiguity, which explains why the snowfall retrieval accuracy is so much superior to the rainfall retrieval accuracy, in particular given the FLOMIS channel selection.

4. Conclusions

The FLORAD small-mission scientific requirements are aimed at the retrieval of hydrological properties of the troposphere, specifically water vapor profiles, cloud liquid content, rainfall, and snowfall. To fulfill the goal of a short revisit time for meteorological monitoring purposes on a quasi-global scale with special focus on a specific target region, a Flower constellation (FC) of minisatellites has been proposed. FC can offer several degrees of freedom in its design and its features have been briefly discussed. Incremental FCs have been illustrated and their comparison with other orbital solutions discussed, showing a revisit time increase on the order of 50% in many cases. The information content of MMW radiometer multiband channels has also been investigated, pointing out the trade-off between performance and complexity within the constraints of a low-cost minisatellite platform. A one-dimensional variational inversion algorithm to retrieve the requested atmospheric parameters has also been introduced and applied to a hypothetical FLOMIS. The overall error budget for various seasons and climatological regions shows that for the 10 selected channels, FLOMIS can provide a valuable accuracy when aiming at the retrieval of humidity and hydrometeor profiles.

The FLORAD small mission exploits the heritage of microwave radiometric applications, which have been consolidated since the late 1980s. The major areas of application are (i) numerical weather prediction (NWP), (ii) meteorological nowcasting, and (iii) climate monitoring. In the context of numerical weather nowcasting, FLORAD...
FIG. 10. Vertical profiles of (left) error bias and (right) std for (top to bottom) temperature, humidity, cloud liquid, and cloud ice retrievals over ocean at midlatitudes. Only cloudy cases are used. The dashed lines denote results for the first guess, while solid lines denote results for the analysis. The dotted lines denote the variability of the true dataset (in terms of std); for temperature profiles the variability is ~6 K (not shown for better readability).
FIG. 11. As in Fig. 10, but over land.
Fig. 12. Vertical profiles (left) error bias and (right) std for (top to bottom) temperature, humidity, rain, and snow retrievals over ocean at midlatitudes. Precipitating cases are used. The dashed lines denote results for the first guess, while solid lines denote results for the analysis. The dotted lines denote the variability of the true dataset (in terms of std); for temperature profiles the variability is $\pm 6$ K (not shown for better readability).
FIG. 13. As in Fig. 12, but over land.
measurements and products can be used both to better parameterize microphysical processes at the mesoscale involving water vapor and hydrometers and to validate thermodynamical and hydrometeorological fields. Even more important is the potential of FLOMIS data to be assimilated into global and mesoscale NWP models using space–time variational techniques or ensemble Kalman filter methods. The frequent temporal availability of FLOMIS measurements and products could significantly improve the performance of numerical prediction of convective systems. The combined sensitivity of FLOMIS observations to temperature, moisture, and humidity profiles is likely to be best exploited in modern data assimilation schemes toward an optimal combination of a priori knowledge, a consistent physical model, and the observations given the generally underconstrained nature of atmospheric analysis. Only optimal analysis with a thorough balance between information contributed by both model and observations will ensure a solution that is useful for forecast model initialization.

Precipitation nowcasting is a high-priority objective of civil protection applications. Time scales of nowcasting are usually smaller than 2 h. The major impairment when trying to exploit LEO satellites is the low time period, which may be on the order of 12 h for scanning radiometers aboard a single sun-synchronous platform. The Flower constellation can minimize this revisit time, as shown in section 2, and in this respect can offer an unprecedented feature for LEO satellites. Coupling FLOMIS data with geostationary IR measurements exploiting the different properties of microwave and infrared atmospheric emission and extinction in the presence of clouds provides another possibility to enhance the accuracy of rainfall products obtained at 15–30-min time scales.

Last but not least, the FLORAD mission can significantly contribute to lengthening the climatic data record, especially that related to temperature and water vapor. Temperature is one of the most evident signals of global warming and the capability of estimating its trends is of particular importance. Satellite measurements of three-dimensional temperature and humidity fields are unique records that can complement surface measurements. To use FLORAD measurements and products for climate applications, a very high radiometric sensitivity of FLOMIS channels is required since very small climate signals have to be detected over decadal periods. Deploying a series of FLORAD to ensure measurement continuity at a fairly low cost and high performance should also be considered.

Acknowledgments. The authors thank the members of the FLORAD project team (see Marzano et al. 2008) for their helpful suggestions and cooperation. The ECMWF staff is acknowledged for its support on numerical computations. This work has been funded by the Agenzia Spaziale Italiana (ASI), Rome, Italy, under Contract ASI N. I/018/08/0 and partially supported by the European Space Agency (ESA), Nordwijk, the Netherlands, under ESTEC Contract 20711/07/NL/HE.


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