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A Review of the Use of Geostationary Satellite Observations in Regional-Scale Models for Short-term Cloud Forecasting

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Abstract

Many research and societal applications such as surface solar irradiance assessment and forecasting require accurate short-term cloudiness forecasts at kilometre and hourly scales. Today limited-area numerical weather prediction models have the potential to provide such forecasts by simulating clouds at high spatial and temporal resolutions. However, the forecast performance during the first 12–24 h is strongly influenced by the accuracy of the cloud and thermodynamic analyses in the initial conditions. Geostationary meteorological satellites provide valuable observations that can be used in data assimilation for frequent cloud analysis determination. This paper provides an up-to-date review of the state of the art in cloud-related geostationary satellite data assimilation with limited-area models dedicated to improve cloudiness forecast performance. Research and operational studies have been reviewed by differentiating between satellite radiance and cloud property retrieval assimilation. This review gives insight into the best practices considering the large variety of limited-area models, data assimilation methods, satellite sensors and channels, cloud property retrieval products and various methodological challenges. Cloud analysis methods for regional models have become more sophisticated in recent years and are increasingly able to exploit observations from geostationary satellites. Important proofs of concept have been performed in this decade, paving the way for an optimal synergy of geostationary satellite data assimilation and convection-permitting limited-area model forecasts. At the same time, the increasing amount of channels of geostationary satellite instruments leads to more opportunities and challenges for data assimilation methods.

Keywords: satellite data assimilation, geostationary satellites, limited-area models, cloudiness forecasting

1 Introduction

Predicting the occurrence and evolution of cloud systems is a key component of atmospheric science and numerical weather prediction (NWP). Moreover, cloudiness forecasts are used in research, defence and societal applications.

Research-wise, continuous efforts are being made to improve the representation of clouds in global and regional NWP models used for weather forecasting and climate projections. Cloudiness forecasts greatly influence other model components such as land surface or hydrological models (Forman and Margulis, 2010; Meetschen et al., 2004). Numerous defence applications require accurate sky conditions on the operation terrain, especially the presence of a cloud free line of sight. Remote monitoring systems using optical and thermal vision, optical communication between ground and airplane or satellite and optronic aiming sight are not operational in cloudy conditions (Cros et al., 2015). Finally, cloud cover presence must also be forecasted for societal applications. Transportation security (e.g. air traffic and roads) needs accurate information about cloud base height, fog, icing and precipitation. Within the health system, cloud information is needed to assess air pollution and ultraviolet exposure.

A wide range of economic sectors are also influenced by cloud forecasts. For example, some leisure activities, such as sailing, trekking, paragliding, photography

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or outdoor shooting, are strongly dependent on cloud cover. More and more tourism and leisure industries are taking such forecasts into account in their current operations and are able to quantify the added economic value of improved cloudiness forecasts.

A currently growing application is solar power forecasting, which requires very accurate and frequently updated cloudiness forecasts. Photovoltaic (PV) power production variations are mainly driven by the attenuation of incoming solar radiation due to clouds passing between the sun and the PV panels. The simulation of cloud optical properties over minute to hourly time scales and at a spatial scale of a few kilometres is necessary to accurately forecast irradiance reaching the Earth's surface (Sengupta et al., 2015). Therefore, PV production management is particularly demanding in terms of cloud forecast performance and can be considered as a guiding application to improve it. For this application, NWP is currently the most suitable solution to produce cloud forecasts for lead times beyond 6 h up to several days ahead (Diagne et al., 2013). Due to an incomplete representation of the complex and often non-linear cloud processes and associated impacts on radiation, NWP models tend to underestimate low-level cloud cover and thus overpredict solar irradiance at the surface. This concerns especially stratus clouds and coastal areas (Haiden and Trentmann, 2015; Inman et al., 2013; Yang and Kleissl, 2016; Yucel et al., 2002). There are also large model uncertainties regarding the evolution of upper level cloudiness (Cintineo et al., 2014).

Nevertheless, the temporal and spatial resolutions of global model output (typically more than 10 km and 1 hour) often do not permit accurate cloud forecasting since cloud processes occur over shorter temporal and spatial scales. The parameterisation of sub-grid scale processes induces important uncertainties of irradiance forecasts since these processes often cause a highly variable cloud cover within a given grid box. Sengupta et al. (2015) gives a comprehensive overview of global models and their utility for solar irradiance forecasting. Bengtsson et al. (2013) evaluate and discuss the benefit of introducing stochastic elements into convective parameterizations.

Among current initiatives to improve NWP models for solar power forecasting, the WRF-Solar project aims at taking the interactions between clouds, aerosols and radiation in the regional NWP model (or limited-area model (LAM)) WRF (Weather Research and Forecasting) better into account (Jimenez et al., 2016). Besides, the choice and combination of parameterisation schemes (e.g. convection, cloud microphysics, radiation and planetary boundary layer) also highly influences the performance of NWP models (Cintineo et al., 2014; López-Coto et al., 2013; Otkin et al., 2017; Otkin and Greenwald, 2008).

An area of research with great potential for improving cloud forecasts produced by NWP models is data assimilation (DA) (Geer et al., 2017). DA is used to determine the most likely state of the atmosphere at a given time, with the resultant analysis providing the initial conditions for a NWP model forecast. The atmospheric initial state is determined by an optimal combination of background information (usually short-range NWP forecasts which are also called first guess) and atmospheric observations (Kalnay, 2003).

Satellites are the primary source of cloud information, and therefore play an important role for cloud analysis determination. By virtue of their high spatial (< 4 km) and temporal (5–15 min) resolutions, geostationary satellite observations are an ideal data source for many of the above mentioned applications of regional cloudiness forecasting, such as weather nowcasting, military applications (Ruggiero et al., 1999) and solar power forecasting (Cros et al., 2014; Lorenz et al., 2014).

However, DA constitutes a wide and complex research domain where various efforts around the globe have been made in the past in order to improve different specific aspects of weather forecasting. Bauer et al. (2011b) list recommendations for improving various aspects regarding the assimilation of satellite-based cloud observations, such as modelling, verification, data assimilation and the exploitation of observations, and call for more collaboration between the different communities. Despite recent progress in the field, the potential for cloud data assimilation in cloud resolving NWP models using geostationary sensors is far from being fully exploited (Gustafsson et al., 2018). Many issues faced within limited-area models are different than those faced in global models that rely far more heavily on polar-orbiting satellite sensors.

Consequently, a detailed review of geostationary satellite data assimilation in regional-scale NWP models for cloudiness forecasting will provide guidance for further research. In this paper, we will identify and describe the most promising methods and their associated limitations, paving the way for developments aimed at improving cloudiness forecasts for demanding applications such as solar energy management.

Section 2 introduces the concepts of cloudiness forecasting using regional NWP with geostationary data assimilation approaches. While Section 3 details the use of radiances as assimilated observations, Section 4 presents the recent efforts concerning the assimilation of satellite-based cloud properties. Section 5 discusses different comprehensive aspects of current research and operational cloud analysis systems. Conclusions are drawn in Section 6.

2 Satellite data assimilation for cloudiness forecasts: basic concepts

LAMs obtain their lateral and initial boundary conditions from global circulation models (GCMs). This allows LAMs to use higher temporal and spatial resolutions than GCMs and potentially simulate cloud processes with more detail. Observations can be taken into

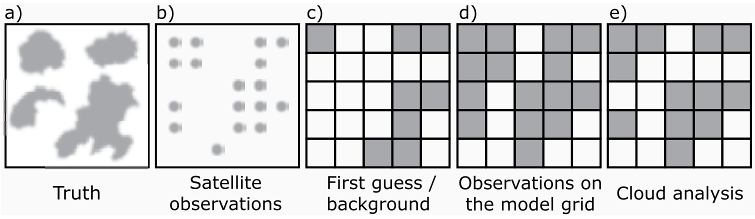

Figure 1: Two-dimensional (horizontal) sketch of different representations of a partly cloudy region as seen from above. The grey areas represent cloud presence while white means no cloud. a) "True" situation of cloud presence. b) Cloud presence observation as seen by the satellite. c) Example of a first guess produced by a regional NWP model. d) Mapping of the satellite observation to the model grid. e) Cloud analysis resulting from c) and d) using data assimilation.

account to produce a more realistic initial representation of the three-dimensional atmospheric state on the whole grid of the LAM. But even with a dense observation network, observations would not be available for every grid box, therefore necessitating the use of DA methods that can spread observational information to other parts of the domain and to unobserved model variables. DA offers the possibility to determine the most realistic estimates of the atmospheric state in the domain of the LAM (the so-called "analysis") by combining the unevenly distributed atmospheric and land surface observations with previous model estimates (the so-called "background" or "first guess").

Determining an atmospheric analysis in the presence of clouds is a complex issue because clouds are captured differently by observations and NWP models. Fig. 1 can be understood as a two-dimensional illustrative example of this issue. The goal is to build a two-dimensional cloud analysis (e) with a certain grid spacing containing the simplified information whether clouds are present or not in a given grid box. In this example the "truth" (a) is a situation with four cloud systems. It is observed by a satellite (b) with a certain resolution and error. A NWP model provides a first guess of the situation (c) with the respective model grid spacing. The satellite observations are mapped to the model grid (d). In the actual DA procedure the cloud analysis (e) is determined by taking into account the first guess, the mapped observations and their respective uncertainties. In reality the situation is much more complex since the vertical and temporal dimensions and other cloud-related parameters like cloud fraction, phase, optical thickness or precipitation are also important and may be part of the cloud analysis that is to be determined.

In the case of cloudiness forecasting, a precise cloud analysis is a priority compared to non-related parameters (e.g. ozone concentration or land surface parameters). Thus, depending on the application of the regional modelling efforts, it is appropriate to focus on the assimilation of a subset of observation types that are directly sensitive to clouds or water vapour. For the forecasting of clouds, these are most commonly satellite radiances or retrieved cloud properties. Global DA experiments have shown that the skill of weather forecasts largely depends on the accuracy of the initial conditions in cloud-covered areas (McNally, 2002). Pincus et al. (2011) performed perfect model experiments with two global models that showed that the assimilation of cloud information is especially advantageous in regions where other observations are sparse.

In the past decades, a variety of data assimilation methods and strategies, such as nudging, optimal interpolation, variational methods such as 3D-Var, 4D-Var, and ensemble Kalman filters (EnKF) have been developed and successfully applied to numerous global and regional NWP models by diverse research institutions and weather offices around the world (Gustafsson et al., 2018). In variational methods the minimisation of a cost function has to be found in order to determine the analysis. As an example, the cost function of the 3D-Var method is given by:

$$J(x) = (x - x_b)^T \mathrm{B}^{-1} (x - x_b) + (y - H(x))^T \mathrm{R}^{-1} (y - H(x)) \quad (2.1)$$

With x being the analysis, x_b the background, y the observations, B the background error covariance matrix, R the observation error covariance matrix and H the observation operator (or forward operator) which maps the model state to the observation space. A radiative transfer model (RTM) that converts model fields (i.e. meteorological variables) into synthetic satellite radiances is a common example of an observation operator. The analysis can be determined by using available observations and a background in a cycling procedure.

Two of the most-widely used DA methods are 4D-Var and EnKF. While 3D-Var considers the three spatial dimensions and aims at minimising the cost function for a given analysis time, the 4D-Var method also includes the temporal dimension. The evolution of the NWP model and the observations is considered during a certain timeframe before the analysis time (usually several hours) in order to derive the atmospheric analysis. This timeframe is called the "assimilation window". The assimilation window length has to be restricted to a few hours since 4D-Var assumes linear dynamic processes because of the need for an adjoint model and also that the NWP model is perfect. These issues limit the utility of this method for high-resolution simulations and therefore motivate using the EnKF. The use of an ensemble allows for better quantification of flow-dependent covariances important for clouds and also allows fully nonlinear forward observation operators. Ensemble forecasting provides a sample of atmospheric states which can be used to estimate the evolution of the mean state and the covariance or the model background uncertainty.

More detailed explanations about DA methods in general are given by Kalnay (2003). The advantages, disadvantages and differences between variational, ensemble-based methods and hybrid methods that combine aspects of variational and ensemble DA are discussed in Bannister (2017) and Kalnay et al. (2007). A detailed review of the EnKF is given by Houtekamer and Zhang (2016). We also mention that recent particle filter developments may improve the data assimilation (Zhu et al., 2017).

Geostationary meteorological satellites provide atmospheric observations on a global scale that are highly valuable for the determination of cloud analyses. Indeed, this source of observation is the only one offering pertinent information about cloud presence, properties and evolution with high spatio-temporal resolution and large geographic coverage. Thus, the assimilation of geostationary satellite observations in regional NWP models satisfies the demanding requirements of some applications such as solar power forecasting. It is worth mentioning that the resolution of geostationary satellite observations decreases with increasing distance from the subsatellite point over the Equator. This circumstance is especially important with increasing latitude (e.g. Scandinavian countries) since in the tropics it can simply be overcome by choosing an appropriate satellite.

The on-board sensors of these satellites measure radiances at different wavelengths or channels, i.e. in the infrared (IR), near infrared (NIR) and visible (VIS) spectrum. The IR channels are often distinguished between those that are primarily sensitive either to water vapour (WV), temperature, atmospheric trace gases (e.g. ozone) or window channels. Window channels provide useful information about cloud top properties when clouds are present and about the surface when clouds are missing from a given scene. Combining spectral signatures from multiple IR, VIS and NIR channels allows for the estimation of many cloud properties, such as cloud top height, phase and optical depth.

Depending on their spectral characteristics, the assimilation of different channels involves different problems. For example, the successful assimilation of window channels requires accurate information about the land-surface emissivity, which is difficult to obtain. Because of this, such observations are typically excluded in satellite DA (Harnisch et al., 2016). Most observations obtained from geostationary satellites for a given location are fundamentally different depending on the presence of clouds (Fig. 2). The figure depicts that different channels are sensitive to different levels of the atmosphere. The vertical height of their maximum sensitivity strongly depends on the presence and vertical location of clouds. While the yellow sensitivity curve in Fig. 2 serves as an example of a water vapour channel, the red and blue curve are examples of the sensitivity of a thermal IR channel in the cloud-free and cloudy case. Either information about the temperature of the lower atmosphere or of the cloud top can be derived. The sensitivity curve of a VIS channel would either peak at the surface or at the cloud top.

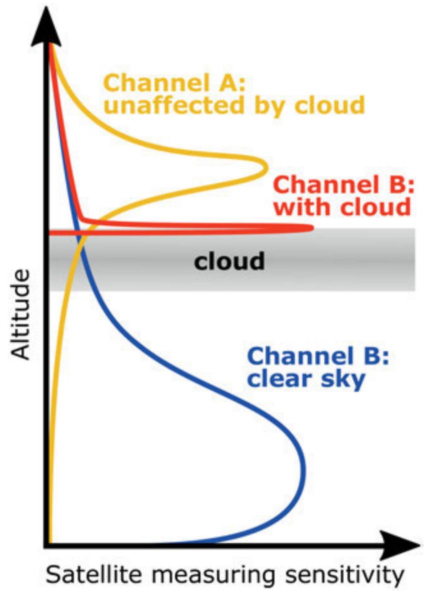

Figure 2: Sketches of the sensitivity of two different satellite channels in the clear-sky and cloudy case. Yellow: channel A is generally unaffected by the cloud; Red: channel B is affected by cloud; Blue: channel B in the clear sky case.

Satellites do not measure quantities like temperature or humidity, but radiances, which are radiometric signals. These can either be assimilated directly or converted into physical cloud properties, called "retrievals", before their assimilation. In radiance assimilation the NWP model variables must be converted into synthetic radiances while in retrieval assimilation the satellite-based variables are converted into model variables. Both techniques have the potential to significantly increase the cloud-related information content of an analysis and thus contribute to better short-term forecasts of cloud features.

The following two sections provide a review of recent efforts in the two fields of radiance and cloud property assimilation. Current methods are assessed regarding their potential to improve the accuracy of high-resolution limited-area short-term forecasts of cloud-related parameters like cloud extent, incoming solar irradiance at the surface or precipitation.

3 The direct assimilation of radiances

The direct assimilation of satellite radiances is the most widely used method to assimilate satellite observations into NWP models. This technique is especially being performed and enhanced for operational GCMs by weather services around the world (Bauer et al., 2011b; Geer et al., 2017).

In the process of direct radiance assimilation, synthetic radiance observations are calculated from the model variables using a forward RTM as the observation operator (H in equation (2.1)). During the data assimilation step, the difference between these synthetic and observed radiances is considered. This difference is called an innovation. The impact on the observed and unobserved fields as a consequence of the combination of the innovation with all other assimilated observations, observation errors, background error covariance and covariance localization, is known as the analysis increment. This ultimately leads to the final analysis, i.e. the updated initial model state for the next model run.

The methodological advantage of radiance assimilation is that it makes direct use of the observed radiances or brightness temperatures (BT) without the need to first convert the observations into some retrieved property. Retrievals are generally more uncertain than radiances since they often rely on assumptions and auxiliary information, possibly from NWP models. The quantification of the radiance observation error is thus more accurate (Migliorini, 2012).

3.1 Clear-sky radiance assimilation

Within the subject of the direct assimilation of radiances it is prudent to distinguish between cloud-free and cloud-affected radiance assimilation. While the assimilation of clear-sky radiances has already been performed for several decades in operational global models, it is still a recent topic in regional modeling. One reason for that is that the analysis is strongly influenced by the initial and lateral boundary conditions of the driving global model. Other reasons include difficulties associated with bias correction given the lack of global data and uncertainties associated with the land surface specification. The latter aspect is more important for regional-scale models given that they are typically located over land. Furthermore, global NWP models traditionally rely on polar-orbiting satellite sensors, which are going to be less useful for regional-scale models given their infrequent coverage of a limited-area domain.

Several recent studies evaluated the impact of clear-sky radiance assimilation on cloud-related parameters, e.g. water vapour profile, cloud mask and precipitation. In the study of Zou et al. (2011) and the follow-up study of Qin et al. (2013) coastal quantitative precipitation forecasts (QPF) were improved by assimilating GOES (Geostationary Operational Environmental Satellite) clear-sky IR radiances in the WRF model using the NCEP (National Centers for Environmental Prediction) GSI (Grid Point Statistical Interpolation) 3D-Var system (Shao et al., 2016). The assimilation of the GOES observations results in a large added value compared to solely conventional data (like synoptic stations, radiosondes, aircraft reports and wind retrievals) in the study of Zou et al. (2011) and likewise in a positive impact in addition to the assimilation of multiple polar-orbiting satellite observations in Qin et al. (2013). Zou and Da (2014) further developed the assimilation strategy and aim at a full utilisation of cloud-free radiance observations. They implemented a regime-dependent cloud mask for the removal of cloud-affected GOES radiance observations. The outcome is a more precise cloud mask determination when assessed using a MODIS (Moderate-resolution Imaging Spectroradiometer) derived cloud mask. These studies prove that even without considering cloud-affected radiances, the assimilation of radiances observed in regions without clouds prior to convective initiation has a positive impact on short-term cloud and QPF forecasts.

A positive impact of clear-sky radiance assimilation on tropospheric moisture in WRF has also been found in experiments by Singh et al. (2010, 2016) with the WRFDA (WRF model data assimilation system) 3D-Var system (Barker et al., 2012) and model domains centred over India: The first-time assimilation of clear-sky water vapour-sensitive radiances of the Indian satellite Kalpana into WRF results in improved analyses and short-term forecasts, especially for mid-upper tropospheric moisture (Singh et al., 2010). While the month-long simulations prove the benefits of this practice, extended experiments with more than one channel are desirable. Consequently, in the experiments of Singh et al. (2016) several channels of the most recent Indian satellite INSAT-3D (Indian National Satellite System) have been considered for the first time. Assimilating INSAT-3D clear-sky temperature and water vapour-sensitive radiances results in improved tropospheric moisture and temperature profiles in the analysis and improved forecasts of moisture, wind, temperature and precipitation.

As Yang et al. (2017) demonstrate by applying a 3DEnVar approach with WRFDA, hybrid methods of variational and ensemble DA methods offer a great potential to improve convection-permitting LAM forecasts of clouds. The case study results over Mexico using GOES imager clear-sky radiances show analysis improvements in terms of temperature and humidity that ultimately lead to improved 24 h precipitation forecasts.

The results of these various studies with WRF are proof of the positive impact of clear-sky radiance assimilation on regional forecasts of cloud-related parameters. In order to avoid radiation from the surface, clear sky radiance assimilation is usually performed using channels whose sensitivity profiles peak in the middle and upper troposphere. To a large extend this explains the positive impact on temperature and humidity profiles in these altitudes, ultimately impacting clouds and precipitation. With a horizontal grid spacing of 25 and 30 km the experiments of Singh et al. (2010, 2016) were performed with rather coarse horizontal resolutions of the LAM. In contrast, Zou et al. (2011) and Qin et al. (2013) used 10 km while Yang et al. (2017) used 4 km. The impact of different domain sizes and resolutions on the assimilation outcome should be the subject of future work. Moreover, all of these studies present case studies. Exhaustive evaluations for several months have not been performed. Those would strengthen the significance of the results, especially regarding the use of new satellites like INSAT-3D. Long-term evaluations of clear-sky radiance assimilation with 4D-Var or ensemble DA systems are likewise missing in the literature. Such studies could bring forth important information about the dependency of clear-sky radiance DA on the lateral boundary conditions and different synoptic weather conditions. Nevertheless, avoiding the use of cloud-affected radiances and only assimilating clear-sky radiances is not comprehensive. While some authors focus exclusively on the impact of clear-sky radiance assimilation, most of the research community has focused on the assimilation of cloud-affected radiances given the large potential benefit that can be derived from these observations.

3.2 Cloud-affected radiance assimilation

3.2.1 General issues

Since the past decade, there have been more concentrated efforts to assimilate cloud-affected radiances into global NWP models (Geer et al., 2017). Processing clear-sky and cloud-affected radiances in a uniform way in global models is currently one of the top priorities in operational satellite data assimilation. Concerning limited-area models, cloud-affected radiance assimilation is also increasingly investigated. The assimilation of cloud-affected radiances is considerably more challenging in both global and limited-area models for several reasons, discussed by several authors (Kostka et al., 2014; Polkinghorne and Vukicevic 2011; Seaman et al., 2010; Vukicevic et al., 2006). The main aspects are:

1. The nonlinearity of moist processes is difficult to take into account.

   The observation operators have to take into account water, which appears in all phases in the cloudy atmosphere, e.g. as vapour, liquid, mixed-phase or glaciated. Radiative transfer processes involving clouds and precipitation are nonlinear, which conflicts with the fact that variational DA systems require linearized and adjoint forms of the forward operators during short time windows (Bauer et al., 2011a,b; Otkin, 2010). Otherwise the convergence of the minimization of the cost function is not guaranteed (Kostka et al., 2014). Errico et al. (2000, 2007a) show that the cost function can become multimodal when moist processes are involved and that the minimization algorithm finds local minima of the cost function but not its global minimum. Consequently, more iterations are needed which increases the computational requirements and spurious noise can be introduced in the adjoint model which then leads to numerical instability (Polkinghorne and Vukicevic, 2011).

2. Detailed information about cloud microphysical variables and their uncertainties are required.

   Clouds and precipitation are discontinuous in time and space and the associated processes and uncertainties are generally not well modelled by NWP models (Bauer et al., 2011b; Vukicevic et al., 2006), which poses problems for the forward operators that require precise profiles of cloud parameters (Weng, 2007). Bennartz and Greenwald (2011) discuss radiative transfer issues related to this circumstance. The accurate description of cloud-resolving model background errors is a highly complex problem regarding the structure of the error covariance matrix (Weng, 2007) that is usually assumed to be isotropic and homogeneous and constant during the assimilation window for variational data assimilation (Bauer et al., 2011a).

3. Cloud location errors are difficult to handle.

   Regarding clouds, four cases are possible in satellite data assimilation: (1) Both the model and satellite have clouds (2) the model has a cloud that is not observed by the satellite (3) the satellite observes a cloud while the model simulates a cloud-free atmosphere (4) or both are clear (Fig. 1(c) and (d)). This uncertainty is referred to as model cloud misplacement or location errors (Kostka et al., 2014; Polkinghorne and Vukicevic, 2011). Location errors also cause problems in the adjoint calculation when observed clouds do not exist in the model. These aspects limit the ability of cloud-affected radiance assimilation in generating new model clouds (Polkinghorne and Vukicevic, 2011; Seaman et al., 2010). As in the case of the nonlinearity problem, EnKFs are more robust than variational techniques concerning cloud location errors (Otkin, 2010; Zupanski et al., 2011).

Another challenge with LAMs is the development of bias correction schemes, especially in the situation where both clear and cloudy sky observations are assimilated. Compared to global NWP models, bias correction is more challenging in LAMs because their small geographic extent makes it unlikely that they will capture a wide range of synoptic weather conditions. This is important because biases may be dependent on the prevailing weather and in the case of all-sky radiance assimilation will also be tied to different cloud types (Otkin et al., 2018). This issue is crucial for polar-orbiting satellite sensors because they only observe the LAM domain two times each day, but it will be less of an issue for geostationary sensors since they provide complete domain coverage, likely with temporal resolutions < 15 min. Even so, the above issues still necessitate development of innovative bias correction methods suitable for application in LAMs.

The diverse issues that radiance assimilation faces explain the fact that up to the present day a large amount of cloud- and/or rain-affected radiance observations are not considered in operational data assimilation systems (Bauer et al., 2011b; Geer et al., 2017). The complex observation operators and the strongly increasing number of channels of new-generation satellite sensors make radiance assimilation computationally costly, which is another disadvantage regarding operational NWP (Migliorini, 2012).

In the following subsections we investigate how recent studies have approached the above-mentioned problems and their implications for future work.

3.2.2 Observation operators for cloud-affected radiance DA

Several publications tackle the problem of the nonlinearity of moist processes by the implementation and testing of new observation operators for cloud-affected radiances. The assimilation strategies for cloudy radiances are adapted to the relevant NWP models and their available assimilation methods while the general goal is to overcome the problems related to cloudy radiance assimilation. Since variational and ensemble-based methods work differently regarding the handling of nonlinearity and other issues, it is important to consider the findings of the studies with respect to the applied DA method.

One early example of an observation operator for both cloud-free and cloudy situations in a LAM is the one that was developed for the 4D-Var DA system of the RAMS (Regional Atmospheric Modeling System) model RAMDAS (Regional Atmospheric Modeling Data Assimilation System). It has been developed and firstly evaluated by Greenwald et al. (2002, 2004). The multi-scattering radiative transfer model computes synthetic radiances of GOES IR and VIS channels under all weather conditions. An important finding of the adjoint sensitivity analysis is that radiances of different channels are sensitive to different types of clouds in terms of their thickness or phase. The system has been further evaluated by Vukicevic et al. (2004, 2006) in case studies of stratus and multi-layered clouds without convection where a positive impact on analyses and short-term cloud forecasts could be found in both cases. Unfortunately the system has not been extensively evaluated for the case of complex and convective cloud situations or in other geographical regions using other satellites.

More fundamental work on cloud-affected radiance assimilation using a 4D-Var system has been done by Stengel et al. (2009, 2010, 2013). The utilised HIRLAM (High Resolution Limited Area Model) model is the first LAM that assimilated SEVIRI (Spinning Enhanced Visible and InfraRed Imager) radiances using 4D-Var (DA scheme initially described by Gustafsson et al., 2001 and Lindskog et al., 2001). The developed observation operator uses the RTTOV (Radiative Transfer for TOVS) RTM that is maintained by EUMETSAT and a simplified moist-physics scheme that was developed at ECMWF (European Centre for Medium-Range Weather Forecasts). The application of the new observation operator results in a reduction of the analysis errors of the total integrated water vapour and a forecast error reduction for geopotential height, humidity and wind direction at most model levels and especially in the upper troposphere. A shortcoming of the experiments is the relatively coarse grid spacing of 22 km. Further experiments should be performed in order to investigate the performance of the system at convection-permitting resolutions where the high spatial resolution of SEVIRI can be better utilised.

RAMS and HIRLAM are two prominent examples using new and functional observation operators for geostationary cloud-affected radiance assimilation for 4D-Var in LAMs in mid-latitudes. Thanks to the frequently available satellite observations 4D-Var takes into account how the atmospheric state evolves. The main achievement of the method that becomes evident in the studies is that especially tropospheric humidity increments are improved, which positively impacts cloud evolution after the model initialisation. However, the computational cost of the adjoint of the observation operator is high for a large number of observations. Moreover, using 4D-Var, the analysis and forecast quality largely depends on the capacity of the model to represent cloud processes. Especially in convective situations and at high resolutions the method reaches its limits, which is to be investigated by future studies. For example, the evaluation of tropical convective events would be an extreme performance test.

Kostka et al. (2014) criticise that not much work has been done regarding the assimilation of VIS and NIR radiances and list several advantages of VIS and NIR compared to IR radiances concerning cloud information content. They tackle this issue with the development of a new observation operator for NIR and VIS reflectances for the COSMO (Consortium for Small-scale Modeling) model and its LETKF (Local Ensemble Transform Kalman Filter) DA system. The kilometre-scale ensemble data assimilation (KENDA) system for the COSMO model, developed by the German Meteorological Service (Deutscher Wetterdienst, DWD) constitutes an ensemble modelling system that includes the assimilation of geostationary satellite observations in a cloud-resolving model. The KENDA system is outlined by Schraff et al. (2016) while further insight is given by Harnisch et al. (2016) and Sommer and Weissmann (2014). In their simulations with the new NIR and VIS observation operator using Meteosat observations Kostka et al. (2014) obtain the best results by horizontally smoothing the observations and by applying a parallax correction, which accounts for the slant satellite viewing angle through the atmosphere. Nevertheless, the usage of VIS observations is constrained to the day-time, which limits their utility. Yet, the development of observation operators for VIS channels constitutes an important contribution to maximise the use of geostationary satellite observations.

3.2.3 Handling observation and model background errors

With an increasing cloud amount the observation and forward operator errors often acquire non-Gaussian error characteristics, which is not in line with the common DA assumption of normally distributed errors. Recent works using COSMO-KENDA attempt to account for this circumstance with new methods for error estimation and bias correction (Harnisch et al., 2016; Otkin et al., 2018). Harnisch et al. (2016) apply a dynamic observation error estimate depending on the cloud impact with COSMO-KENDA – a technique that has previously been applied in the assimilation of microwave observations in a GCM (Geer and Bauer, 2011) and thus been transferred to infrared radiance assimilation in a LAM. The positive result is that the first-guess departure (observation minus first-guess) statistics become closer to a normal distribution. Otkin et al. (2018) present a new bias correction approach based on a Taylor series polynomial expansion of the observation departures that is able to remove both linear and nonlinear conditional biases from all-sky satellite brightness temperatures. Passive monitoring experiments using BTs from two WV channels on SEVIRI showed that the bias in the observation departures was greatly reduced when using higher order Taylor series terms and bias predictors sensitive to clouds and water vapour. Although these studies present important proofs of concept to improve all-sky (cloud-free and cloud-affected) IR radiance assimilation with a highly-resolved LAM (2.8 km grid spacing), a long-term evaluation of the methods and an extension to more channels would be desirable.

Further studies with the RAMS model and cloud-affected GOES radiances have been performed, addressing the above-mentioned problems (2) and (3). Polkinghorne et al. (2010) compute mean model background error statistics at cloud-resolving grid spacing of 4 km in order to further improve the RAMDAS 4D-Var assimilation system. They introduce a simple cloud mask and distinguish between clear-sky observations and those with either low or high clouds. This way, cloud location errors can be reduced during the assimilation by choosing only points with the same type of cloud in both the model background and the observations. Nevertheless, the cloud type agreement between observations and model is often poor due to the imperfect representation of the modelled cloud situation. Polkinghorne and Vukicevic (2011) further evaluate the impact of the established model background error statistics in a larger domain while Seaman et al. (2010) investigate the assimilation of cloud-affected IR radiances with a cloud-free model background of RAMS at a grid spacing of 6 km. The latter investigation also addresses the cloud location error problem. In the studied case a mid-level cloud is present in the observations (Fig. 3(c)) but not in the dry model background (Fig. 3(a)). The difficulty for the 4D-Var system is to generate a physically consistent state between temperature, humidity, wind and clouds. The authors find that the temperature and humidity profiles are modified in the correct direction after the assimilation of GOES radiances, bringing the model closer to the generation of the observed mid-level cloud (Fig. 3(b)). Nevertheless, the model does not necessarily assume a consistent and realistic cloud as a consequence of the assimilated radiances (Fig. 3(d)). The study of Seaman et al. (2010) is one of the rare studies that explicitly examines the influence of the domain size on the DA results. In the studied case, increasing the domain size changes the initial model state and the observed cloud covers a smaller proportion of the domain which does not necessarily lead to improved results. The impact of different LAM domain sizes needs to be studied with other models, at different resolutions and under various meteorological conditions.

The different RAMS case study experiments (Polkinghorne et al., 2010; Polkinghorne and Vukicevic, 2011; Seaman et al., 2010) show a high sensitivity of the 4D-Var DA system to diverse parameters like assimilation window length, allowed difference of observed and modelled BT, background error decorrelation length, domain size and the studied case. These are important findings that stress the difficulty of correctly configuring a 4D-Var cloud-affected radiance DA scheme for a cloud-resolving LAM. The works are a step forward in solving the cloud location error problem, but do not completely solve or circumvent it. The generation of model clouds with 4D-Var radiance assimilation in case of a cloud-free background is a major issue for which no comprehensive solution exists today.

3.2.4 Preparing for the assimilation of new geostationary satellite observations

On the side of EnKF systems, besides the above-cited works with the COSMO model, several Observing System Simulation Experiments (OSSE) have been performed with the WRF model and the DART (Data Assimilation Research Testbed) (Anderson et al., 2009) system (Cintineo et al., 2016; Jones et al., 2013a, 2014, 2017, Otkin 2010, 2012a,b). While Jones et al. (2017) evaluate the potential impact of geostationary hyperspectral observations, the other studies have in common that they aim at evaluating the impact of assimilating simulated GOES-R radiance observations at cloud-resolving resolutions. Otkin (2010) showed that the assimilation of both clear-sky and cloud-affected synthetic GOES-R ABI (Advanced Baseline Imager) IR brightness temperatures improved cloud analyses for a convective case across the central U.S. Otkin (2012b) subsequently showed that the analysis and forecast accuracy are noticeably impacted by the choice of the covariance localization radius. Following these studies, the impact of WV-sensitive IR brightness temperatures was firstly evaluated by Otkin (2012b) resulting in improved cloud and moisture analyses for a cool season weather event. Cintineo et al. (2016) and Jones et al. (2013a, 2014)

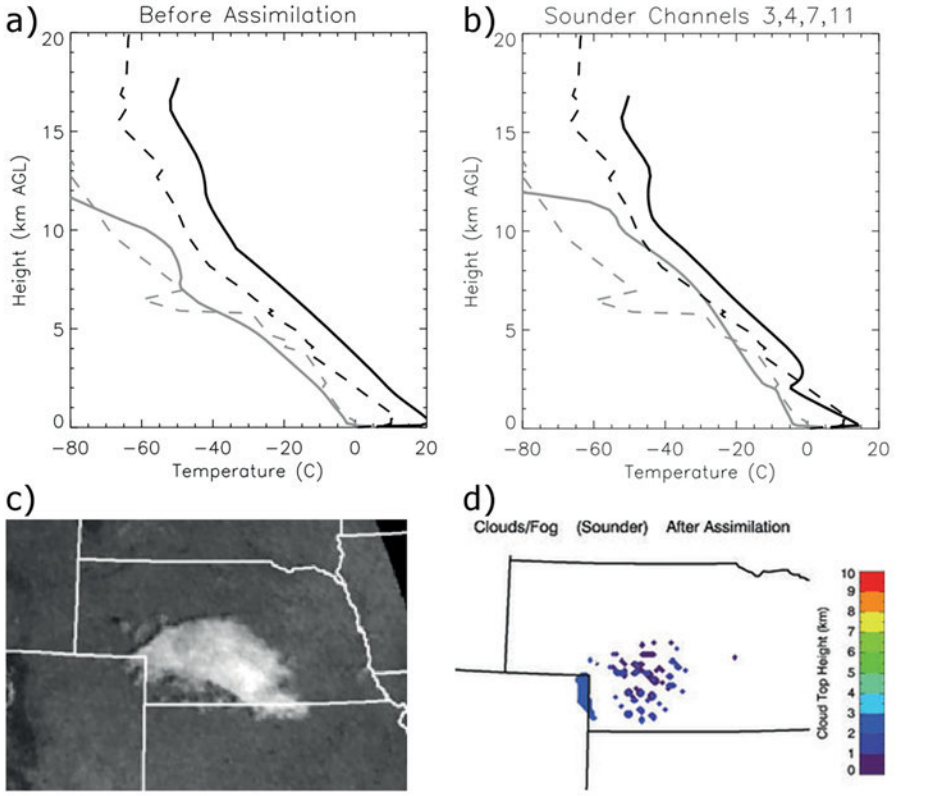

Figure 3: Illustrations of RAMS 4D-Var radiance assimilation experiments over Nebraska on 2 November 2001 with a cloud-free RAMS background. a–b) Soundings of temperature (black) and dew point (grey) at North Platte, Nebraska observed at 1200 UTC (dashed lines) and simulated by RAMS at 1145 UTC (solid lines) before assimilation (a) and after assimilation of GOES Sounder channels 3, 4, 7 and 11 (b). c) GOES visible image of an altocumulus cloud extending between 4.2 and 4.7 km above mean sea level taken at 1445 UTC. d) Model location and height of cloud top in km above ground level (AGL) after assimilation of GOES Sounder channels 7 and 11 with decorrelation lengths doubled revealing the largest cloud (along the Nebraska-Colorado border) from any experiment that may be considered 'mid-level' with a top height of 2.5 km AGL. Original figures adapted from Seaman et al. (2010). © 2010 The Authors. Published by Taylor & Francis. Used with permission.

assimilate both synthetic GOES-R BT and radar observations, showing that the two complement each other and that the satellite observations are vital. Distinct improvements of analysis and forecast accuracy and the simulated cloud field can be found throughout the experiments thanks to the assimilated synthetic satellite observations. The works constitute an important preparation for the usage of real GOES-R ABI observations with state-of-the-art cloud-resolving ensemble DA modelling systems. Since GOES-R is now operational as the GOES-16 satellite, the system should be thoroughly evaluated for real cases.

Besides the diverse works with GOES and SEVIRI observations, efforts to assimilate Himawari-8 all-sky radiance observations at cloud-resolving resolutions are also being made. Okamoto (2017) performed the first evaluation of simulated Himawari-8 all-sky IR radiances from four channels with the JMA (Japan Meteorological Agency) non-hydrostatic model (JMA-NHM). Okamoto (2017) suggests beginning with the assimilation of only WV-sensitive channels for further developments. Moreover, it is emphasised that the successful assimilation of cloud-affected IR radiances requires improvements of both the NWP model and the RTM. The diverse problems (1–3, Section 3.2.1) are thus left unsolved once more. This is one of the few studies on radiance assimilation that compares the performance of the two most widely used observation operators RTTOV and Community Radiative Transfer Model (CRTM), finding a slightly better performance for the CRTM. However, this finding is to be confirmed in actual assimilation experiments with an ensemble-based or variational DA system.

3.2.5 Alternative methods

Alternative assimilation methods to 3D-Var, 4D-Var or EnKF have been tested by Raymond et al. (2004) and Zupanski et al. (2011). The former study assimilated GOES brightness temperatures from a channel sensitive to upper-tropospheric water vapour by iteratively modifying the upper-tropospheric humidity in the CRAS (CIMSS (Cooperative Institute for Meteorological Satellite Studies) Regional Assimilation System) model at 40 km grid spacing. Zupanski et al. (2011) perform a WRF case study with a grid spacing of 15 km of an extratropical cyclone over Europe with a maximum likelihood ensemble filter (MLEF) and the assimilation of synthetic all-sky IR GOES-R radiances of a window channel. It is an ambitious case study because of strong cloud location errors. Both studies are successful proofs of concept showing positive impacts of the assimilation on cloud-related parameters like upper-tropospheric moisture (Raymond et al., 2004) and cloud ice (Zupanski et al., 2011). Extended studies of the methodologies at cloud-resolving scales, over a longer evaluation period, with more channels and real observations from GOES-R or SEVIRI or synthetic observations of Meteosat Third Generation (MTG) would strengthen the proofs of concept.

3.2.6 Concluding remarks

In summary, radiance assimilation is the common approach for satellite data assimilation adapting the NWP model's representation of the atmosphere to the satellite's view of the atmosphere. All-sky IR radiance assimilation holds a lot of promise but has not traditionally been performed with LAMs because of the many challenges associated with it. Diverse problems occurring in cloudy situations are difficult to handle and solutions for these problems are being developed and tested. Meanwhile, radiance assimilation proves to be very beneficial for cloudiness forecasting, even if cloud-affected observations are not considered. Some important proofs of concept have been performed that still have to be supported by long-term evaluations. In particular, the topic of cloud-affected radiance assimilation in LAMs at cloud-resolving resolutions has received limited attention so far. Since 4D-Var systems struggle with accurate estimates of the model background error and the capacity of the models to simulate clouds, convection-permitting simulations with these systems are challenging and require a thorough adjustment of the modelling and DA system. Especially in the case of a cloud-free model background when clouds have to be entirely generated, the 4D-Var approach reaches its limits as a result of the unknown formulation of a balanced B-matrix for cloud parameters. This is less critical for EnKFs which would draw more attention to members already containing clouds. EnKFs are thus more robust and allow to focus more directly on the assimilation of cloud-affected radiances in combination with the general improvement of LAMs and forward operators. So far, to our knowledge, there is no peer-reviewed article that evaluates hybrid (meaning both variational and ensemble) DA methods for all-sky radiance assimilation with LAMs.

4 The assimilation of physical cloud properties

Observed radiances of geostationary meteorological satellites are routinely converted into various meteorological quantities, such as physical cloud properties. In this section we focus on the assimilation of cloud property retrievals since they are expected to have the largest impact on cloudiness forecasts. Physical cloud properties derived from geostationary satellite observations include cloud cover, cloud top pressure (CTP), cloud top height (CTH), cloud top temperature (CTT), liquid water path (LWP), ice water path (IWP), single-layer or double-layer cloud amount, effective cloud amount (ECA), cloud optical depth, phase and effective particle size (Bayler et al., 2000; Derrien and Le Gléau, 2005; Jones et al., 2013b; Minnis et al., 2008; Watts et al., 2011; Yucel et al., 2002). The goal of cloud property assimilation is to convert the satellite observations into vertical distributions of cloud water and ice for each model column (Yucel et al., 2002).

Cloud property assimilation can be advantageous compared to radiance assimilation. For example, most satellite-derived cloud properties can be directly compared to the properties derived by NWP models. This avoids the computationally costly and complex application of RTMs in the data assimilation procedures (Jones et al., 2013b) and makes the assimilation process more independent of a given satellite.

4.1 Historical overview

In the last two decades, various approaches aimed at deriving atmospheric analyses for limited-area models with more realistic cloud presence estimations, using geostationary satellite observations. The first works on this subject appeared in the 1990s, e.g. with the works of (Lipton and Vonder Haar 1990a,b). They compared several analysis methods using retrievals of atmospheric temperature and water vapour mixing ratio profiles and surface temperatures, retrieved by the VISSR (Visible and Infrared Spin Scan Radiometer) Atmospheric Sounder (VAS) on GOES and assimilated the observations using a model first-guess of the RAMS model. The applicability of the method was proven in a two-dimensional simulation of a vertical cross section in a mountainous region (Lipton and Vonder Haar, 1990b) and a summertime case study (Lipton and Vonder Haar, 1990a).

Afterwards, studies using cloud shading retrievals were performed. Lipton (1993) and McNider et al. (1995) made use of GOES visible observations in cloud shading assimilation experiments where they analysed the impacts of the modified surface temperature due to cloud shading on the planetary boundary layer and cloud development. The method of McNider et al. (1995) was later used by several other authors for land surface and air quality related experiments.

Also in the 1990s, Macpherson et al. (1996) applied the DA system MOPS (Moisture Observation Preprocessing System) and the UKMO (UK Met Office) mesoscale model, testing the assimilation of Meteosat IR imagery together with other sources of observations. The observations were used to generate a three-dimensional analysis of cloud fraction that has been converted into synthetic humidity profiles that are assimilated the same way as radiosondes. The concept of generating a three-dimensional cloud analysis from several observation sources had also been applied operationally with the limited-area model NAE (North Atlantic/European) using a 4D-Var DA system (Renshaw and Francis, 2011; Taylor et al., 2008).

Another often-cited cloud analysis scheme that makes use of several sources of observations is the ARPS (Advanced Regional Prediction System) Data Analysis System (ADAS). Souto et al. (2003) present a historical overview of the development of ADAS, whose cloud initialization procedure is an advanced version of NOAA's (National Oceanic and Atmospheric Administration) LAPS (Local Analysis and Prediction System) system (described by Albers et al., 1996). Numerous physical cloud properties are implemented in the analysis package, which enables the determination of a three-dimensional cloud and precipitation analysis.

4.2 Modern methods

The historical overview shows that many early studies on cloud property assimilation are still relevant since the concepts are often transferred to new models. Common conceptions and difficulties of state-of-the-art methods are examined in the following, and particularly important works are highlighted.

4.2.1 Handling the four possible clear-cloudy cases

As mentioned earlier, four cases can be distinguished in all-sky DA, depending on whether cloud presence is satellite-observed (yes/no) and model-simulated (yes/no). Several recent studies considered these four cases and designed the cloud analysis scheme in a way that it can handle each case. Evidently, the case in which clouds are observed by the satellite but not simulated by the model is the most difficult one since the complete three-dimensional cloud characterisation has to be created in the model. Generally, cloud property assimilation offers more possibilities to improve the cloud analysis than radiance assimilation, since it allows a more direct and distinct modification of modelled cloud fields.

Yucel et al. (2002) developed an innovative cloud analysis scheme for the RAMS model that handles the four cases. The scheme makes use of GOES VIS imager derived estimates of the vertically integrated cloud water/ice. The critical case in which clouds are not simulated by the model but observed by the satellite is solved by incrementally increasing the whole-column mass of cloud water until it equals the satellite observation. Positive impacts of this cloud injection procedure on short-term forecasts of downward surface shortwave and long-wave radiation and cloud cover are found. A major disadvantage of the method is that it is based on VIS observations and thus not suitable for night-time simulations. Yucel et al. (2003) accounted for this by including IR derived cloud-top BT and height observations in the cloud injection algorithm. The improved method was tested in a case study with the fifth-generation Pennsylvania State University–National Center for Atmospheric Research (PSU–NCAR) Mesoscale Model (MM5) at 4 km grid spacing. A positive impact on short-term forecasts of downward surface solar irradiance and precipitation can be found. The biggest problem is that this positive impact rapidly decreases with increasing forecast lead time due to the mismatch between the updated model cloud cover and the unchanged vertical wind speed field. The problem of finding a consistent atmospheric state in the cloud analysis scheme has been tackled in some studies which are mentioned in the next subsection.

4.2.2 Assimilating cloud-top information

As in the works of Yucel et al. (2002, 2003), in many recently developed cloud property assimilation methods that have been applied to diverse LAMs the focus is mostly set on the assimilation of cloud-top information, e.g. cloud top temperature or pressure/height (de Haan and van der Veen, 2014; Guidard et al., 2006; Mathiesen et al., 2013; Renshaw and Francis, 2011; Schomburg et al., 2014; Taylor et al., 2008; van der Veen, 2013; White et al., 2018), since optical and thermal sensors are not able to directly capture information inside clouds. As satellite-derived cloud properties may have large errors, all methods have in common that the vertical position, extent, and number of cloud layers may not represent the truth. Some authors make use of other sources of observations (e.g. cloud base height or radiosondes) to better account for this limitation. Using additional observations is obvious in regions where several types of observations and a dense ground-based observation network are available. Nevertheless, this means that the respective methods are not globally applicable. In regions where geostationary satellites are the only considerable source of observations, more sophisticated methods to derive the vertical properties of clouds are needed.

One technique for the determination of the cloud-top height of the modelled clouds has been applied by several authors: In the DA methods of Yucel et al. (2003), Guidard et al. (2006), Mathiesen et al. (2013) and van der Veen (2013) the CTH is defined by the model layer whose temperature equals the satellite-derived CTT. This is a suitable approach since satellite-derived cloud-top information are rather accurate in the presence of optically-thick clouds and no additional information than the satellite observation is necessary. The shortcoming of this method is that it implies that the simulated vertical temperature profile is correct, which is not necessarily the case. Schomburg et al. (2014) use a different approach to determine the model cloud top and find a compromise between observation and model. In their approach the layer that is at the same time close to the observation and close to saturation is found by minimising a cost function. Since ensemble DA is used in their study, the ensemble members that are closer to the observation get a higher weight. Further approaches are imaginable to optimize the CTH assignment in the cloud analysis. For example, future methods might consider uncertainty information about CTH provided by an ensemble, considering all ensemble members.

4.2.3 The modification of vertical profiles

A common technique to initialise clouds is the direct modification of modelled profiles and fields according to the observed retrievals, e.g. profiles of humidity or water vapour, temperature and/or liquid/ice water content (Mathiesen et al., 2013; van der Veen, 2013; Yucel et al., 2002). The technique is risky since it might introduce numerical instability. That is because the entirety of atmospheric fields is not coherent anymore after the cloud analysis – A problem which can be reduced by horizontal and vertical smoothing (Mathiesen et al., 2013) or digital filtering (van der Veen, 2013). This circumstance shows that cloud property assimilation is more experimental than radiance assimilation. Most cloud property assimilation methods focus on vertical columns at the analysis time rather than including the temporal and three-dimensional evolution of cloud properties. This is another major general point of criticism that should be approached with greater detail by future methods. Some methods which are oriented towards that direction are discussed in Subsection 4.2.7.

4.2.4 Impacts on the wind field analysis

As mentioned before, a major conceptual difficulty of cloud property assimilation is that the focus is often exclusively set on cloud-related atmospheric parameters like humidity, without changing the initial three-dimensional wind field of the model (Guidard et al., 2006; Lauwaet et al., 2011; Mathiesen et al., 2013; Taylor et al., 2008; van der Veen, 2013; Yucel et al., 2002). Hence, the cloud analysis might be more accurate after the assimilation but the short-term forecast does not necessarily improve due to the unsuitable wind field. It can be assumed that this problem becomes more important with increasing horizontal resolution and at cloud-resolving scales. This circumstance has not yet been analysed in peer-reviewed literature. Introducing a cloud into the analysis where there was none before might subsequently change the dynamic fields (e.g. the wind field). Therefore, Chen et al. (2015) suggest to analyse the interactions between cloud microphysics and the model dynamics in order to further enhance cloud analysis schemes. A nudging approach which tackles the problem entirely from the dynamical point of view has been tested by White et al. (2018). In their method that has been applied to WRF, CTT and cloud albedo observations are used to modify the vertical velocity and divergence fields of the WRF analysis. The changes of vertical velocity have a direct impact on convection and thus the generation and dissipation of clouds. Nevertheless, since a purely dynamic approach is used, this method is not capable of considering the vertical cloud structure and cloud type or multi-layered clouds. Future cloud analysis methods based on cloud products should take account of the dynamical response of an “injected” cloud analysis.

Wind field adjustments could be provided from a different observing system such as radar, atmospheric motion vectors (AMVs) or cloud motion vectors (CMVs). A review of the assimilation of these properties is beyond the scope of this paper. Nevertheless, to our knowledge geostationary-observed AMVs or CMVs have not yet been used within geostationary-observed cloud property assimilation schemes for LAMs. This is a potential future field of research.

4.2.5 Multi-layered cloud analyses and the use of multiple cloud properties

Cloud property assimilation methods generally manage to place clouds at the correct locations, according to the satellite observations, but not necessarily their true characteristics and vertical properties. For example, many methods do not favour the development of multi-layered clouds in the NWP model (Guidard et al., 2006; Kumar and Varma, 2016; Mathiesen et al., 2013; Taylor et al., 2008; van der Veen, 2013). The method presented by Bayler et al. (2000) is innovative since it allows multi-layered clouds in the cloud analysis, which is not the case for many later works. In the case that a low cloud exists in the model and the observed cloud top is considerably higher, the original cloud is left unchanged and an additional higher cloud layer is added. Besides GOES-derived CTP the method based on a successive corrections algorithm also uses an ECA product. The shortcoming of their algorithm is that it does not take into account the cloud type but only cloud presence. The principle of the method might be revived and improved by making use of multi-layered cloud products.

Integrating multi-layered cloud products to determine a cloud analysis is one potential strength of cloud property assimilation. Minnis et al. (2008) have developed multi-layered and nearly global cloud products derived from multiple geostationary satellites and named Global Geostationary Gridded Cloud (G3C) products. Chen et al. (2015, 2016), whose method is discussed in Section 4.2.7, are the only ones who made use of the G3C products in a LAM so far. However, they did not make use of multi-layer information. A sophisticated use of multi-layer cloud properties could open new opportunities for cloud property assimilation and should be considered in future methods.

Multi-layered clouds are explicitly excluded in a cloud analysis method for WRF named Cloud Data Assimilation (CLDDA) (Mathiesen et al., 2013). The method that aims at improving solar irradiance forecasts focusses on coastal stratocumulus clouds in California which are expected to have a rather stable thickness. It makes use of GOES-derived CTT and determines the cloud-base height using an empirical calculation. WRF-CLDDA has been further tested by Yang and Kleissl (2016) who applied CLDDA in combination with a preprocessing scheme that uses additional NWP input. WRF-CLDDA significantly improves short-term solar irradiance forecasts in California in cases with a strong influence of stratocumulus clouds in both studies. Schipper and Mathiesen (2015) adapted the cloud analysis scheme to the Meteosat-based MPEFs (Meteorological Products Extraction Facility) Optimal Cloud Analysis (OCA) product. They attest its positive impact on solar power forecasts in a comparably long evaluation time of eight months. In summary, CLDDA is a simple and easily adaptable cloud analysis scheme which might be further improved for multi-layer clouds and different cloud types and tested with cloud products of other satellites, in different geographical regions.

An innovative system that makes use of radiances from multiple polar-orbiting and geostationary satellites to detect multi-layer clouds and retrieve their vertical extent is the Multivariate Minimum Residual (MMR) scheme (Auligné 2014a,b; Descombes et al., 2014; Xu et al., 2015). The scheme derives the cloud fraction for each vertical model level using observed and model-derived radiances. It has been successfully applied to the global model of ECMWF (the Integrated Forecasting System (IFS)) and to WRF. The good performance of the system can especially be achieved thanks to the intensive use of polar-orbiting satellite observations with many channels. A comparison with the other methods and studies discussed in this paper which focus only on geostationary satellite observations, is therefore inappropriate here. Nevertheless, the ability of the system to derive a multi-layer cloud analysis is remarkable and the method will likely influence future developments in the field of cloud analysis determination, particularly concerning new geostationary satellites with more channels.

4.2.6 The use of multiple cloud products

Most recently developed cloud property assimilation methods use a relatively small selection of retrieved cloud properties, but not the majority of available properties at the same time to create an as complete cloud analysis as possible. The method of Lauwaet et al. (2011) for example is one of the rare methods that make use of cloud optical thickness, but no additional cloud properties. The focus on a specific choice of properties is due to the fact that the chosen ones have to be compatible with the model variables and the capabilities of the DA system. For example, Jones et al. (2013b) describe that assimilating both GOES cloud water path and cloud ice path is challenging for deep, multiphase clouds due to the detailed distinction of the cloud phase in the LAM and the binary distinction between liquid or ice of the satellite. Other factors like uncertainty treatment, quality control and computational efficiency also influence the choice of cloud properties to be used in the assimilation method (Errico et al., 2007a).

Besides, for certain regions of the earth the cloud products of multiple geostationary satellites over the same region might be used. Over the Indian Ocean and India for example, three geostationary satellites (INSAT-3D, Meteosat-8 and Kalpana) could currently be used in order to derive a comprehensive cloud analysis.

4.2.7 Variational and EnKF methods

Many of the previously mentioned publications more or less forcefully inject or remove clouds in the LAM analysis for deterministic forecasts and thus constitute computationally fast alternatives to variational or EnKF methods. Besides these developments, a few authors focus on the development of observation operators for variational or EnKF DA systems that make use of retrieved cloud properties.

One example for cloud property assimilation with an EnKF system at the convective scale (2.8 km grid spacing) is the work of Schomburg et al. (2014) who present a new method to assimilate SEVIRI-derived cloud mask, cloud classification and CTH information. The actual variables that are assimilated to the COSMO ensemble are derived pseudo observations of CTH and relative humidity. Tested for single-observation experiments, the method leads to improved profiles of cloud-related variables. Non-assimilated variables (e.g. temperature and wind) are modified through cross-correlations of the background ensemble. Besides the ideas in the previous sub-sections to further improve the methodology, an extension of the method to assimilate more than cloud-top information, e.g. multi-layer cloud properties, might be done in the future. Moreover, the method might be put to the test for convective summertime cases and the impact of the assimilation on the wind field might be analysed.

Jones et al. (2013b) are the first to assimilate cloud water path (CWP) at convection-permitting resolution (3 km grid spacing). A forward operator for the assimilation of CWP with an EnKF (WRF-DART) is evaluated in this work. At the same time the study focusses on cloud property assimilation with a LAM using an EnKF. The application of the new forward operator in a case with pronounced convection over the continental US shows an improved analysis of shortwave downward solar irradiance. Fig. 4 illustrates the impact that this kind of cloud property assimilation can have on the analysis. The CWP difference plots of conventional observation assimilation (CONV) and conventional plus CWP assimilation (PATH) reveal the ability of the method to both remove and create clouds in the LAM and thus correct for cloud location and extent. While variational radiance DA without the use of an ensemble has difficulty to produce entirely new model clouds (Fig. 3, Seaman et al., 2010), the assimilation of CWP with an EnKF proves to introduce new clouds effectively. Nevertheless, a thorough comparison of the two methods would require their application to the same weather situation. This would allow to examine the limits and differences between purely variational and purely ensemble-based DA as well as pure radiance and pure cloud property

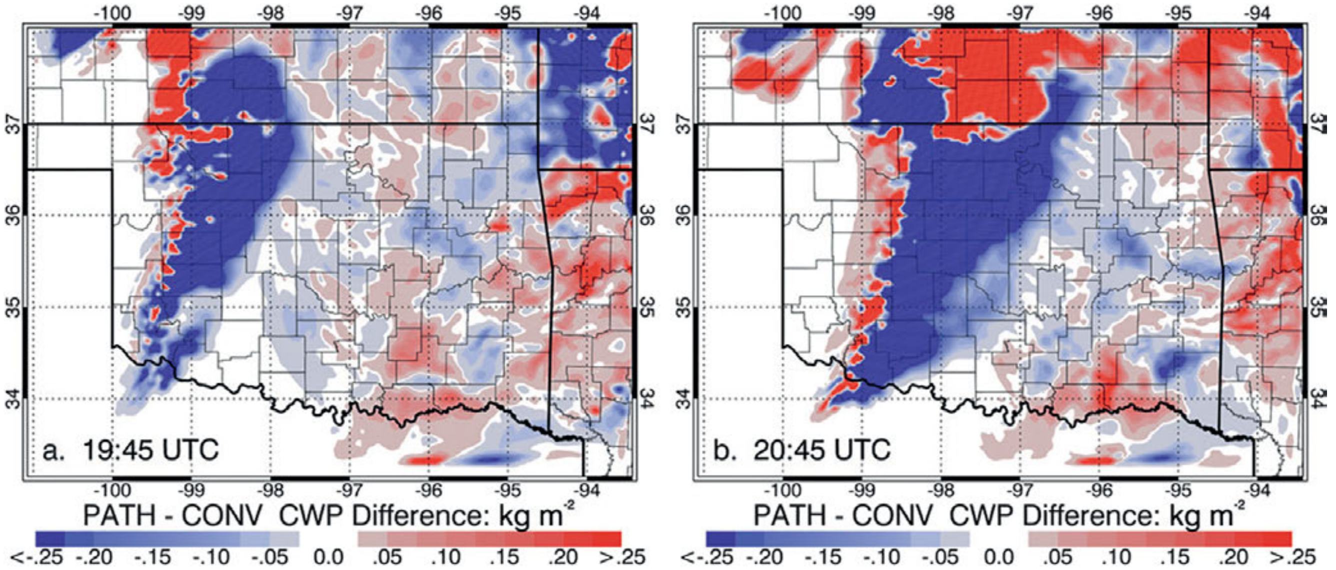

Figure 4: Difference in WRF 40 member ensemble mean CWP over Oklahoma and neighbouring states after assimilation of conventional observations (CONV) and GOES CWP observations in addition to the same conventional observations (PATH) at 1945 UTC (a) and 2045 UTC (b) on 10 May 2010. Blue regions indicate where PATH generates lower values of CWP than CONV whereas red regions indicate that PATH generates higher CWP values. Original figure reprinted from Jones et al. (2013b). ©American Meteorological Society. Used with permission.

assimilation. After the successful proof of concept and a follow-up case study by Jones et al. (2015) that includes radar DA in addition to the CWP DA, an evaluation over a longer period and under various conditions is needed to strengthen the verification results for this method.

CWP has also been assimilated by Chen et al. (2015, 2016) who are the first to do this with a 3D-Var system in a LAM. Their forward operator for cloud ice water path and cloud liquid water path for WRFDA has been tested over a 10 day period with a model grid spacing of 12 km (Chen et al., 2015). Positive impacts on diverse variables, especially in the lower stratosphere are found. A subsequent study investigated the performance of the method in combination with different microphysics schemes with a 12 km/4 km two-way nest setup (Chen et al., 2016). The authors stress that in order to further improve cloud property assimilation with a 3D-Var system, the background error covariance for hydrometeors should be anisotropic, inhomogeneous and flow-dependent. This could be achieved with a hybrid DA method using background information provided by an ensemble. The experiments of Jones et al. (2013b, 2015) and Chen et al. (2015, 2016) for CWP assimilation might be extended to the use of multi-layer cloud information. Besides, the authors list several ideas to further improve the forward operators. Future methods might take up these examples and try to make better use of multiple derived cloud properties and newly available cloud properties (for example from GOES-R, Himawari-8 and Meteosat Third Generation) to more accurately map the observed cloud situation into the LAM.

An innovative work that performs rainfall retrieval assimilation with a 4D-Var system (WRFDA) is presented by Kumar and Varma (2016). They are also the first to our knowledge to assimilate a geostationary satellite-based rainfall product (INSAT-3D Hydro-Estimator rainfall) with a LAM. Assimilating rainfall with 4D-Var is problematic since precipitation rate errors are not normally distributed. The advantage is that there is no need to develop a new sophisticated observation operator for the satellite product as modern 4D-Var systems are already able to assimilate conventional rainfall observations. The method has been tested for a summer monsoon case study and proves to improve short-term rainfall forecasts. The authors suggest that an improved model background would lead to better results. One reason for this, among others, is that less observations would be rejected in quality control when the difference to the first guess is too large. An idea that has not been exploited so far is to make use of the high temporal availability of cloud property observations in 4D-Var over the duration of the assimilation window. The works of Kumar and Varma (2016) and Chen et al. (2015, 2016) can be considered fundamental for the achievement of this goal. Future studies can build upon this work and aim at making a more sophisticated use of modern cloud products in 4D-Var DA.

4.2.8 Concluding remarks

In summary, there is a huge variety of cloud property assimilation methods that all have their specific strengths and deficits. Two general strategies can be distinguished: "forced" cloud injection mostly via the modification of cloud-related variables in vertical columns and computationally much more expensive variational or ensemble-based methods that are technically closer to radiance assimilation. This variety, together with the fact that the method always has to be tailored to the applied model, makes it practically impossible to determine the most effective method. Comparisons of different models and methods under identical conditions would be necessary in order to measure the individual impact of the methods. This, in turn, would require standardised evaluation procedures for cloud property assimilation.

5 Discussion

After the critical overview of the particularities of radiance and cloud property assimilation methods in the previous sections, this section discusses comprehensive aspects of geostationary satellite data assimilation in LAMs for short-term cloudiness forecasting. Moreover, the differences between satellite DA in research and the operational application and future perspectives are discussed.

Bauer et al. (2011a) and Vukicevic et al. (2006) remark that NWP models produce spatial and statistical averages of clouds while the information content about clouds provided by satellite observations is of a different nature. This circumstance explains the complexity of determining four-dimensional cloud analyses and why many authors focus on moisture analyses rather than the adaptation of variables linked with hydrometeors. It is this issue on the side of the weather models and the complete exploitation of available cloud observations on the side of remote sensing which still offer much room for improvements.

Several studies in both fields of radiance and cloud property assimilation raise the crucial question how long the assimilated information provided by satellite observations is influential in the model forecast. The answer to this question illustrates the impact of satellite data assimilation, which can be considerably large. Several works (Bauer et al., 2011a,b; Bayler et al., 2000) hypothesize that the additional information by cloud-affected satellite data vanishes after the first few hours of simulation. Yucel et al. (2003) assume that this is because of potential discrepancies between the unchanged dynamic field and the updated cloud analysis. While a loss of cloud information within the first 24 hours is found in several publications (Chen et al., 2015, 2016; Lipton and Modica, 1999; Singh et al., 2010; Taylor et al., 2008), there are also multiple examples in which regional forecasts improve for lead times beyond 24 hours thanks to geostationary satellite data assimilation (van der Veen, 2013; Zapotocny et al., 2005; Zou et al., 2011). This proves that the impact can potentially be large and that further improvement of the methods might lead to longer lasting impacts. Nevertheless, the predictability of clouds depends on their type. Due to their limited predictability, convective clouds cannot be expected to display long impact durations when assimilated. Hohenegger and Schär, (2007) demonstrate that the high degree of nonlinearity in cloud-resolving models limits predictability at cloud-resolving scales.

Many studies evaluate the functionality of their new developments in case studies, which is probably due to limited computational capacities, particularly regarding ensemble-based methods. Apart from the satellite DA method, the configuration and tuning of the model also plays a big role regarding the impact duration, ensuring that the injected clouds do not directly disappear after the initialisation. For example, Chen et al. (2016) found that among several tested microphysics schemes the use of the WRF Double Moment 6-class (WDM6) scheme leads to the longest impact duration in their case. In general, more studies should evaluate the applied DA methods in connection with the model configuration in order to optimise the forecast impact duration. The LAM domain size certainly plays an important role regarding the impact duration, since the information given from the global to the limited-area model via the lateral boundary conditions highly influences and "washes out" the initial information in the regional domain at some point (Gustafsson et al., 2018). We suppose that this effect becomes smaller the larger the domain is, as some studies mentioned in the previous sections indicate. This is to be validated in detail by future studies.

Moreover, to our knowledge no peer-reviewed paper compares the impact duration of radiance and cloud property assimilation in LAMs. Both strategies are able to produce positive impacts but a definite decision regarding which one has the larger impact on short-term forecasts of clouds cannot be made at this time.

The majority of the studies focuses on the assimilation of few channels or cloud properties in order to achieve a positive impact. Thus, the entirety of available channels and cloud properties is still far from being exploited. This is because for a respective NWP and DA system, diverse issues like bias correction, quality control or error estimation have to be thoroughly handled before extending the number of utilised observations.

Moreover, physical cloud property DA is linked to the errors induced by cloud property retrieval algorithms, additionally to the error of the observed radiances. Since the initial observations are radiances, the information content about cloud and precipitation physics is limited (Errico et al., 2007b) and sometimes biased, especially when optically thin clouds create a mixed signal of radiation from the background and the cloud (Polkinghorne and Vukicevic, 2011). Such problems can be overcome by using NWP output to correct the cloud information. Therefore, in the data assimilation scheme of the same model, the same background information is used twice, which might lead to suboptimal analyses (Migliorini et al., 2008). The use of NWP background information in retrieval algorithms is thus a major shortcoming of cloud retrieval assimilation.

According to the majority of studies in Section 3, radiance assimilation especially improves upper-tropospheric moisture and cloud features in situations with "smooth" cloud systems like stratus clouds, but has less attested impact on convective clouds and their evolution. Cloud property assimilation methods allow to inject clouds more radically and thus have more potential to improve short-term forecasts in convective situations. Unfortunately, only a few cloud property assimilation studies consider ensembles. Important uncertainty information might be derived from the ensemble and further improve the methods. In this regard, the implementation of stochastic elements in parameterization schemes might provide enhanced information about the ensemble spread (Bengtsson et al., 2013). Furthermore, there is a lack of extensive 4D-Var studies of radiance assimilation with the widely-applied WRF model. These could be compared to the diverse ensemble-based radiance DA developments.

For these various reasons, the realisation of long-term comparison studies is desirable in order to fully evaluate the potential of the innovations and the forecast impact duration. Moreover, long-term studies of both radiance and cloud property assimilation methods with the same model would allow a more thorough assessment of the impact of the approaches with a limited influence of the model configuration and tuning. The complexity of cloud property assimilation methods is diverse (de Haan and van der Veen, 2014; Schomburg et al., 2014; White et al., 2018). Some methods are tailored for certain cloud types (Mathiesen et al., 2013) or cloud properties (Jones et al., 2013b; Kumar and Varma, 2016). Comparing the performance of different methods under similar conditions would reveal whether more complex or computationally expensive methods perform better than simpler methods. Nevertheless, the conduction of such studies requires a common and globally applicable verification framework to assess the impact of the different methods. Such a framework does not currently exist and every author group uses different data for cloud analysis and forecast evaluation, like polar-orbiting satellite observations, reanalyses, radar, irradiance or other ground-based observations.

The evolution of clouds is far from being exhaustively considered in the process of determining a cloud analysis in both radiance and cloud property assimilation. Smoothing data assimilation methods (van Leeuwen, 2001) aim at improving the temporal consistency and have not yet been extensively applied to the diverse cloud analysis issues. The shortcoming is that they are computationally expensive and require four dimensional adjoint models (Vukicevic et al., 2006). Nevertheless, it is desirable for both radiance and cloud property assimilation to better account for observed cloud evolution in the assimilation process.

Differently than in research, operational activities require a definite choice of the applied data assimilation procedure. Furthermore, while the impact of different satellite data assimilation methods on cloudiness forecasts can be investigated in detail in a research context, the operational context requires decisions to be made. The choice of an operational assimilation method always depends on the chosen model and its available data assimilation capabilities. The method has to be customised for the applied NWP model and its state or moisture variables. It is rather the entirety of available observations of all types that is considered in an operational context as well as the improvement of scores of all forecasted variables in the entire three-dimensional model domain. By trying to assimilate a maximum of available observations, the borders between radiance assimilation and cloud property assimilation become blurred. A comparison of research and operational activities and achievements reveals that there is a transition going on in operational cloud analysis determination and short-term forecasting of cloud-related parameters: Clear-sky radiance assimilation using cloud mask/cloud type classifications and the assimilation of simple cloud information like cloud-top temperature can be considered the operational standard with LAMs (Gustafsson et al., 2018). This is now being updated by a more sophisticated assimilation of elaborated cloud products and all-sky radiances.

Several systems – especially operational ones – use multiple observations to make an exhaustive three-dimensional cloud analysis. Previously mentioned examples are the systems or models ARPS, LAPS, MMR and NAE. Two operational state-of-the-art systems that have not been mentioned yet are the Rapid Refresh (RAP) model and the AROME (Application de la Recherche à l'Opérationnel à Méso-Échelle) model.

For short-term forecasting with a forecast length of 18 hours NCEP operationally runs RAP, which replaced the Rapid Update Cycle (RUC) model in 2012 (NOAA NCEI 2017). Rapid Refresh is an assimilation/modelling system, based on RUC, WRF and GSI (Benjamin et al., 2016b) that uses a hybrid 3D-Var/Ensemble data assimilation approach. GOES-derived cloud-top height temperature are incorporated as it had already been the case in the RUC system (Benjamin et al., 2004). Hu et al. (2007) and Weygandt et al. (2006) provide further information about the cloud analysis scheme of RUC/RAP. Since August 2016 the assimilation system also integrates GOES radiances (Benjamin et al., 2016a).

In the AROME model, operated by Météo-France, SEVIRI clear-sky radiances are selected using a cloud type product and assimilated with a 3D-Var system (Guidard and Fourrié, 2010) in an hourly assimilation cycle (Brousseau et al., 2016). The model is highly resolved with a grid spacing of down to 1.3 km and the impact of using a higher resolution on convective events in conjunction with DA has been analysed by the latter authors.

Unfortunately, detailed evaluations of the impact of only geostationary satellite observations in such operational systems are usually not available and the systems are tailor-made for certain geographical regions and the respective observations.

6 Conclusions

In this paper we present a comprehensive review about the assimilation of atmospheric observations made by geostationary meteorological satellites in limited-area models with the goal of improving short-term forecasts of cloud-related parameters.

Two fundamentally different approaches can be distinguished: sensor-observed radiance or brightness temperature assimilation and retrieved cloud property assimilation. The question of which assimilation strategy is the most suitable one for a certain application depends on several factors: the available computational capacity, the requirements of the performed simulations in terms of forecasted variables and computational cost and the sophistication of the NWP model with its associated DA system. Generally, cloud property assimilation is rather targeting computationally spare and frequently updated forecasts of short-term cloud evolution, while radiance assimilation is usually applied in connection with computationally costly variational or ensemble-based DA systems which are designed to incorporate various sources of observations for short-term and long-term forecasts of not only cloud-related parameters. It is thus primarily a matter of lead time and application which technique should be focussed on, while in the end both methods aim at finding optimal NWP initial conditions.

The review shows that in both fields, radiance and cloud property assimilation, numerous improvements have been made recently. All radiance assimilation studies have found a positive impact on analyses and/or forecasts of cloud-related parameters through assimilation of geostationary satellite radiances. Reduced errors are mainly found for moisture and temperature fields especially in the mid-to-upper troposphere and for cloud-related parameters (e.g. cloud mask or precipitation). Although clear-sky radiance assimilation in LAMs still can be improved, many studies directly aim at assimilating cloud-affected radiances to maximise the use of available observations. Nevertheless, even without considering cloud-affected radiances, clear-sky radiance assimilation has the potential to improve short-term regional-scale forecasts of cloud-related parameters. Compared to variational DA methods, ensemble-based DA has the advantage of providing flow-dependent information about the model background error that may be especially useful for all-sky radiance assimilation. This matter has not yet been exploited using hybrid DA methods in LAMs.

Cloud property assimilation methods also improve short-term cloud forecasts, while a quantitative comparison of their outcome is rather difficult due to the diversity of methods and retrievals and their evaluation in individual case studies. The complexity extends from rather simple methods that primarily modify model cloud-top properties like cloud-top temperature via methods that also try to take the dynamical fields into consideration up to computationally expensive variational/ensemble-based methods. The latter are the minority since a common objective of cloud property assimilation methods is the possibility to create as complete cloud analyses as possible without large computational efforts. Existing cloud property assimilation methods are often targeted for specific LAMs, geographical regions or synoptic conditions and often depend on additional observations than those provided by geostationary satellites. Little efforts have been made in order to design and evaluate cloud property assimilation methods for LAMs that are applicable anywhere in the world and that exploit geostationary retrievals without the necessity of involving further observation types. Moreover, vertical columns are considered in many methods rather than the three-dimensional evolution of cloud properties and the dynamical implications of modified cloud analyses are often neglected.

Many DA systems for LAMs, especially operational ones, are tailored for a certain geographical region and the assimilation of the specific observations that are available for that region. Such systems are not readily applicable to all locations or satellites. In order to evaluate the full potential of developed data assimilation methods using geostationary satellite observations and limited-area models, future developments should be tested with different limited-area models and satellites. With the target of providing more accurate cloudiness forecasts for demanding applications like solar power forecasting that require frequently updated short-term forecasts, cloud analysis methods should be evaluated on a long-term basis, for different geographical regions (e.g. mid-latitudes and the tropics), and for locations where other observations are sparse in order to make the best use of geostationary satellites.

Several publications that are referred to in this paper tackle diverse issues of cloud DA by further developing the assimilation strategies and methods. Nevertheless, only some of the publications evaluate the methods at convection-permitting scales. The potential advantage of limited-area models of providing high-resolution forecasts of clouds in combination with geostationary satellite DA is thus unexploited so far.

The ability of a data assimilation system to assimilate cloudy observations is closely tied to the ability of the LAM to produce realistic clouds in the model background. Improvements of model parameterisation schemes, e.g. by introducing stochastic elements, are thus expected to positively influence DA performance and keep increments small. Likewise, improved radiative transfer models directly impact satellite DA performance and facilitates the assimilation of observations from new satellites.

New generations of geostationary satellites like Himawari-8, MTG and GOES-R bring more channels and higher temporal and spatial resolution. This imposes new challenges and brings more opportunities for data assimilation methods and NWP. It should lead to an increased exchange between researcher communities and institutions in order to use the newly available observations as efficiently as possible with the diverse LAMs that exist.

This review shows that both the assimilation of radiances and cloud properties in regional NWP offer great potential for short-term forecasting of cloudiness. The reason is that the topic comes along with diverse problems and challenges to be overcome, e.g. the choice of satellite channels or retrieved cloud properties and their optimal processing, the non-linearity of cloud processes, observation quality control, bias correction and subsampling, cloud classification and localisation, observation and background error estimation, computational efficiency, domain size, domain location and grid spacing optimisation.

The future lies in combined approaches that make the best possible use of available observations, radiance and cloud property assimilation methods and hybrid data assimilation techniques. The optimal use of cloud-free and cloud-affected radiance assimilation as well as available derived cloud properties will lead to more accurate cloud analyses and short-term cloudiness forecasts.

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